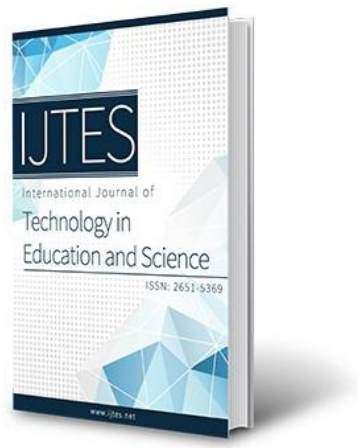

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To cite this article:

Keyhan, J. (2025). Designing a model for an AI-based intelligent assistant for personalized learning in higher education. *International Journal of Technology in Education and Science (IJTES), 9*(2), 255-269. https://doi.org/10.46328/ijtes.616

International Journal of Technology in Education and Science

2025, Vol. 9, No. 2, 255-269 https://doi.org/10.46328/ijtes.616

Designing a Model for an AI-Based Intelligent Assistant for Personalized Learning in Higher Education

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Article Info

Article History

Received:
18 November 2024

Accepted:
18 May 2025

Keywords

AI-based assistant
Artificial intelligence
Personalized learning
Higher education

Abstract

In recent years, remarkable advancements in artificial intelligence technology have created new opportunities for transforming educational systems and enhancing student learning. This study focuses on designing a model for an AI-based intelligent assistant to provide a personalized learning experience in higher education. A qualitative approach and grounded theory strategy were used to conduct the research. The study population included all experts, professors, and senior managers in the fields of educational sciences and software engineering in higher education, with 21 individuals selected through purposive sampling and theoretical strategy for interviews. Semi-structured interviews were employed as the research tool. For qualitative data analysis, open, axial, and selective coding methods were utilized. The study results indicated that data analysis, artificial intelligence and adaptive learning, machine learning and modeling, assessment and feedback systems, support and counseling, educational technologies, and infrastructure were considered strategies for designing an AI-based intelligent assistant for personalized learning in higher education. It can be concluded that through the use of machine learning algorithms and natural language processing, the intelligent assistant will be capable of providing effective educational recommendations by collecting data on learners' performance, behavior, and preferences. The study also examines potential challenges and barriers in implementing such a system in educational environments and ultimately provides solutions to realize this model. The ultimate aim of this research is to improve learning quality and facilitate access to education using modern technologies.

Introduction

The landscape of higher education is undergoing a profound transformation influenced by the rapid advancements in digital technologies and the diverse, global needs of students. While traditional teaching methods remain effective in certain areas, they often fall short in providing personalized support and immediate feedback, especially in fields that require deep study, critical thinking, and analytical skills. These areas, encompassing topics like creativity, critical analysis, and social and cultural studies, become challenging for students without adequate support. This has driven increased interest in innovative solutions to enhance the learning experience and optimize educational outcomes in these domains (Radford et al., 2022).

Artificial intelligence (AI) and natural language processing (NLP) are promising technologies with the potential to transform the landscape of higher education. These technologies have been applied across various fields, including environmental science, healthcare, and crisis management, to improve data and information communication. For example, techniques like word embedding are used in critical situations to facilitate information retrieval (Anderson, 2023). The emergence of AI-powered tools, such as virtual educational assistants, provides a unique opportunity to bridge traditional teaching methods with the evolving needs of students. These virtual educational assistants can offer personalized support, instant feedback, and adaptive learning experiences, ultimately enhancing student engagement, satisfaction, and learning outcomes (Thompson, 2022).

Moreover, AI-based solutions are not limited to text. Advanced deep learning models are employed in generating synthetic images, augmenting visual data, and analyzing images. These models can be valuable in fields such as programming, mathematics, statistics, and even visual inputs (Georgia, 2024). With AI, NLP, and virtual educational assistants, codes, mathematical equations, and statistical models can be interpreted and useful feedback provided. Additionally, these assistants can process and respond to visual inputs like charts, tables, images, videos, and maps, expanding their application across diverse educational fields (Miller, 2020).

Web technologies also play a crucial role in integrating large language models and chatbots with modern engineering education. These technologies assist in areas such as advanced modeling and analytical tools, providing real-time processing and visualizing complex data to help students understand and manipulate advanced models. When it comes to programming libraries, web technologies enable immediate guidance, code suggestions, and troubleshooting advice, helping engineering students use these libraries more effectively (Prashnai, 2023).

The convergence of large language models, chatbots, and web platforms is redefining educational methodologies. In this context, web-based chatbots powered by large language models can simulate ethical dilemmas, aid in reflection, and provide immediate feedback, ensuring that students excel not only in technical skills but also adhere to the ethical standards of their professions. However, the effectiveness of virtual educational assistants in supporting diverse student learning needs in these various domains still requires further examination.This study introduces a new web-based framework for an AI-powered virtual learning assistant designed to enhance student learning in educational sciences. Leveraging JavaScript support, this AI uses artificial intelligence and natural language processing to create an engaging, interactive platform. This platform aims to reduce students' cognitive load, provide easy access to information, and facilitate knowledge assessment. The AI's capabilities include understanding and responding to student questions, generating quizzes and flashcards, and offering personalized support based on individual learning needs and styles. By introducing this innovative framework, this article contributes to ongoing efforts to integrate AI-driven technologies and web systems in education, with the goal of improving the effectiveness of educational support in the educational sciences field.

The potential impact of this article is particularly significant, as it can provide valuable insights into the design, implementation, and evaluation of AI-based virtual assistants in higher education. The findings from this study can aid in developing innovative educational tools that have the potential to dramatically improve learning outcomes, engagement, and student satisfaction. Additionally, this article can contribute to the broader discourse on integrating AI and natural language processing in education, offering empirical evidence on the effectiveness of these technologies in enhancing teaching and learning methods. Consequently, this research not only advances scientific knowledge in this area but also has the potential to improve educational processes and enhance learning quality across various educational levels.

In this regard, this study seeks to explore the potential of AI-based virtual assistants in education by addressing the following questions: How can AI-based virtual assistants be effectively integrated with learning management systems to provide real-time, personalized learning support? What types of educational content and data are most effective for adapting materials using AI to meet students' needs? How can AI-based virtual assistants be designed to support different learning styles, particularly in areas requiring textual learning and critical analysis? What challenges arise in implementing AI-based virtual assistants in higher education, and how can these challenges be addressed?

Recent advancements in artificial intelligence (AI) are revolutionizing education, especially through the development of AI-based intelligent assistants that provide personalized learning experiences in higher education. These assistants leverage machine learning (ML) and natural language processing (NLP) to analyze student data and deliver tailored recommendations, which improve engagement by addressing individual learning preferences and needs. Adaptive learning models, central to these AI systems, allow for dynamic content adjustments and personalized feedback, enhancing student learning outcomes and retention. Furthermore, AI-driven assessment and support mechanisms enable real-time feedback and counseling, benefiting both students and educators. Research shows that such systems not only help identify students’ learning gaps but also enhance teaching effectiveness. However, the implementation of AI in higher education faces challenges, including data privacy concerns, ethical considerations, and the need for substantial infrastructural investment and technical expertise. Despite these barriers, ongoing research suggests that with adequate support and ethical guidelines, AI-based intelligent assistants have the potential to improve accessibility and quality of learning, ultimately creating more inclusive and effective educational environments.

Method

This study is an applied-developmental research project aimed at designing an AI-based intelligent assistant model for personalized learning in higher education. Employing a qualitative approach, the research utilizes the grounded theory strategy. The choice of this methodology reflects the unique characteristics of Iran's higher education system in terms of its management, structure, culture, and overall environment. This system’s distinct context necessitates a tailored approach, as theoretical frameworks derived from research in other countries may not align with Iran’s specific educational landscape.

Grounded theory, as a qualitative strategy, was chosen to develop a coherent set of concepts, providing a comprehensive theoretical explanation of a central phenomenon—namely, the AI-based intelligent assistant for personalized learning in higher education. For data analysis, the Strauss and Corbin systematic approach was adopted, which is well-suited for systematically collecting and analyzing qualitative data through a structured, step-by-step process.The research field consisted of experts, professors, and senior administrators in the field of educational sciences in Tehran's higher education sector. To select participants, a purposive sampling method combined with theoretical sampling was used. Ultimately, 21 individuals participated in the interviews. Data collection continued until theoretical saturation was reached. Two main criteria guided the selection of experts: (a) expertise and experience in education as a scientific field, and (b) familiarity with the structure and practices of Iran's higher education system.

Interviews were conducted in person by one of the researchers and lasted an average of 50 minutes each. The general structure of the interviews included five sections: (1) demographic information of the interviewee, (2) time and date of the interview, (3) interview location, (4) background information on the interviewee, and (5) interviewer details. While a preliminary interview protocol was designed beforehand, the conversations were flexible, adapting based on responses and emerging themes during each interview. All interviews were recorded and fully transcribed. Additionally, some interviews were conducted via video or audio calls due to geographical distances.

Results

In this study, based on the theory of fundamental conceptualization, open coding and selective coding methods were used to analyze and interpret the findings. In the open coding phase, the initial codes extracted from the interviews (coding key points) were examined. In this phase, codes that referred to common themes were categorized, and concepts were formed. Then, through comparison and classification of these concepts, the main categories were identified.

Table 1. Demographic Factors

quantity	Sub-factors	Demographic Factors
5	Faculty Members of Software Engineering	"Job and Organizational Position
12	Faculty Members of Educational Management and Curriculum Planning	
3	Managers of Technology Incubators	
2	Less than 5 years	Work Experience
5	5 to to 10 years	
10	10 to 20 years	
3	More than 20 years	

In the axial coding phase, using the paradigmatic model, the main categories were related to sub-categories. This model helps identify the key elements of axial coding, such as causal conditions, the core phenomenon, intervening conditions, contextual factors, strategies, and consequences. Finally, through selective coding, and considering the relational patterns among categories, the research results were explained, and the final structure of the theory was developed.

In this study, semi-structured interviews were used as the data collection tool. To ensure the credibility of the data, the participant feedback method was utilized. Additionally, for reliability assessment using the test-retest method, three interviews from the conducted ones were selected. Each of these interviews was coded by the researcher in two rounds within a 14-day interval.

The results obtained from these coding are presented below:

Table 2. Calculation of Test-Retest Reliability

Test-Retest Reliability (Percentage)	Number of Disagreed Codes	Number of Agreed Codes	Total Codes in Two Phases	Interviewee Code	Row
90%	12	58	128	4	1
90%	11	62	137	6	2
92%	10	52	112	9	3
95%	8	50	105	15	4
92%	41	222	482	total	

The results obtained from the interview reliability using the inter-coder agreement method are shown in Table 3.

Table 3. Calculation of Inter-Coder Reliability

Test-Retest Reliability (Percentage)	Number of Disagreed Codes	Number of Agreed Codes	Total Codes in Two Phases	Interviewee Code	Row
92%	14	61	132	2	1
91%	14	61	134	11	2
93%	10	52	111	12	3
90%	18	48	106	17	4
92%	56	222	483	total	

Qualitative Results

The data analysis in this study was based on three stages of open coding, axial coding, and selective coding, following the theory of Strauss and Corbin. In the open coding stage, the data were broken down into smaller components, compared, conceptualized, and categorized. This stage began with identifying concepts and eventually led to the discovery of categories. Concepts are mental labels that the researcher assigns to events, incidents, and phenomena, while categories are more abstract and general concepts derived from grouping the concepts. In this study, the analysis of data from 21 in-depth interviews in the open coding stage resulted in the identification of 328 open codes and 95 subcategories.

In the axial coding stage, the researcher establishes new relationships among the categories. This stage is carried out using a paradigmatic model that includes causal conditions, the central phenomenon, context, intervening conditions, strategies, and consequences. Causal conditions refer to events and factors that lead to the occurrence or development of a phenomenon. The central phenomenon is the event or incident that strategies are designed to control or manage and is considered the main focus of the process. Context refers to the environment and conditions in which the phenomenon occurs, while intervening conditions may facilitate or limit the strategies. Strategies include the actions and steps taken to control and manage the phenomenon, and finally, consequences are the results of the actions and steps taken in response to or managing the phenomenon.

In this study, the concepts, subcategories, and main categories were presented in response to the research questions. For example, in response to the first question, the central category of this study regarding the AI-based intelligent assistant for personalized learning in higher education included two main categories: "the performance of the intelligent assistant in personalized learning" and "key features of the intelligent assistant." These categories were identified and introduced.

Table 4: Main Category of the Model

Sample Conceptual Statements	Subcategories	**Main Category**
"The assistant must be able to customize curricula based on individual student needs."	Customization of learning	Performance of the intelligent assistant in personalized learning
"The presence of the intelligent assistant provides access to educational resources at any time."	24/7 support	
"This assistant must be able to analyze learning data and provide personalized feedback."	Analysis of learning data	
"The intelligent assistant can facilitate communication and create more interactions between students and professors."	Increased interaction between students and professors	
"This system should be able to create a space for group learning and student collaboration."	Facilitation of social learning	
"This assistant must support multiple languages to be usable for international students."	Multilingual support	Key features of the intelligent assistant
"The assistant must be able to provide users with accurate and reliable information."	Ensuring the quality of information	
"This system should be able to track the learning progress of each student accurately."	Tracking learning progress	

Table 5. Causal Conditions of the Model

Sample Conceptual Statements	Subcategories	**Main Category**
"The development of adaptive learning techniques allows us to customize learning based on individual student needs."	Development of adaptive learning techniques for customizing learning	Innovation in educational methods
"Focus on skill-based education enables students to progress based on their actual abilities."	Interest in competency-based education	
"The demand for lifelong learning requires flexible and adaptive teaching methods."	Growth in demand for adaptive education in lifelong learning	

Sample Conceptual Statements	Subcategories	**Main Category**
"Learning pathways must be designed in a way that allows students to choose and adapt according to their needs."	Need for more flexibility in learning pathways	
"The demand for AI-driven tutoring systems indicates a shift in educational approaches."	Growing demand for AI-driven tutoring systems	
"Pressure to create customized courses indicates that needs are changing."	Pressure to create customized courses	
"Rapid changes in the workplace require educational programs that match the job market."	Rapid changes in the work environment and job market needs	
"Predictive analytics can help identify students who need additional support."	Need for predictive analytics to predict academic success	Learning analysis and assessment
"The quality of feedback to students needs to be improved so they can learn more effectively."	Need to improve the quality of feedback to students	
"Assessment systems need to be continuously implemented to keep students' progress up to date."	Increasing need for continuous assessment systems	
"The growth of adaptive assessment systems shows a need for innovation in assessment methods."	Growth in the use of adaptive assessment systems	
"Personalized feedback can help students learn better and faster."	Need for personalized feedback tools	
"Assessment methods must be developed based on students' real skills."	Need to develop skill-based assessment methods	
"Precise learning data analysis can help improve learning quality."	Need for more accurate learning data analysis	
"The growth of online students shows a need for access to learning resources from anywhere."	Increase in the number of online and non-residential students	Support and educational services
"Hybrid learning environments require solutions that address diverse student needs."	Complexity of student needs in hybrid learning environments	
"Students with special needs must have access to appropriate support."	Need to support students with special needs	
"Faculty must deal with large amounts of data and students, which requires management tools."	Pressure on faculty to manage large numbers of students and data	
"Increased interactions between faculty and students can enhance learning effectiveness."	Demand for improved faculty-student interactions	
"Students must have quick access to learning resources to facilitate the learning process."	Need for quicker access to learning resources	
"Interactions among students need to be	Need to increase student	

Sample Conceptual Statements	Subcategories	**Main Category**
strengthened to facilitate group learning."	interactions	
"The growing demand for non-residential education indicates a shift in learning patterns."	Growing demand for online and non-residential education	
"By enhancing digital skills, students can easily use new technologies."	Need to enhance students' digital skills	Development of digital skills

Table 6. Intervening Conditions of the Model

Sample Conceptual Statements	Subcategories	**Main Category**
"Legal limitations on access to AI educational data must be considered."	Legal limitations on access to AI educational data	Legal and ethical challenges in AI
"Policies governing the ownership of data generated by AI need to be revised."	Policies governing the ownership of AI-generated data	
"Legal limitations on the use of collected data should be carefully examined."	Legal limitations on the use of collected data	
"Legal and ethical issues in using AI for assessments must be addressed."	Legal and ethical issues in using AI for assessments	
"Intervention algorithms can be used to prevent student academic decline."	Intervention algorithms to prevent academic decline	Learning analysis and assessment
"The quality of input educational data into AI systems impacts the accuracy of analysis results."	Quality of input educational data into AI systems	
"Risks associated with using incorrect or insufficient data can lead to serious problems."	Risks related to using incorrect or insufficient data	
"The complexity of developing neural network models requires expertise and adequate resources."	Complexity in developing neural network models	AI technology complexities
"Computational limitations for processing large educational data can hinder effective implementation."	Computational limitations for processing large educational data	
"The complexity of using AI technologies in educational environments may present challenges."	Complexity in using AI technologies in educational environments	
"The negative cultural and social impacts of using AI in education must be examined."	Negative cultural and social impacts of using AI in education	Social and cultural impacts
"The potential negative effects of using AI in human interactions have raised concerns."	Potential negative effects of AI on human interactions	
"Concerns related to scientific and ethical credibility in the use of technology must be addressed seriously."	Concerns regarding scientific and ethical credibility in technology	

Sample Conceptual Statements	Subcategories	**Main Category**
"The social and cultural impacts of using AI in universities can affect the educational process."	Social and cultural impacts of AI in universities	

Table 7. Strategies of the Model

Sample Conceptual Statements	Subcategories	**Main Category**
"Developing advanced learning analytics to examine educational data can improve the learning process."	Developing advanced learning analytics to examine educational data	Data analysis and review
"Using learning analytics to optimize educational processes can lead to improved learning effectiveness."	Using learning analytics to optimize educational processes	
"Implementing AI-based recommendation systems can personalize the learning experience."	Implementing AI-based recommendation systems	AI and adaptive learning
"Designing AI-based adaptive platforms can meet individual learning needs."	Designing AI-based adaptive platforms	
"Using AI to simulate educational scenarios can aid experiential learning."	Using AI to simulate educational scenarios	
"Developing AI-based adaptive self-learning systems can support students' self-directed learning."	Developing AI-based adaptive self-learning systems	
"Using machine learning to identify students' learning patterns can assist in analyzing their behavior."	Using machine learning to identify students' learning patterns	Machine learning and modeling
"Developing reinforcement learning models to improve learning can support more effective student learning."	Developing reinforcement learning models to improve learning	
"Leveraging deep learning to provide adaptive education can enhance the quality of teaching."	Leveraging deep learning to provide adaptive education	
"Using automated feedback systems for real-time assessment can help students improve their learning."	Using automated feedback systems for real-time assessment	Support and counseling
"Developing AI-driven grading systems for automatic assessment can improve the accuracy of evaluations."	Developing AI-driven grading systems for automatic assessment	
"Developing AI-driven mentorship programs for student guidance can improve academic outcomes."	Developing AI-driven mentorship programs for student guidance	Support and counseling
"Creating AI-based peer-assisted learning	Creating AI-based peer-assisted	

Sample Conceptual Statements	Subcategories	**Main Category**
systems can strengthen group interactions."	learning systems	
"Integrating AI tools with learning management systems can improve the efficiency of educational systems."	Integrating AI tools with learning management systems	Educational technologies and infrastructure
"Using big data to optimize the learning process can help identify effective patterns."	Using big data to optimize the learning process	
"Designing virtual assistants to help manage educational activities can reduce faculty workload."	Designing virtual assistants to help manage educational activities	
"Improving content personalization tools using AI algorithms can enrich the learning experience."	Improving content personalization tools using AI algorithms	
"Implementing AI-driven content generation systems can support the creation of more effective educational content."	Implementing AI-driven content generation systems	
"Using AI-driven adaptive testing systems can help assess students' skills more accurately."	Using AI-driven adaptive testing systems	

Table 8. Outcomes of the Model

Sample Conceptual Statements	Subcategories	**Main Category**
"Increasing the alignment of educational pathways with students' needs can contribute to more effective learning."	Increasing the alignment of educational pathways with students' needs	Innovation in learning and teaching
"Enhancing the personalized and adaptive learning experience allows students to optimize their learning."	Enhancing the personalized and adaptive learning experience	
"Strengthening students' self-learning capabilities can help them with independent learning."	Strengthening students' self-learning capabilities	
"Improving the accuracy in identifying students' academic strengths and weaknesses can contribute to better learning."	Improving the accuracy in identifying students' academic strengths and weaknesses	Data analysis and learning improvement
"Improving learning quality based on up-to-date data can lead to increased educational effectiveness."	Improving learning quality based on up-to-date data	
"Facilitating the analysis of educational data to predict future needs can contribute to better planning."	Facilitating the analysis of educational data to predict future needs	

Sample Conceptual Statements	Subcategories	**Main Category**
"Ongoing improvements in educational and assessment processes can lead to enhanced quality of education."	Ongoing improvements in educational and assessment processes	Development and enhancement of educational processes
"Increasing the efficiency and productivity of educational systems can contribute to providing better education."	Increasing the efficiency and productivity of educational systems	
"Reducing administrative and operational burdens on faculty allows them to focus more on teaching."	Reducing administrative and operational burdens on faculty	
"Facilitating access to customized educational content can support personalized learning."	Facilitating access to customized educational content	Technology and access to educational resources
"Reducing educational inequalities through access to smart technologies can improve educational conditions."	Reducing educational inequalities through access to smart technologies	
"Expanding AI-based learning opportunities can lead to enhanced learning experiences."	Expanding AI-based learning opportunities	
"Improving the quality of student-faculty interactions in educational environments can contribute to more effective learning."	Improving the quality of student-faculty interactions in educational environments	Interactions and collaborations
"Strengthening interdisciplinary and inter-institutional collaborations can lead to knowledge expansion and innovation."	Strengthening interdisciplinary and inter-institutional collaborations	
"Promoting academic integrity through intelligent monitoring can contribute to improved educational quality."	Promoting academic integrity through intelligent monitoring	Assessment and educational credibility
"Reducing human errors in the assessment process can increase the accuracy of evaluations."	Reducing human errors in the assessment process	
"Increasing the alignment of learning with individual students' needs can improve their academic outcomes."	Increasing the alignment of learning with individual students' needs	

Discussion

In the present era, with the rapid advancement of new technologies, the role of artificial intelligence (AI) in the field of education is becoming increasingly important. The design of an AI-based intelligent assistant model for personalized learning in higher education can create a revolutionary shift in learning and teaching methods. This model, designed to address the needs and expectations of students and professors, should be capable of effectively and efficiently utilizing educational resources and improving the learning experience. The intelligent assistant,

through analyzing student learning data, can identify their strengths and weaknesses, and suggest suitable educational content based on their individual needs. For example, if a student faces challenges in a particular course, the system can provide additional resources or related exercises to assist in their learning.
Thus, the objective of this research is to design an intelligent model for an AI-based assistant for personalized learning in higher education, which can help organizations and administrators achieve both individual and organizational goals. In this study, a comprehensive and process-based model has been presented using a systematic approach. Based on the research findings, the designed model includes 25 main categories and 95 sub-categories, which can aid in improving learning processes and enhancing the quality of education at higher levels.

The results of this research align with the findings of previous studies by Naman et al. (2023), Porshani et al. (2023), Saja et al. (2023), Li (2023), and Perkins et al. (2023). Moreover, in terms of strategies for designing an AI-based intelligent assistant for personalized learning, this research is consistent with the work of Naman et al. (2023), Porshani et al. (2023), and Perkins et al. (2023).This model can be highly effective and beneficial in enhancing the quality of education and improving the learning experience in the educational system. Given that human resources are the most crucial factor in the success or failure of educational programs, this intelligent assistant can serve as a key tool in improving learning and teaching processes. In educational systems that leverage this technology, the ability to offer personalized learning experiences tailored to each student's needs will be significantly enhanced.

The intelligent assistant must be designed in a way that effectively utilizes educational resources and responds to the specific needs of students. With the ability to analyze educational data, this technology can help identify students' strengths and weaknesses and optimize their individual learning paths accordingly. In light of these points, designing an AI-based intelligent assistant not only enhances the efficiency and effectiveness of educational processes but also helps reduce educational inequalities and improve the quality of interactions between students and instructors. Ultimately, the use of this intelligent assistant in higher education can lead to the continuous improvement of the learning experience and the enhancement of students' knowledge and skills, enabling them to approach their academic goals with greater confidence and to play a more impactful role in society in the future. Furthermore, based on the findings of this research, designing such a model not only supports and facilitates the learning process but also allows students to shape their learning paths according to their personal needs and interests. This intelligent assistant, using analyzed data and advanced algorithms, can help identify students' learning strengths and weaknesses and, based on this, recommend appropriate educational resources and activities. Additionally, by emphasizing the importance of integration and coordination between this model and existing educational infrastructure, it can be hoped that this system will contribute to the improvement of education quality and the enhancement of students' skills in higher education.

Conclusion

In conclusion, the design of an AI-based intelligent assistant model for personalized learning is a necessity in the higher education system. It can serve as an efficient tool to increase the effectiveness and efficacy of university-level education and to achieve the educational and research goals of educational institutions. This model not only supports the professional development of administrators and professors but can also lead to the creation of a unique learning experience tailored to the individual needs of each student.

Recommendations

Given the significant potential of AI-based intelligent assistants to enhance personalized learning in higher education, it is recommended that educational institutions invest in the development and integration of these technologies. To successfully implement AI-driven learning tools, institutions should focus on establishing robust data privacy policies to address ethical concerns, ensuring transparency and safeguarding students' personal information. Furthermore, investment in infrastructure and technical support, along with training for educators on effectively using these tools, will be essential. Collaboration between educators, software engineers, and AI experts should be prioritized to design systems that align with academic goals and support diverse learning needs. By embracing AI thoughtfully, higher education can enhance learning experiences, support student engagement, and improve educational outcomes, positioning institutions to meet the demands of modern, personalized education.

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