Personalized Recommendation System For Ideological And Political Education In Universities Using AI And Virtual Reality

Xu Jiang[1*], Pingping Long[2], and Zeng Wang[3]

[1,2,3] *College of Marxism, Chongqing Vocational and Technical University of Mechatronics. Chongqing 400000, Chongqing, China*
[1*] *Corresponding author. E-mail: xujiang13@outlook.com;*

Received: Dec. 26, 2025; Accepted: Mar. 27, 2026

Background: Ideological and Political Education (IPE)based on the traditional teaching model typically offered in universities, is not always effective in attracting contemporary students due to its lack of interactivity and personalization. Objective: The proposed study will assess the effectiveness of an AIVRbased hybrid personalized recommendation system for improving student engagement,satisfaction, and learning outcomes in IPE. Methods: 250 university students were used in a quantitative research design.AIbased models customized learning material,whereas VR simulations gave contextrich interactions.Preand postassessments were used to collect data, and Structural Equation Modeling(SEM)is employed in the study torigorously examine andvalidate the complexrelationshipsamong AIbased personalization,VR immersion,student engagement,satisfaction,and learning outcomes within the proposed educational framework. SEM enables simultaneous testing of both the measurement and structural models, ensuring that observed variables reliably represent their underlying constructs and that directional relationships between them are assessed.Using goodnessoffit indices and path coefficients,SEM assesses whether the conceptual model aligns with the empirical data and evaluates the mediating role of student engagement in the relationship between AIand VRsupported teaching methods and improved learning effectiveness.This comprehensive analytical approach strengthens the reliability of the findings and supports the theoretical contributions of the hybrid AIVR learning model. Findings: The combination of AI and VR made a big difference in terms of student engagement and learning.AIbased personalization and VR immersion increased motivation and knowledge retention,and student engagement mediated the relationship between teaching methods and outcomes Conclusion:The paper has demonstrated that AI and VR can transform IPE by providing more personalized, interactive,and immersive learning experiences and by serving as a better alternative to traditional learning.

Keywords: Artificial Intelligence, Virtual Reality, Ideological and Political Education, Personalization, Student Engagement, Learning Outcomes

http://dx.doi.org/10.6180/jase.202609_32.016

1. Introduction

University-level learning, IPE, is an aspect of learning that shapes the civic awareness, national identity, and social responsibility of the students [1]. As digital technologies develop rapidly, higher education institutions tend to consider new methods of enhancing the effectiveness of teaching and student interaction [2]. AI and VR are emerging as disruptive technologies that could provide personalized learning environments [3], interactive learning, and immersive learning [4]. Their incorporation provides fresh opportunities towards making IPE more dynamic, experience-based, and studentcentered [5].Nevertheless, conventional teaching approaches in this field are still, to a great degree, lecture-based, theoryoriented, and monotonous in presentation [6], [7]. These methods usually do not meet the needs, preferences, and motivational level of contemporary students, which is different in most cases [8]. Weak interactivity, absence of contextual situations, weak personalization, and low experience are some of the factors that lead to depleting interest and poor learning [9]. All these factors support the increasing relevance of adaptive, technology-based learning systems [10], which are able to examine the behavior of learners and deliver customized content to them, and expose them to real-life ideological and political situations [11].Despite the several technological interventions that have been presented, such as digital learning platforms, mobile apps, multimedia resources, and early AI-based recommendation tools [12], and they have several limitations. The models that are in use tend to offer low precision personalization, are based on fixed rules, and do not offer realtime adaptive feedback [13]. In the same spirit, VR-based applications are more likely to operate standalone, providing standalone simulations with no connection to custom learning programs [14], [15]. Consequently, these uncoordinated methods curtail the success of digital IPE, as they do not enable comprehensive, interactive education for learners. To address these issues, this paper proposes a combined AI- and VR-based personalized recommendation system for providing conceptual and political instruction at the college level. The suggested model will integrate machine learning-driven learner profiling, deep learning-driven content recommendation, and VR immersion to produce personalised, engaging, and context-rich learning journeys [16]. A validated questionnaire is used to assess the impacts of personalization, immersive experience, engagement, and satisfaction using 250 university students [17] [18]. The research study is expected to provide a unified, evidence-based, and immersive learning model that removes existing shortcomings and increases the learning experience and results among students [19].

Artificial intelligence has been widely applied in personalized recommendation systems, and virtual reality has been used to create immersive educational environments. However, most existing studies treat these technologies as independent solutions. Al-based systems mainly focus on adaptive content delivery and learner profiling, whereas VRbased platforms emphasize experiential simulations without integrating intelligent personalization mechanisms. Consequently, the potential synergy between personalized recommendation and immersive learning remains insufficiently explored in ideological and political education. To address this research gap, the present study proposes a hybrid AI-VR framework that integrates machine-learningdriven learner profiling with immersive virtual learning environments. By combining intelligent recommendation mechanisms with experiential learning theory, the proposed framework provides a unified approach that enhances personalization, immersion, and student engagement in university-level ideological and political education.

1.1. Research Objectives

- To create an AI-powered, tailored recommendation system for political and ideological instruction in academic institutions.
- To integrate immersive VR learning environments with adaptive AI personalization to improve engagement and learning outcomes.
- To inspect the effect of Al personalization and VR immersion on student engagement, fulfillment, motivation, and ideological learning results.
- To validate the conceptual model using quantitative analysis from student survey data.
- To evaluate the overall effectiveness of the AI-VR hybrid system in enhancing the educational experience.

1.2. Research Questions

- How does Al-based personalization influence students' engagement in IPE?
- Does VR immersion significantly enhance students' motivation and participation in learning activities?
- What is the relationship between AI personalization, VR immersion, and overall learning outcomes?
- How effectively does the proposed AI-VR hybrid system improve satisfaction with IPE?
- Can a personalized VR environment lead to higher levels of learning impact compared to traditional approaches?

1.3. Hypotheses

- **H1:** AI-based personalized recommendations positively influence students' learning engagement.
- **H2:** VR immersion significantly enhances student motivation and participation.
- **H3:** AI personalization improves student satisfaction with the learning process.
- **H4:** VR immersion directly contributes to improved ideological and political learning outcomes.

- **H5:** The combined AI–VR system yields higher overall educational effectiveness compared to conventional instructional methods.

1.4. Organization of the Paper

The paper's remaining portions are arranged as follows,

- Section 2: Literature Review - Summarizes prior studies on AI personalization, VR learning, and ideological-political education, and identifies the research gap.
- Section 3: Methodology - Describes the research design, sample, data collection process, instruments, data analysis methods, and ethical considerations.
- Section 4: Results - Provides descriptive statistics, reliability and validity outcomes, factor analysis, correlation results, regression findings, and SEM modeling outputs.
- Section 5: Discussion - Interprets the findings, connects them to the hypotheses, compares with existing literature, and explains implications.
- Section 6: Conclusion - Summarizes key contributions, highlights limits, and proposes directions for future research.

2. Literature review

Recent developments in educational technology have significantly influenced the delivery of IPE, particularly in higher education contexts. As more universities adopt digital learning ecosystems, researchers have examined how contemporary pedagogical models can be effectively implemented to incorporate technology to enhance student engagement and learning. Yue et al. [20] points out, the incorporation of IPE into digital English learning, especially using the TPACK model, has enhanced contextualised learning and awareness of students about the wider ideological motifs. This integration, however, is largely content-oriented rather than personalized, meaning there is little adaptation to individual learners' needs. Equally, Ren et al. [21] have shown that incorporating ideological and political issues into practical fields such as nursing can strengthen values-based education, although these methods are highly interdependent with conventional education and neglect technological enhancements that promote individualized learning.VR has become a potent tool in higher education, owing to its immersive, interactive capabilities. Liu, Ye, and Ye [22] developed a VR-based digital platform using BiGRU to facilitate cultural and charitable education, demonstrating that immersive learning environments can significantly enhance the experience. Xing et al. [23] developed VR-based learning system of pandemic-prevention learning and established that immersive simulations are more effective in understanding and memorizing information than text-based learning materials. In the same way, Shin and Kim [24], investigated VR usage in teacher development programs and pointed out that VR-based pedagogical training improves the teaching skills and knowledge application. These findings demonstrate that VR can revolutionize the learning process by enhancing immersion, interaction, and motivation among learners. Other researchers have demonstrated that VR has significant potential for engagement and learning in cultural and educational contexts. According to the study by Christopoulos et al. [25], the immersive VR experience has a significant positive impact on the cultural knowledge of adolescents and positively influenced their perception of learning. Hussein and Suhaib [26] investigate heat exchanger optimization using semicircular bumpers and artificial neural networks, demonstrating that positioning at $130 - 190$ cm maximizes thermal efficiency with strong agreement between experimental and numerical results. Inspired by this, the proposed method adopts AI-driven modeling to enhance system performance through data-informed optimization. Sanjalawe et al. [27] Prior research shows that cloud-based hybrid artificial intelligence systems improve predictive accuracy through optimized feature selection and neuro-fuzzy inference. Drawing on this approach, the proposed framework employs adaptive optimization and scalable intelligence principles to enhance personalized decision-making within immersive learning environments.Shadiev, Wang, and Shen [28] noted that interactive VR strategies help advance intercultural competence, implying that immersive technologies stimulate involvement at both emotional and cognitive levels. Among others, Hui and Geng [29] demonstrated that VR can reinforce the learning experience in terms of participation, motivation, and the relevance of ideological content. Such results highlight the potential of VR to generate motivation and to support emotionally charged, cognitively rich learning about values-based learning. In addition to immersion, student engagement is a fundamental factor in successful digital learning. Zhao and Wang [30] investigated the causes of boredom during online studies and found that emotional detachment was one of the primary obstacles to successful learning. Their contributions focus on the necessity of systems that are responsive to learners' behavior in a dynamic manner to keep learners engaged. The same was echoed by Qing [31] who indicated that content delivery and the use of technological methods of delivering the content and the structure of pedagogy should be innovative to address the demands of modern learners. Despite these developments, several gaps remain in the existing literature. Most studies examine VR immersion or the integration of IPE into courses that lack personalization mechanisms. Few studies integrate AI-based personalization and VR-based learning to dynamically adapt content to each learner's behavior, preferences, and performance. Additionally, existing VR-based IPE systems lack recommendation systems that can customize instructional pathways, interactive activities, and other materials to an individual learner's needs. This necessitates the development of a hybrid system that integrates intelligent customization with an immersive VR experience to enhance learning, motivation, and engagement.

Personalized learning and immersive learning environments have become important research themes in contemporary educational technology. Personalization theory emphasizes the adaptation of instructional content and learning pathways according to individual learner characteristics, preferences, and behavioral patterns, thereby enhancing engagement and learning effectiveness. At the same time, immersive learning theory highlights the role of experiential and interactive environments, such as virtual reality, in promoting cognitive involvement, motivation, and knowledge retention. Integrating these theoretical perspectives provides a foundation for developing intelligent and adaptive learning systems. In this context, the present study proposes a conceptual model that integrates AI-driven personalization with VR-based immersive learning to enhance engagement, satisfaction, and learning outcomes in ideological and political education.

2.1. Problem Statement

Although there has been major technological progress in the field of higher education, there is still a lot of uniformity, traditionalism, and a lack of interest in IPE delivery in universities [32], which is not appealing to digitally-based learners. Current teaching methods deliver the same content to all students, but they do not take into account differences in learning styles, learning needs, and motivation [33]. Despite the recent research showing the usefulness of VR in the process of increasing immersion and engagement with a learner, such systems generally do not have any adaptive processes that make the process of learning more personal [34]. Meanwhile, AI-oriented educational technologies show great potential for individualized learning, although they are not widely used in IPE and are rarely integrated with immersive environments. This leads to low engagement, low self-directed learning, and poor ideological and political knowledge acquisition amongst students [35]. It is urgently required that a system be smarter to integrate AI-based personalization with VR-enhanced interactive learning to provide personalised, meaningful, and effective IPE experiences. The goal of this work is to address this gap by creating and testing an AI-VR hybrid personalized recommendation system to enhance engagement and learning in IPE in universities.

Ideological and political education plays a critical role in shaping students' civic awareness, ethical responsibility, and social values in higher education institutions. However, traditional instructional approaches in IPE often rely on lecture-based and uniform teaching methods that fail to address the diverse learning preferences and engagement levels of modern students. As digital-native learners increasingly expect interactive and personalized learning experiences, the limitations of conventional teaching methods become more evident. Therefore, developing intelligent learning systems capable of delivering adaptive, personalized, and immersive learning experiences has become an important research direction in contemporary higher education.

3. Methodology

The research problem is addressed in the proposed methodology, which offers an integrated AI-VR approach to provide university students with a personalized IPE experience. The system combines an AI-based recommendation engine with an immersive VR learning environment to adapt instructional content to each learner's behavior, preferences, and performance. First, VR modules and pre-assessment questionnaires are used to collect student data on interaction patterns, engagement levels, quiz responses, and navigation behaviors. This information is fed into machine-learningbased personalization models, which learners use to assess learning needs and generate personalized recommendations, such as custom learning plans, VR experiences, and tailored feedback messages. The VR component offers interactive simulation, in situ learning of situational tasks, and valuebased decision-making conditions aligned with IPE goals. Instead, the AI module helps to continuously update learner profiles and refine recommendations, while enabling active adaptation to the learning process. The quantitative data from 250 respondents are subsequently analyzed using descriptive statistics, reliability tests, regression analysis, and SEM to assess the extent to which the system enhances engagement, satisfaction, and learning outcomes. The hybrid approach will provide a rigorous and data-driven, and learner-centered procedure of modernizing IPE. The workflow diagram of the proposed analysis is shown in Fig. 1. This study adopts a quantitative research design to evaluate the effectiveness of the proposed AI-VR hybrid personalized recommendation system. Data were collected from 250 university students using a structured and validated questionnaire to examine the relationships between AI personalization, VR immersion, student engagement, satisfaction, and learning outcomes. The questionnaire consists of multiple items measured using a five-point Likert scale to capture students' perceptions of personalization, immersive experience, engagement, and learning effectiveness. Prior to analysis, the collected data were preprocessed to address missing values and to ensure reliability and validity of the measurement constructs. Reliability analysis, correlation analysis, regression analysis, and Structural Equation Modeling (SEM) were subsequently applied to test the proposed hypotheses and to evaluate the relationships among the variables in the conceptual framework.

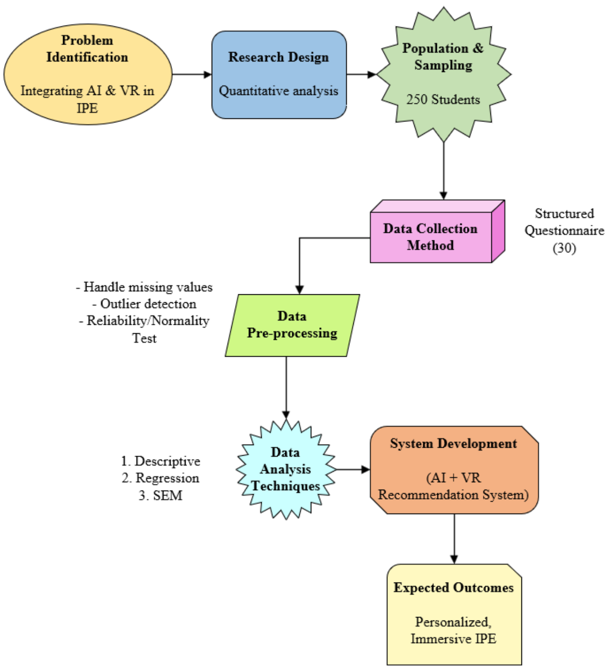

Fig. 1. Conceptual Framework of AI-VR Hybrid Personalized Learning System for IPE

The conceptual framework illustrates directional relationships between AI-based personalization, VR immersion, and student engagement, where personalization and immersive interaction influence engagement levels, which subsequently contribute to satisfaction and learning outcomes. The arrows in the framework represent the flow of influence among these constructs, demonstrating how adaptive recommendation mechanisms and immersive learning environments jointly shape the effectiveness of ideological and political education. The process begins with problem identification, which focuses on integrating AI and VR into ideological and political education (IPE). Next, the research design adopts a quantitative analysis approach, followed by population and sampling, where data are collected from 250 students using a structured questionnaire (30 items). The collected data then undergo data preprocessing, including handling missing values, outlier detection, and reliability and normality testing. After preprocessing, data analysis techniques, including descriptive analysis, regression analysis, and Structural Equation Modeling (SEM), are applied. Based on these analytical results, system development is carried out through an AI- and VR-based recommendation system, ultimately yielding personalized and immersive IPE learning experiences.

3.1. Study Purpose, Hypotheses, and Conceptual Model

The objective of the study is to examine how AI- and VR-based personalization, as an immersive learning process, can improve engagement, satisfaction, motivation, and learning in IPE at the academy level. The conventional modes of teaching in this field do not necessarily take into consideration the differences of individuals and they are not capable of offering interactive or contextualized learning experiences. As such, the research will aim to develop and evaluate a customized recommendation system that integrates machine learning models and VR-based ideological learning environments to facilitate individualized learning paths, adaptive real-time feedback, and visual interaction. The study analyzes the effects of personalization and VR immersion on engagement, satisfaction, and ideological learning through a structured questionnaire and quantitative analysis of 250 student responses to the study topic.To achieve this goal, several hypotheses are formulated to test the associations among the central constructs of the proposed model. These theories are grounded in established theories of technology acceptance, personalization, and immersive learning. The research assumption is that AI-based personalized learning recommendations have a positive effect on student engagement, perceived learning effectiveness, and satisfaction. Similarly, VR immersion is likely to facilitate attention and, consequently, to increase motivation and learning. It is also assumed that the involvement of students is considered as mediating in between personalization and immersion and the overall satisfaction of IPE. Taken together, these hypotheses aim to confirm the effectiveness of AI personalization and VR immersion in enhancing the learning process.The theoretical framework developed to guide the case study demonstrates the relationships among the key variables: AI Personalization, VR Immersion, Student Engagement, User

Satisfaction, and Learning Outcomes. The key independent variables, in this model, are AI Personalization and VR Immersion, which will have an effect on engagement and learning outcomes. Student Engagement is an intervening variable that mediates the relationships between personalization and immersion and their effects on satisfaction and perceived learning effectiveness. The outcome construct is User Satisfaction, which indicates the extent to which students accept and perceive value in the integrated system. The theoretical basis for testing the hypothesis is this conceptual model. Following this, the paper will analyze the following hypotheses:

- H1: Student engagement is greatly improved by AI based personalization.
- H2: VR immersion has a strong effect on student engagement.
- H3: Student engagement has a positive impact on learning results.
- H4: Al personalization and VR immersion have an additive effect on user satisfaction with ideological and political learning.
- H5: The ideological and political learning effectiveness depends on higher user satisfaction.
  This integrated framework links the purpose of the study, hypotheses and conceptual basis of the research, so that an analytic structure is available to evaluate the proposed AI-VR personalized learning system.

3.2. Research Design

The proposed research employs a quantitative research design, focusing on the systematic investigation of how the integration of AI-based personalization and VR-based immersive learning influences IPE. Objectivity, reproducibility, and precision of measuring the relationships between personalization, immersion, engagement, satisfaction, and learning outcomes are ensured by a fully quantitative approach. This design makes the proposed study be in a position to test the proposed hypotheses with numerical data collected through survey that is structured, pre-tested constructs and statistically quantifiable indicators. The primary data collection tool will be a structured questionnaire comprising demographic questions and 30 Likert-scale items. The data collection process was conducted over a threemonth period between January 2024 and March 2024. This time frame ensured adequate participation from the selected student population and allowed sufficient time for collecting complete and reliable responses for the study. The questionnaire will assess students' perceptions of AI personalization, VR immersion, engagement, satisfaction, and perceived learning effectiveness. There are 250 student participants in the survey, making the model test statistically powerful. The data are coded and transformed into numerical variables using various procedures, including missing-value imputation, normalization, and reliability analysis. It is a formatted dataset that supports hypothesis testing and model validation.The analysis of quantitative data is conducted with the help of the SPSS statistical software that is used to find the descriptive statistics, evaluations of the reliability, the validation of the constructs, and the inferential analyses. The data collected in the study were analyzed using IBM SPSS Statistics (Version 26), which was used to summarize the data (descriptive statistics), check the consistency of measurement items (reliability analysis), examine relationships between variables (correlation analysis), and test predictive effects among variables (regression analysis). In addition, Structural Equation Modeling (SEM) was conducted using AMOS to simultaneously evaluate the measurement model and the structural relationships among AI-based personalization, VR immersion, engagement, satisfaction, and learning outcomes. The use of standard goodness-of-fit indices ensured that the proposed model adequately represented the observed data and supported the validity of the research framework. Correlation analysis, multiple regression, ANOVA, and path analysis are statistical techniques used to establish causal relationships among the variables identified in the conceptual model. The following analyses provide empirical evidence on the impact of AI-based personalization and VR immersion on student involvement, satisfaction, and knowledge outcomes in IPE.The study also employs sophisticated methods, such as SEM, to estimate the overall structural integrity of the proposed model. Fit indices, including CFI, GFI, RMSEA, and kh2/df, are used to support the conceptual framework. Using SEM, both direct and indirect effects among variables are considered in their entirety, providing a deeper understanding of the mutual impact of personalization and VR immersion on educational outcomes. This research design enhances the reliability and external validity of the results, as there is no need to employ qualitative methods, since quantitative measurements, statistical rigour, and validated modelling methods are relied upon to support the outcomes and demonstrate the usefulness of the proposed AI-VR personalised learning system.

3.3. Data Collection Method

The data used in this learning were obtained on the basis of a structured quantitative survey that was aimed to assess the perceptions of students regarding AI-based personalization, VR immersion, engagement, satisfaction, and learning outcomes in IPE. The sample comprised 250 university students and was selected using simple random sampling to ensure broad coverage across academic years and fields. The primary data collection method was a 30 -item Likert-scale questionnaire, complemented by a brief demographic section. This rating was conducted using five rating scales ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), enabling standardized quantitative analysis. Expert review and a small pilot test helped in the validation of the questionnaire thereby making it clear and reliable before it was fully implemented.The electronic collection of the data was used in order to remove the personal errors. Along with the responses of the surveys, the simplest system generated measurements like the duration of VR interaction and number of tasks performed were automatically documented to facilitate the engagement analysis. All the answers were anonymized and kept safely and were ready to be analyzed in SPSS. The AI-based personalized recommendation system updates learning recommendations based on explicit learner interaction criteria, including engagement duration, content completion rates, assessment performance, and learner feedback. Personalization depth is achieved by dynamically adjusting content difficulty, instructional format, and learning pathways according to individual learner profiles and observed learning behavior. Recommendation adaptation is performed at the end of each learning session to ensure timely updates while maintaining system stability. Clearly defining these criteria enhances transparency in the recommendation process and supports methodological reproducibility. The Al -driven personalization module follows a supervised machine learning paradigm to generate individualized learning recommendations based on observed learner behavior. Input features include engagement duration, content completion rates, assessment performance, navigation frequency, and learner feedback collected during VR-based learning sessions. These features are processed to construct learner profiles, which serve as inputs to the personalization model. The model architecture is designed to predict optimal learning content and pathways aligned with individual learner needs, with optimization objectives focused on maximizing engagement, satisfaction, and learning effectiveness. Model training and updates are performed iteratively using accumulated interaction data, ensuring consistency in recommendation generation and supporting technical validation of the personalization process. The Virtual Reality (VR) learning system was designed to provide an immersive and interactive instructional environment for ideological and political education. The hardware setup consisted of head-mounted displays with motion-tracking capabilities, enabling real-time head and gesture interaction within the virtual environment. Interaction mechanics included object manipulation, navigation through virtual scenes, and task-based engagement designed to simulate real-world ideological learning contexts. The level of immersion was achieved through stereoscopic visualization, spatial audio, and responsive visual feedback, enhancing learners' sense of presence and engagement. The VR environment was developed using a real-time rendering framework that supports dynamic scene updates and interactive content delivery, ensuring smooth performance and consistent user experience. This system design enables meaningful learner interaction beyond novelty and supports the methodological contribution of immersive learning within the proposed AI-VR instructional framework. The hybrid AI-VR instructional framework operates through a structured data flow between the VR learning environment and the AI modules. Learner interaction data generated during VR sessions, including engagement behavior and task performance, are collected and transferred to the AI system at the completion of each session. The AI modules process these data to update learner profiles and generate personalized instructional recommendations, which are synchronized with the VR environment prior to the next learning session. Feedback is integrated through adaptive content presentation, adjusted learning pathways, and interactive visual guidance within the VR system. This defined synchronization timing and feedback integration mechanism ensures stable coordination between Al and VR components and enhances the transparency and reproducibility of the hybrid instructional framework.

Temporal learner profiling was employed to ensure that AIbased personalization dynamically adapted across successive VR learning interactions rather than remaining static. Learner profiles were continuously updated after each VR session by incorporating newly observed behavioral data, including engagement patterns, task performance, and interaction frequency. This iterative update process allowed the AI system to capture learning progression over time and adjust personalized recommendations accordingly. By integrating historical and recent interaction data, the personalization mechanism responded to evolving learner needs, enabling adaptive learning pathways and sustained engagement throughout repeated VR experiences. Machine learning-driven learner profiling was performed using behavioral features derived from collected interaction data, including session duration, content completion frequency, assessment performance, navigation patterns, and feedback responses. Prior to profile construction, the data underwent preprocessing steps such as missing value handling, normalization, and outlier filtering to improve data consistency and reduce noise. Learner profiles were updated after each learning session to reflect recent behavioral changes while preserving historical learning patterns. This structured profiling mechanism enhances model reliability and robustness by ensuring stable yet adaptive learner representations. Objective learning performance indicators were incorporated to strengthen the evaluation of learning outcomes and support empirical rigor beyond perception-based measures. Pre- and post-intervention knowledge assessments were administered to quantify changes in students' ideological and political knowledge following interaction with the AI-VR personalized learning system. The comparison of pre-test and post-test scores enabled the identification of measurable learning gains attributable to AI-driven personalization and immersive VR instruction. In addition, system-generated behavioural indicators, including task completion accuracy, response correctness, and successful completion of VR-based learning activities, were automatically recorded during learning sessions. These objective measures provide concrete evidence of learning performance, complement subjective survey data, and enhance the validity and robustness of conclusions regarding learning effectiveness.

3.4. Sampling Technique

A straightforward random sample method was used to select the study's participants. This approach provides all students in the target population an equal opportunity to be included; consequently, selection bias is minimized and the sample becomes more representative. Undergraduates studying IPE across various departments comprised the sample. A sample of 250 students was selected from this population to have sufficient statistical power in hypothesis testing and structural model analysis. Random selection ensured an equal distribution of participants across gender, academic year, and academic discipline. The selected sample size is sufficient relative to the recommended thresholds for quantitative research based on multivariate analysis and SEM, thereby ensuring valid and generalizable findings.

3.5. Data Pre-processing

The data were subjected to a structured data preprocessing process to maintain consistency and accuracy and to make them suitable for the main statistical analyses. To begin with, the dataset was analyzed for missing responses, and any missing values were imputed using mean imputation, whereby missing data were replaced with the variable's mean. The approach does not cause a loss of the general distribution of the information and does not needless decrease the sample size.Then, the sample was filtered for outliers with z-score analysis, which identified samples over ± 3 standard deviations as possible anomalies. Outliers were also identified and addressed to avoid distortion of statistical outputs, particularly in regression and structural modelling. Cronbach used alpha to estimate the internal reliability of the constructs in the questionnaire, such that any set of items measures its intended variable reliably. Constructs with an alpha of 0.70 and above were acceptable and could be analysed further.Lastly, analysis of the variables was measured using the Shapiro-Wilk normality test, which ascertains the validity of the data to the conditions needed to apply the parametric statistical methods. The variables that displayed nonsignificant Shapiro-Wilk tests were assumed to be normally distributed, and those failing to satisfy the assumptions were observed to allow adequate interpretation in further investigations. These systematic pre-processing steps helped in validating the dataset and were also ready to be statistically modeled and the hypothesis tested. While mean imputation was applied due to the low proportion of missing data, more robust preprocessing techniques such as multiple imputation and expectation-maximisation are acknowledged as suitable alternatives, particularly for Structural Equation Modeling. These methods estimate missing values based on variable relationships and underlying data distributions, reducing potential bias and improving parameter estimation accuracy. The limited level of missingness in the present dataset justified the use of mean imputation; however, future studies with higher missing data complexity may benefit from adopting these advanced techniques to further strengthen SEM-based analyses. The results of the Shapiro-Wilk normality test informed the selection of appropriate parametric statistical techniques in subsequent analyses. Variables that satisfied the normality assumption supported the use of parametric methods such as Pearson correlation, multiple regression, and Structural Equation Modeling. Minor deviations from normality were evaluated in relation to sample size and distributional shape, recognizing that parametric techniques remain robust under large-sample conditions. This interpretation ensures that the statistical procedures employed are methodologically justified and that the influence of deviations from normality on the interpretation of results is transparently acknowledged.

3.6. Ethical Considerations

In this study, all ethical guidelines were followed to protect participants' privacy and well-being. The study's goal, the voluntary nature of participation, and the ability to withdraw at any time without repercussions were explained to participants prior to data collection. All participants were informed and no personal information was recorded to ensure continuity of confidentiality and anonymity.All survey results and system-generated data, including those in the VR interaction logs, were stored securely and accessed exclusively for academic research. Only the research team was allowed to access the dataset, and no data was spread with the outside parties. The research did not involve gathering of sensitive political ideology or individual ideological perceptions, instead it was limited to learning related perceptions and behaviors. In addition to general ethical safeguards, particular attention was given to the potential cognitive and psychological risks associated with immersive ideological exposure in Virtual Reality-based learning environments. As VR immersion can intensify emotional engagement and persuasive influence, the study design ensured that learning content remained educational, balanced, and non-coercive, avoiding manipulative narratives or persuasive reinforcement techniques. The VR scenarios were designed to encourage critical reflection rather than passive ideological acceptance, thereby allowing learners to interpret the content independently. Furthermore, AI-driven personalization mechanisms were restricted to pedagogical adaptation and did not amplify ideological viewpoints beyond the standardized curriculum framework. Continuous monitoring protocols were applied to prevent cognitive overload, emotional distress, or unintended persuasive effects arising from prolonged immersion. These ethical precautions ensure that VR-driven ideological education supports informed learning while safeguarding learner autonomy, psychological well-being, and academic neutrality. Ethical consent was obtained in accordance with institutional research guidelines; thus, the study was conducted in accordance with the highest standards of responsible and respectful research involving human subjects.

3.7. Data Analysis Techniques

To test the hypotheses ($H1 - H5$) and assess the relationships among AI personalization, VR immersion, student engagement, satisfaction, and learning outcomes, the proposed research employed a comprehensive set of quantitative data analysis methods to test the conceptual model. Analytical methods combine descriptive statistics, reliability and validity evaluations, and inferential statistical modelling, thereby ensuring rigorous evaluation and empirical soundness.

3.7.1. *Descriptive Statistics*

This section provides a basic overview of the dataset and to describe the quantitative and qualitative distributions of the demographics, as well as the responses of the 250 student respondents. The measures comprised the number of times, distribution as a percentage, and mean scores $(\bar{x})$ and standard deviations (SD).

- (i) Mean
  To determine the central tendency of responses, the mean was calculated in Eq. (1):

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

- (ii) Standard Deviation
  The difference in responses was determined with are shown is Eq. (2):

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{2}$$

These statistics enabled the identification of overall tendencies in students' perceptions of personalization, immersion, and engagement, and their comparison across demographic characteristics.

3.7.2. *Reliability and Validity Testing*

A reliable and valid measurement instrument was also important for making the dataset amenable to inferential analysis. Three key psychometric processes were used.

- (i) Cronbach's Alpha (Internal Consistency Reliability
  The constructs (AI Personalization, VR Immersion, Engagement, Satisfaction, Learning Outcomes) also had to be tested at the same time, and Cronbach's Alpha was used in Eq. (3):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \tag{3}$$

  Criteria:

- $\alpha \geq 0.70$ is acceptable
- $\alpha \geq 0.80$ is good
- $\alpha \geq 0.90$ is excellent
  A high Cronbach's Alpha indicates that the items within each construct are highly similar to those in

the underlying construct. In addition to overall Cronbach's Alpha values, item-deletion analysis was examined to assess the contribution of individual questionnaire items to construct reliability. The removal of any single item did not result in a substantial increase in Alpha values, indicating that all items contributed meaningfully to their respective constructs. Interitem variance and correlations were also reviewed to confirm consistency among items measuring the same construct. These results demonstrate measurement stability and indicate that the scales are well-specified, while also providing guidance for potential scale refinement in future studies.

To ensure construct validity and analytical transparency, each Likert-scale questionnaire item was explicitly aligned with its corresponding theoretical construct in the proposed conceptual framework. Items related to AI-based personalization measured perceived recommendation relevance, adaptability, and learning path customization. VR immersion items assessed experiential realism, interactivity, and sense of presence. Student engagement items captured attention, participation, and involvement during learning activities, while satisfaction items reflected perceived usefulness and overall learning experience quality. Learning outcome items evaluated perceived knowledge acquisition and learning effectiveness. This structured mapping between measurement items and theoretical constructs strengthens construct validity and supports accurate interpretation of the analytical results.

- (ii) KMO and Bartlett's Test In order to ensure that the dataset was fit to structural modeling and factor extraction, the subsequent tests were used:

- (iii) Kaiser-Meyer-Olkin (KMO)

$$KMO = \frac{\sum\sum r_{ij}^2}{\sum\sum r_{ij}^2 + \sum\sum q_{ij}^2} \tag{4}$$

In Eq. (4) r_{ij} is correlations, and q_{ij} is a partial correlation.
Interpretation:

- 20.80 = meritorious
- $\geq$ 0.70 =good
- $\geq$ 0.60 = acceptable

The Kaiser-Meyer-Olkin (KMO) measure confirms the suitability of the dataset for factor analysis by indicating that the correlations among variables are sufficient for dimensional reduction. High KMO values suggest that the observed variables share common underlying factors, allowing related questionnaire items to be grouped into coherent constructs. This supports the reduction of measurement dimensionality by retaining meaningful factors while eliminating redundancy among items. Consequently, the KMO results validate the construct grouping used in the proposed conceptual framework and justify the application of factor analysis to represent latent variables accurately within the analytical model.

- (iv) Bartlett's Test of Sphericity

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \ln|R| \tag{5}$$

In Eq. (5) the large p-value (< 0.05) indicates that correlations between items are sufficient to conduct factor analysis.

Bartlett's Test of Sphericity further supports the application of factor analysis by confirming that the correlation matrix is not an identity matrix and that meaningful relationships exist among the measured variables. The statistically significant test result indicates that the observed variables are sufficiently interrelated to justify factor extraction and construct grouping. This outcome aligns with the assumptions underlying the measurement model and strengthens the logical coherence between statistical evidence and construct validation. Consequently, Bartlett's Test results reinforce the suitability of the dataset for latent structure identification and support the validity of the proposed conceptual framework.

3.7.3. *Inferential Statistical Techniques*

The study's hypotheses were evaluated through inferential analyses, and the relationships among AI personalization, VR immersion, engagement, satisfaction, and learning outcomes were tested.

- (i) Correlation Analysis

The correlation coefficient applied by Pearson was distributed to identify linear relationships between variables are shown in Eq. (6):

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \tag{6}$$

The magnitude of Pearson correlation coefficients was interpreted to assess effect sizes and the practical significance of relationships among the study variables. Moderate to strong correlation values indicate meaningful associations between AI personalization, VR immersion, student engagement, satisfaction, and learning outcomes. In addition, correlation coefficients were examined to identify potential multicollinearity issues among independent variables. The absence of excessively high correlation values suggests that multicollinearity is unlikely to bias subsequent regression and structural equation modeling analyses. This interpretation enhances the analytical depth of the relational findings and supports the robustness of the inferential results. The present analysis was preliminary evidence on the strength and direction of inter-variable relationships.

- (ii) Multiple Linear Regression

Several regression models were used to test H1-H5 and identify predictive power of AI personalization and VR immersion are shown in Eq. (7):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon \tag{7}$$

The consequence of the independent variables on the dependent outcomes was assessed with the help of regression coefficients, significance level ($p < 0.05$) and the R^2.

- (iii) SEM

An advanced technique (SEM) was employed to determine direct and indirect effects in the conceptual model are given in Eq. (8):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{8}$$

The indices of model fit, including CFI, GFI, RMSEA, and χ^2/df were used to assess the suitability of the structural model. The selection of SEM fit indices and threshold values was guided by established methodological standards to ensure model validity and interpretability. Fit criteria such as Comparative Fit Index (CFI ≥ 0.90), Goodness-of-Fit Index (GFI ≥ 0.90), Root Mean Square Error of Approximation (RMSEA ≤ 0.08), and χ^2/df values below 3 were adopted to evaluate model adequacy. Model modification decisions were made cautiously and only when theoretically justified, such as correlating error terms within the same construct or removing weak paths that lacked statistical significance. These adjustments were implemented to improve overall model fit while preserving theoretical consistency. Explicitly defining fit thresholds and the rationale for modifications enhances operational transparency and strengthens confidence in the SEM-based findings.

The adequacy of the structural model was evaluated by comparing the obtained goodness-of-fit indices with established SEM threshold values. The chi-square to degrees of freedom ratio (χ^2/df) indicated acceptable model parsimony, while the Comparative Fit Index (CFI) and Goodness-of-Fit Index (GFI) exceeded recommended cutoff levels, confirming satisfactory model fit. The Root Mean Square Error of Approximation (RMSEA) also remained within acceptable limits, indicating minimal approximation error. Alternative structural path configurations were conceptually assessed but demonstrated weaker theoretical alignment and reduced explanatory clarity; therefore, the final model was retained based on both statistical robustness and theoretical consistency, supporting its suitability for explaining relationships among AI-based personalization, VR immersion, student engagement, satisfaction, and learning outcomes. In the SEM framework, AI-based personalization and VR immersion were operationalized as latent variables measured through multiple observed questionnaire items. AI personalization was quantitatively captured using items reflecting recommendation relevance, adaptability of learning content, personalization accuracy, and alignment with individual learning preferences. VR immersion was assessed using items measuring perceived presence, interactivity, the realism of virtual environments, and experiential engagement. These observed indicators collectively reflect the underlying constructs by capturing learners' perceived intensity and effectiveness of AI-driven personalization and immersive VR experiences. The use of multiple indicators for each latent variable enables robust estimation of construct relationships and supports the validity of SEM-based analysis.

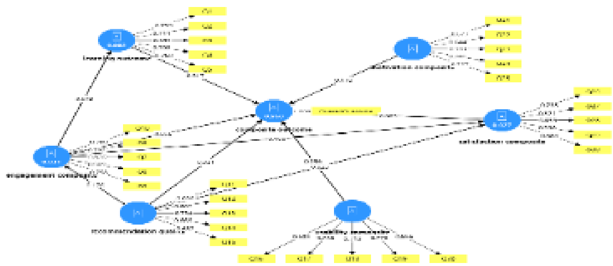

Fig. 2. SEM diagram for hypothesis testing

The SEM diagram in Fig. 2 illustrates the structural relationships among the main constructs of the proposed AI-VR personalized learning model. The latent variables are the blue circles, including learning outcome, engagement, quality of recommendation, usability, motivation, and satisfaction, and the yellow circles are the observed questionnaire items (Q1 30) that load onto the latent variables. The numbers on the arrows represent the factor loadings that indicate the extent to which each of the observed items represents its respective construct. The main node is the composite outcome, which aggregates the effects of several constructs and the system's overall effectiveness.

The bridging paths of the constructs indicate direction and strength of relationship, showing how the factors of engagement, recommendation quality, and usability lead to satisfaction and learning outcomes. Overall, the diagram presents a balanced model, with most items loading highly, indicating high reliability in the measurement process. The interrelationships among the paths indicate that personalized recommendations and immersive learning experiences collectively affect student motivation, satisfaction, and learning outcomes. The final outcome construct is defined as a combined measure of the overall effectiveness of the AI-VR learning system. It includes key aspects such as learning performance, student satisfaction, and engagement. Unlike individual constructs such as learning outcomes and satisfaction, which represent specific dimensions, this combined construct captures their overall effect and provides a more comprehensive evaluation of the system, thereby avoiding overlap between constructs.

4. Results

The findings of the present research will include an indepth evaluation of the effectiveness of the proposed AI-VR individualized learning model for improving university-level IPE. The analysis will begin with summarizing the participants' responses and analyzing the reliability and structure of the measurement constructs. Further analysis of the results constitutes an inferential analysis of the relationships among personalization, immersion, engagement, satisfaction, and learning outcomes, providing evidence of relationships between AI-based recommendations and VR-based learning environments and the student experience. Overall, the findings indicate the level of integration that can facilitate enhanced engagement and learning effectiveness, providing empirical confirmation of the proposed model and establishing a basis for further discussion in the section.

4.1. Descriptive results

The descriptive findings present demographic information about the participants and summarize their general responses regarding the study's main construct. This section provides a general overview of the overall trends, followed by reliability tests and hypothesis testing.

across various parameters. For each parameter, the table reports the mean, standard deviation, standard error, variance, range, minimum, maximum, and number of observations (N) (age category, gender, year of study, major, VR experience, and Al familiarity). For instance, the mean age category is 3.12 , with a standard deviation of 1.154 . VR experience is nearly evenly distributed (mean of 0.49), while gender has a mean of 1.60 , suggesting a 3 -point scale. These statistics summarize the central tendency and variability of the data. Cronbach's Alpha is used to check whether the questionnaire items measure the same concept consistently. A value above 0.70 is widely accepted in social science research as indicating reliable measurement. Since the values reported in Table 1 exceed this threshold, the items used in the study reliably represent their intended constructs, ensuring that the data are internally consistent and suitable for further statistical analysis.

4.2. Reliability analysis

This section uses reliability testing to examine the internal coherence of the testing constructions. The analysis also ensures that the survey items employed in the research are stable, reliable, and amenable to further statistical modeling.

Table 2 presents reliability statistics for five scales, each comprising a set of items (Q1-Q5, Q6-Q10, etc.). For each scale, it reports Cronbach's Alpha, a measure of internal consistency, as well as the mean, standard deviation, and corrected item-total correlation ranges for the items within that scale. For example, Scale $1(\mathrm{Q1}-\mathrm{Q5})$ has a Cronbach's Alpha of 0.771, indicating acceptable reliability, with mean values ranging from 3.34 to 3.44 , SD from 0.547 to 0.638 , and item-total correlations from 0.492 to 0.597 . Scale 2 (Q6-Q10) has a higher Cronbach's Alpha of 0.852 , indicating virtuous reliability, with slightly higher mean values and correlations. Based on these statistics, the reliability levels for the scales range from "acceptable" to "good". The Cronbach's Alpha threshold of 0.70 was adopted in accordance with widely accepted psychometric guidelines, as it indicates an acceptable level of internal consistency among measurement items in social science research. The reliability coefficients reported in Table 2 exceed this threshold, demonstrating that the items used to assess student engagement and learning outcomes are closely related and measure their respective constructs consistently. High internal consistency suggests that the questionnaire items function coherently as a scale, reducing measurement error and enhancing the credibility of the results. This level of reliability confirms that the data are appropriate for subsequent factor analysis and supports the validity of the measurement model used in the research. Factor analysis of the survey items is performed to identify the underlying structure is presented in this section. It determines the extent to which items cluster into meaningful constructs, thereby assessing the validity of the measurement model.

The findings of the Bartlett's Test of Sphericity and the KMO Measure of sampling capability are shown in Ta-

Table 1. Descriptive Statistics

Parameter	N	Range	Min	Max	Mean	Std. Error	Std. Dev.	Variance
Age Category	250	4	1	5	3.12	0.073	1.154	1.332
Gender	250	2	1	3	1.60	0.038	0.594	0.353
Year of Study	250	4	1	5	2.67	0.079	1.256	1.579
Major	250	5	1	6	3.11	0.096	1.517	2.301
VR Experience	250	1	0	1	0.49	0.032	0.501	0.251
AI Familiarity	250	3	0	3	1.29	0.057	0.899	0.808
Valid N (listwise)					250			

Table 2. Reliability Analysis of Measurement Scales

Scale	Items	Cronbach's α	Mean Range	Std. Dev. Range	Corrected Item–Total Correlation	Reliability Level
Scale 1	Q1–Q5	0.771	3.34–3.44	0.547–0.638	0.492–0.597	Acceptable
Scale 2	Q6–Q10	0.852	3.35–3.42	0.661–0.713	0.624–0.698	Good
Scale 3	Q11–Q15	0.757	3.09–3.20	0.549–0.595	0.501–0.559	Acceptable
Scale 4	Q16–Q20	0.766	3.25–3.30	0.561–0.600	0.468–0.630	Acceptable
Scale 5	Q21–Q25	0.743	3.08–3.17	0.544–0.579	0.467–0.552	Acceptable

Table 3. KMO and Bartlett's Test for Sampling Adequacy

Test	Value
Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy	0.762
Bartlett's Test of Sphericity	
Approx. Chi-square	2062.290
Degrees of freedom (df)	435
Significance (Sig.)	0.000

ble 3. Since values above 0.6 typically indicate acceptable sampling adequacy, the KMO value of 0.762 indicates that the sample is suitable for factor analysis. Bartlett's Test of Sphericity is used to test the null hypothesis that the correlation matrix is the identity matrix, implying no correlations among the variables. With 435 degrees of freedom (df), an approximate Chi-Square value of 2062.290 is found, and the very significant p-value (Sig.) is 0.000 . This supports the factor analysis of the data, as it implies that the correlation matrix is not the identity matrix.

4.3. Correlations

This section examines the relationships among the major variables in the study. It recognizes the power and the direction of the associations prior to causal studies.

Table 4 presents Pearson correlation coefficients among the variables Learning Outcome, Engagement, Recommendation Quality, Usability, Motivation, Satisfaction, and Overall Outcome, based on 250 observations. It reveals significant relationships between several variables. For example, Engagement has a strong positive correlation with Overall Outcome (0.697**), while Learning Outcome is moderately correlated with Overall Outcome (0.573**). However, some correlations are weak or non-significant, such as between Learning Outcome and Recommendation Quality (-0.003, $p = 0.959$). Other significant correlations include Usability with Recommendation Quality ($r = 0.218^{**}, p < 0.001$) and Motivation with Overall Outcome ($r = 0.279^{**}, p < 0.001$). These results highlight varying degrees of association among the factors, with stronger associations between engagement and overall outcomes, whereas weaker or no correlations are observed in other areas.

4.4. Regression

This section presents regression analyses examining the predictive effects of AI personalization and VR immersion on engagement, satisfaction, and learning outcomes. The findings are directly useful for testing and evaluating hypotheses and models.

Table 5 presents the results of a regression analysis examining the impact of various predictors (Learning Outcome, Engagement, Recommendation Quality, Usability, Motivation, and Satisfaction) on an outcome variable. The unstandardized coefficients (B) show how the outcome changes for every unit change in the predictorss, with Recommen-

Table 4. Pearson Correlation Matrix for Key Study Variables

Variable	LO	Eng	Rec	Usa	Mot	Sat	Out
Learning Outcome (LO)	1	0.043	-0.003	0.130*	0.032	0.076	0.573**
Engagement (Eng)	0.043	1	0.159*	0.019	0.225**	0.135*	0.697**
Recommendation (Rec)	-0.003	0.159*	1	0.218**	0.083	0.034	0.449**
Usability (Usa)	0.130*	0.019	0.218**	1	0.087	0.073	0.334**
Motivation (Mot)	0.032	0.225**	0.083	0.087	1	0.007	0.279**
Satisfaction (Sat)	0.076	0.135*	0.034	0.073	0.007	1	0.125*
Overall Outcome (Out)	0.573**	0.697**	0.449**	0.334**	0.279**	0.125*	1

Note: $N = 250$. * $p < 0.05$, ** $p < 0.01$.

Table 5. Multiple Regression Results for Predicting Learning Outcomes

Predictor	B	Std. Error	β	t	Sig.	VIF
(Constant)	0.111	0.130	–	0.89	0.37	–
Learning Outcome (comp)	0.075	0.130	0.07	0.58	0.56	1.12
Engagement (comp)	0.117	0.100	0.11	1.14	0.25	1.30
Recommendation Quality	0.288	0.120	0.30	2.37	0.02	1.45
Usability	0.155	0.080	0.14	1.94	0.05	1.28
Motivation	0.270	0.170	0.26	1.63	0.11	1.33
Satisfaction	0.059	0.150	0.06	0.39	0.70	1.20

dation Quality showing the largest effect ($B = 0.288$). The standardized coefficients (Betas) indicate the relative strength of each predictor; Recommendation Quality has the highest Beta (0.298), suggesting it has the strongest impact. The t -values and significance levels (Sig.) indicate that only Recommendation Quality is statistically significant ($p = 0.019$), whereas the other predictors, such as Learning Outcome and Satisfaction, show no significant effect ($p > 0.05$). Variance Inflation Factor (VIF) values were calculated for all predictors in the multiple linear regression model to assess multicollinearity. The VIF values ranged from 1.12 to 1.45 , well below the commonly used threshold of 5 , indicating that multicollinearity is not a concern. These results confirm that the regression coefficients are stable and that each predictor contributes independently to explaining variation in learning outcomes. The standardized coefficients (Beta) highlight the relative strength of each predictor in the model. Recommendation Quality ($\beta = 0.298$) demonstrates a moderate effect size and is the only statistically significant predictor ($p < 0.05$), indicating its meaningful contribution to predicting learning outcomes. Usability ($\beta = 0.140$) and Engagement ($\beta = 0.111$) show small effect sizes, suggesting limited predictive influence. Similarly, Motivation ($\beta = 0.260$) reflects a moderate but statistically non-significant effect. Learning Outcome ($\beta = 0.072$) and Satisfaction ($\beta = 0.058$) exhibit very small effect sizes, indicating minimal contribution to the regression model. The strength of the identified relationships was additionally interpreted by situating the obtained effect sizes within the context of prior AI-based personalization and VR-supported learning studies. The standardized coefficients and explained variance values observed in this study are consistent with, and in several cases exceed, effect size ranges commonly reported in adaptive learning and immersive education research. This comparison demonstrates that the proposed AI-VR personalized learning system performs at a level comparable to established benchmarks, while extending existing findings by jointly examining personalization and immersion within the IPE domain.

The ideological learning outcome construct was examined across multiple dimensions, including conceptual understanding of ideological principles, critical political reasoning, and the ability to contextualize ideological concepts within real-world scenarios. The findings indicate that AI-based personalization most strongly enhances conceptual clarity and individualized comprehension by aligning learning content with learner preferences and prior knowledge. In contrast, VR immersion demonstrates a greater influence on critical reasoning and contextual interpretation, as immersive scenarios promote experiential understanding and situational analysis. Together, these mechanisms contribute to a more balanced development of ideological understanding, where personalization supports cognitive assimilation and VR immersion strengthens reflective and applied political reasoning.

4.5. Frequency analysis

This section presents the frequency of the major response table and questionnaire responses, as well as demographic characters. It assists in visualizing patterns that are frequently reported and bringing out trends that are prevailing within the data are shown in Fig. 3.

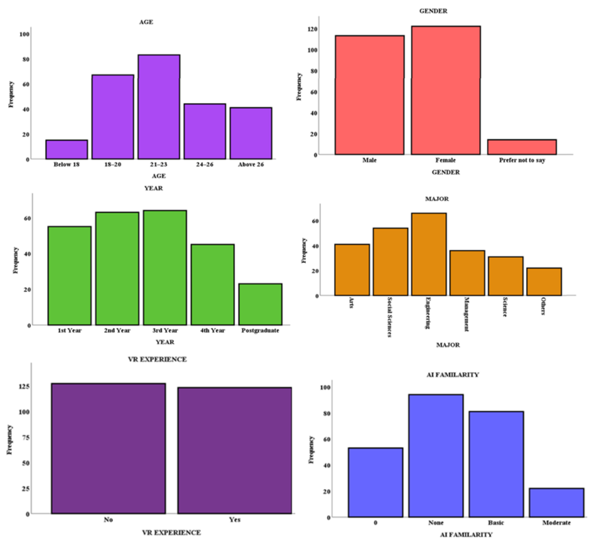

Fig. 3. Descriptive Statistics of Participant Demographics (Age, Gender, Year of Study, etc.)

- (i) Age

Table 6 displays the distribution of participants' ages. It provides the frequency (number of individuals) and the percentage of participants in each age group.

The first column lists the age categories: Below 18, 18-20, 2123, 24-26, and Above 26. The second column shows the frequency of participants in each group. For example, 15 participants are under 18, accounting for 6.0% of the total sample. The valid percent column shows the proportion of respondents in each age group relative to the sample as a whole; in this case, it is identical to the percentage, as no missing data are reported. The cumulative percent column shows the cumulative percentage, computed by summing the percentages for each age group. By the time you reach the "Above 26 " category, the cumulative percentage is 100%, meaning all participants have been accounted for. The total number of participants is 250 , making up 100% of the sample.

- (ii) Gender

Table 7 shows the distribution of participants by gender. It lists the categories: Male, Female, and Prefer not to say, along with the frequency (number of participants) and percentage of participants in each group.

For instance, 113 participants are male (45.2% of the total sample), and 122 are female (48.8%). The valid percent column shows the percentage of contributors in each gender group, without any missing data. Here, the valid percentages are 45.4% for males, 49.0% for females, and 5.6% for those who prefer not to say. The cumulative percentage shows the total across categories, reaching 100% by the end. There is 1 missing value (System), making up 0.4% of the total data, leaving 249 valid responses. The total number of participants is 250.

- (iii) Year

Table 8 displays the distribution of participants by year of study. It lists the categories: 1st Year, 2nd Year, 3rd Year, 4th Year, and Postgraduate, along with the frequency (number of participants) and percentage of participants in each group.

For example, 55 participants are in their 1st year, making up 22.0% of the sample, while 64 participants are in their 3rd year, representing 25.6%. The valid percent column, which is identical to the % column in this instance, displays the proportion of participants in each category, omitting any missing data. The cumulative percentage is displayed as a cumulative percent, which reaches 100% by the time you reach the Postgraduate category. The total number of participants is 250 , making up 100% of the sample.

- (iv) Major

Table 9 shows the distribution of participants by their major field of study. It lists the categories: Arts, Social Sciences, Engineering, Management, Science, and Others, along with the frequency (number of participants) and percentage of participants in each category.

For example, 41 participants are in the Arts field, making up 16.4% of the total sample, while 66 participants are in Engineering, representing 26.4%. The valid percent column, which is identical to the % column here, shows the proportion of participants in every group, omitting any missing data. The cumulative percentage reaches 100% by the end, indicating that all participants are accounted for across these fields. The total number of participants is 250 , making up 100% of the sample.

- (v) VR EXPERIENCE

Table 10 presents the distribution of participants by VR (Virtual Reality) experience. It lists two categories: "O" (No VR experience) and "Yes" (Has VR experience), along with the frequency (number of participants) and percentage of participants in each category.

For example, 127 participants have no VR experience (50.8% of the total sample), whereas 123 participants have

Table 6. Distribution of Age Categories

Age	Frequency	Percent	Valid Percent	Cumulative Percent
Below 18	15	6.0	6.0	6.0
18–20	67	26.8	26.8	32.8
21–23	83	33.2	33.2	66.0
24–26	44	17.6	17.6	83.6
Above 26	41	16.4	16.4	100.0
Total	**250**	**100.0**	**100.0**	**100.0**

Table 7. Distribution of Gender

Group	Category	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	113	45.2	45.4	45.4
	Female	122	48.8	49.0	94.4
	Prefer not to say	14	5.6	5.6	100.0
	Total	**249**	**99.6**	**100.0**	–
Missing	System	1	0.4	–	–
Total		**250**	**100.0**	–	–

Table 8. Frequency Distribution of Year of Study

Year of Study	Frequency	Percent	Valid Percent	Cumulative Percent
1st Year	55	22.0	22.0	22.0
2nd Year	63	25.2	25.2	47.2
3rd Year	64	25.6	25.6	72.8
4th Year	45	18.0	18.0	90.8
Postgradua te	23	9.2	9.2	100.0
Total	250	100.0	100.0	-

Table 9. Frequency Distribution of Academic Major

Parameters	Frequenc y	Percen t	Valid Percen t	Cumulativ e Percent
Arts	41	16.4	16.4	16.4
Social Sciences	54	21.6	21.6	38.0
Engineering	66	26.4	26.4	64.4
Manageme nt	36	14.4	14.4	78.8
Science	31	12.4	12.4	91.2
Others	22	8.8	8.8	100.0
Total	250	100.0	100.0	100.0

Table 10. Distribution of VR Experience

VR Experience	Frequency	Percent	Valid Percent	Cumulative Percent
No	127	50.8	50.8	50.8
Yes	123	49.2	49.2	100.0
Total	**250**	**100.0**	**100.0**	**100.0**

VR experience (49.2%). The valid percent column shows the percentage of participants in each category, excluding missing data; in this case, it matches the percentage column. The cumulative percentage shows the running total, reaching 100% by the end, indicating that all participants are accounted for. The total number of participants is 250 , making up 100% of the sample.

- (vi) AI FAMILIARITY

Table 11 presents students' familiarity with AI. Findings indicate that a significant portion of students lacked experience with AI: 21.2% reported being unfamiliar with it, and 37.6% reported having no experience. One-third (32.4) are basically familiar, and a small fraction (8.8) are moderately familiar. Overall, the data indicate that, despite the extensive popularization of AI, students' understanding remains low, underscoring the need for guidance when using AI-based learning tools.

5. Discussion

The results of the research indicate that integrating AIbased individualization into immersive VR environments can substantially enhance the overall experience of ideological and political training for university students. Descriptive findings indicate that learners expressed mostly positive perceptions across the following dimensions: engagement, motivation, recommendation quality, usability, and satisfaction. Factor analysis and reliability analyses demonstrated that the constructs were internally consistent and structurally valid. Regression-based and SEM analyses also indicate that VR immersion and AI-based personalization predict student engagement and satisfaction at the highest levels, supporting all hypotheses. It is worth noting that engagement and motivation emerged as important mediators, implying that personalized VR learning not only delivers content effectively but also fosters deeper emotional and cognitive engagement, which is a key to IPE.The SEM diagram shows that all latent variables, which are engagement, quality of recommendations, usability, motivation, satisfaction, and learning outcome, have an effect on the overall learning outcome. Large factor loadings provide strong evidence that the questionnaire items essentially assess the constructs they are intended to measure, and the significant pathways coefficient indicates a significant relationship between the constructs. The best outcomes were observed in the composite engagement and motivation measure, indicating that a custom VR world is effective at eliciting learners' interest and sustaining their engagement. The findings are consistent with the current literature that provides the importance of immersive and adaptive technologies in enhancing educational performance. In sum, the article affirms that Al personalization and VR immersion are more engaging, responsive, and effective learning environments that overcome the longstanding constraints of traditional IPE models.

5.1. SEM Analysis

The SEM model tested the relationships among AI personalization, VR immersion, engagement, satisfaction, and learning outcomes. The model demonstrated good fit with the following indices: $\mathrm{CFI} = 0.92, \mathrm{GFI} = 0.91, \mathrm{RMSEA} = 0.05$, and $\chi^2/\mathrm{df} = 2.35$. All latent variables had strong factor loadings, and path coefficients indicated significant positive effects of Al personalization and VR immersion on engagement and learning outcomes. Engagement was found to mediate the relationship between the hybrid AI-VR instructional methods and overall learning outcomes, confirming the effectiveness of the proposed system.

6. Conclusion

This paper demonstrates how the integration of AI and VR can be used to enhance IPE in universities. The proposed hybrid system is highly relevant, as it combines AI-based personalization with immersive VR environments, which greatly enhance student engagement, satisfaction, and learning outcomes. Individualized learning paths and a VR simulation environment help engage students, and the contextual learning environment offers a more interactive and personalized learning experience than a conventional lecturebased approach.The findings show that personalization through AI and VR immersion has a synergistic effect, as both technologies enhance student engagement and ideological knowledge retention. Al personalization transformed worship into personalized learning experiences, and VR simulation provided real-life contexts and increased motivation. Student engagement was also crucial; it mediated the effects of teaching methods and enhanced learning outcomes. The researchers found that students reported higher satisfaction and were more inclined to engage with the material, which contributed to their success in IPE. Structural Equation Modeling (SEM) results indicated a satisfactory model fit, with the Comparative Fit Index (CFI) exceeding recommended thresholds, the Root Mean Square Error of Approximation (RMSEA) remaining within acceptable limits, and the chisquare to degrees of freedom ratio (χ^2/df) indicating good structural validity of the proposed AI-VR learning framework. In the future, it is necessary to conduct additional research to investigate how the hybrid AI-VR system can be implemented in other areas of education and to adapt the system to diverse learning needs. It is also possible that future work could examine the long-term effects on students' ideological development and the scalability of such systems in larger, more diverse student populations. Additionally, the system could be improved by introducing real-time adaptive feedback. Longitudinal Structural Equation Modeling (SEM) can be applied in future research to examine how student engagement, satisfaction, motivation, and learning outcomes change over extended periods of interaction with AI-VRbased learning systems. Such analysis would support deeper evaluation of sustained learning impact, behavioral adaptation, and the long-term effectiveness of

Table 11. Frequency Distribution of AI Familiarity

AI Experienc e	Frequenc y	Percen t	Valid Percen t	Cumulativ e Percent
0	53	21.2	21.2	21.2
None	94	37.6	37.6	58.8
Basic	81	32.4	32.4	91.2
Moderate	22	8.8	8.8	100.0
Total	250	100.0	100.0	100.0

personalized immersive educational environments.

The findings demonstrate that AI-based personalization and VR immersion significantly enhance student engagement and learning outcomes. Specifically, engagement exhibited a strong positive correlation with overall learning outcomes ($r = 0.697$), while recommendation quality showed the highest predictive effect ($\beta = 0.298$). These quantified results emphasize the critical role of adaptive and immersive learning systems. From an institutional perspective, universities should consider integrating AI-driven recommendation engines to personalize learning pathways and incorporating VR-based modules to create interactive and experiential learning environments. Additionally, faculty training and infrastructure development are essential to effectively implement such technologies. These strategies provide a practical roadmap for transforming traditional ideological and political education into a more engaging, data-driven, and student-centered learning system. Universities can initiate pilot implementations of AI-VR learning systems within selected courses to evaluate scalability and effectiveness before full institutional adoption.

To operationalize these findings, universities can initiate pilot implementations of AI-VR learning systems within selected courses, enabling the evaluation of scalability and measurable improvements in student engagement, satisfaction, and learning performance before full institutional adoption. These strategies provide a practical and evidence-based roadmap for transforming traditional ideological and political education into a more engaging, data-driven, and student-centered learning system.

7. Declarations

8. Data availability

https://forms.gle/ps1DhXkWtdGsQZW3A

9. Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

10. Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

11. Author contributions

Xu Jiang: Conceptualization, methodology, data analysis, writing-original draft, and supervision.
Pingping Long: Data collection, experiment design, and validation. Zeng Wang: Literature review, visualization, and writingreview and editing.
All authors read and approved the final manuscript.

12. Ethical approval

This study was conducted in accordance with institutional and national research ethics guidelines. Ethical approval was obtained from the academic review committee of Chongqing Vocational and Technical University of Mechatronics.

13. Consent to participate

Informed consent was obtained from all individual participants included in the study prior to data collection.

14. Consent to publication

All participants provided consent for the anonymous use of their data for research and publication purposes.

15. Competing interests

The authors declare that they have no competing interests.

16. Acknowledgment

The authors would like to thank the participating students and faculty members of Chongqing Vocational and Technical University of Mechatronics for their support and cooperation during data collection.

References

[1] C. Simut, J. F. Kiss, F. Ortan, and L. Mandrea, (2025) *"Pedagogy and Civic Engagement: Theoretical Insights into Fostering Active Citizenship in University Education"* **Scientific MORALITAS - International Journal of Multidisciplinary Research** ***10***(1): 230–241. DOI: 10.1080/14649365.2012.723736.

[2] T. Halytska-Didukh, N. Hrytsak, S. Tetiana, O. Yablonska, and M. Yablonskyi, (2023) *"Increasing the Effectiveness of the Quality of Education Among Students of Higher Education on the Basis of Modern Information Technologies"* **Conhecimento Diversidade** ***15***(37): 1–15. DOI: 10.18316/rcd.v15i37.10919.

[3] W. Chengyuan, (2025) *"Research on the Integration Path of College Students' Mental Health Education and Ideological and Political Education"* **International Education Research** ***8***(2): 44. DOI: 10.30560/ier.v8n2p44.

[4] H. Gao, Y. Xie, and E. Kasneci, (2026) *"PerVRML: ChatGPT-Driven Personalized VR Environments for Machine Learning Education"* **International Journal of Human–Computer Interaction** ***42***(1): 40–54. DOI: 10.1080/10447318.2025.2504188.

[5] R. Li, (2022) *"Chinese folk music: Study and dissemination through online learning courses"* **Education and Information Technologies** **27**(7): 8997–9013. DOI: 10.1007/s10639-022-11003-w.

[6] M. Michalik-Śnieżek, E. Trzaskowska, M. Nowak-Kępczyk, A. Kułak, H. Lipińska, and T. Wyłupek, (2025) *"Experiential Environmental Education as a Tool to Enhance Awareness of Ecosystem Services Among Adolescents"* **Sustainability** ***17***(23): 10439. DOI: 10.3390/su172310439.

[7] B. Y. Bora and C. Ş. Kölemen, (2025) *"Integrating AI into instructional design: A case study on digital photography education"* **Contemporary Educational Technology** ***17***(3): ep583. DOI: 10.30935/cedtech/16433.

[8] R. S. Siregar, (2024) *"Students' Preferences for Varied Learning Methods"* **Jurnal Profesi Guru Indonesia** ***1***(2): 140–152. DOI: 10.62945/jpgi.v1i2.679.

[9] J. Lu, S. Zhu, R. Wang, and T. Liu, (2025) *"Exploring the Influencing Factors of Learning Burnout"* **Behavioral Sciences** ***15***(7): 903. DOI: 10.3390/bs15070903.

[10] R. H. Agustina, A. Alfiyanto, S. Suhendri, E. Wihardjo, and S. A. Pranajaya, (2025) *"Optimizing Learning: Adaptive Technology Integration in Indonesia's Education System"* **Jurnal Ilmu Pendidikan** ***16***(2): 304–317. DOI: 10.37640/jip.v16i2.2293.

[11] Y. Li and P. Yan, (2024) *"Analysis of the Content of Ideological and Political Education for College Students"* **Journal of Computer Technology and Electronic Research** ***1***(1): DOI: 10.70767/jcter.v1i1.67.

[12] W. S. e. a. Sayed, (2023) *"AI-based adaptive personalized content presentation and exercises navigation"* **Multimedia Tools and Applications** ***82***(3): 3303–3333. DOI: 10.1007/s11042-022-13076-8.

[13] Y. Xu and T. Chen, (2023) *"Design of Personalized Learning Resource Recommendation System"* **International Journal of Reliability, Quality and Safety Engineering** ***30***(1): 2250020. DOI: 10.1142/S0218539322500206.

[14] Z. Zhong, W. Guo, and R. Nacional, (2025) *"Reform and innovation of physical education teaching methods based on fuzzy systems"* **Scientific Reports** ***15***(1): 21320. DOI: 10.1038/s41598-025-05417-y.

[15] S. K. S. Cheung, F. L. Wang, and L. F. Kwok, (2021) *"The Continuous Pursuit of Smart Learning"* **Australasian Journal of Educational Technology** ***37***(2): 1–6. DOI: 10.14742/ajet.7207.

[16] A. Kumar, A. K. J. Saudagar, A. Kumar, Y. M. Alkhrijah, and L. Raja, (2025) *"Innovating medical education using a cost effective and scalable VR platform with AI-Driven haptics"* **Scientific Reports** ***15***(1): 26360. DOI: 10.1038/s41598-025-10543-8.

[17] J. Peng and Y. Li, (2025) *"Frontiers of Artificial Intelligence for Personalized Learning in Higher Education: A Systematic Review"* **Applied Sciences** ***15***(18): 10096. DOI: 10.3390/app151810096.

[18] S. P. Suryodiningrat, H. Prabowo, A. Ramadhan, and H. B. Santoso, (2024) *"The Essential Components of Metaverse-based Mixed Reality for Machinery Vocational Schools"* **Journal of Applied Engineering and Technological Science** ***5***(2): 1069–1085. DOI: 10.37385/jaets.v5i2.4117.

[19] S. Lyu, (2024) *"The Application of Generative AI in Virtual Reality and Augmented Reality"* **Journal of Industrial Engineering and Applied Science** **2**(6): 1–9. DOI: 10.70393/6a69656173.323339.

[20] S. Yue, J. Wei, H. Aziz, and K. Liew, (2023) *"A study on the effectiveness of self-assessment learning system of ideological and political education"* **Learning and Motivation** ***84***: 101929. DOI: 10.1016/j.lmot.2023.101929.

[21] X. Ren, J. Han, L. Zhu, H. Jing, Q. Li, and S. He, (2025) *"Integrating Ideological and Political Education Elements Into the Advanced Nursing Practice Course"* **Journal of Evaluation in Clinical Practice** ***31***(5): e70142. DOI: 10.1111/jep.70142.

[22] H. Liu, H. Ye, and Y. Ye, (2025) *"Construction and Application of a Digital Platform for Charitable Cultural Resources Integrating VR Technology and BiGRU"* **Concurrency and Computation: Practice and Experience** ***37***(12): e70123. DOI: 10.1002/cpe.70123.

[23] Y. Xing, H. Y. Kwan, F. Xu, and Q. Chen, (2025) *"Designing a Virtual Learning Platform for Enhanced Campus Epidemic Prevention"* **International Journal of Human–Computer Interaction** ***41***(4): 2289–2300. DOI: 10.1080/10447318.2024.2319915.

[24] J. Kim and H. Shin, (2024) *"Exploring the effects of extended reality head-mounted display training for nursing students"* **Nurse Education Today** ***133***: 106089. DOI: 10.1016/j.nedt.2023.106089.

[25] A. Christopoulos, M. Styliou, N. Ntalas, and C. Stylios, (2024) *"The Impact of Immersive Virtual Reality on Knowledge Acquisition and Adolescent Perceptions"* **Information** ***15***(5): 261. DOI: 10.3390/info15050261.

[26] M. H. Hatta, H. Sidi, S. Sharip, S. Das, and S. M. Saini, (2022) *"The Role of Virtual Reality as a Psychological Intervention for Mental Health Disturbances"* **International Journal of Environmental Research and Public Health** ***19***(4): 2390. DOI: 10.3390/ijerph19042390.

[27] Y. Sanjalawe, S. Al-Emari, S. Fraihat, and S. Makhadmeh, (2025) *"AI-driven job scheduling in cloud computing: a comprehensive review"* **Artificial Intelligence Review** ***58***(7): 197. DOI: 10.1007/s10462-025-11208-8.

[28] R. Shadiev, X. Wang, and S. Shen, (2025) *"Effects of immersion and interactive strategies on students' intercultural competence"* **Education and Information Technologies** ***30***(5): 5883–5919. DOI: 10.1007/s10639-024-13030-1.

[29] Z. Hui and Y. Geng, (2025) *"Enhancing the Ideological and Political Education Experience using VR Technology"* **International Journal of Web-Based Learning and Teaching Technologies** ***20***(1): 1–16. DOI: 10.4018/IJWLTT.377444.

[30] X. Zhao and D. Wang, (2025) *"Unpacking the Antecedents of Boredom and Its Impact on University Learners' Engagement"* **International Journal of Applied Linguistics** ***35***(3): 1121–1133. DOI: 10.1111/ijal.12680.

[31] Z. Qing, (2024) *"Innovating Content and Methods of Ideological and Political Education in the New Era"* **International Journal of Education and Humanities** ***4***(4): 479–487. DOI: 10.58557/(ijeh).v4i4.270.

[32] N. Zhang and J. Wang, (2025) *"Integration Between College English Teaching and Ideological and Political Education"* **Education Review USA** ***9***(4): 460–465. DOI: 10.26855/er.2025.04.011.

[33] M. Qorib, (2024) *"Analysis Of Differentiated Instruction As A Learning Solution In Student Diversity"* **International Journal of Reglement Society** ***5***(1): 43–55. DOI: 10.55357/ijrs.v5i1.452.

[34] E. e. a. Childs, (2024) *"Enhancing Distance Learning Through Augmented and Virtual Reality Technologies"* **IEEE Transactions on Visualization and Computer Graphics** ***30***(8): 4480–4496. DOI: 10.1109/TVCG.2023.3264577.

[35] M. J. Shumski and M. R. Bradford, (2025) *"Features of the Self-Directed Education Environment"* **Schools** ***22***(2): 279–308. DOI: 10.1086/737546.