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Artificial intelligence (AI) adoption and satisfaction in management education research: An explanatory-predictive hybrid SEM-RF approach

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ABSTRACT

The accelerated diffusion of artificial intelligence (AI) tools in management education research presents both strategic opportunities and ethical challenges for business schools and higher education institutions. Even as AI applications promise enhanced analytical efficiency and research productivity, concerns regarding academic integrity, critical thinking development, and data confidentiality complicate their integration. Despite these tensions, empirical evidence explaining and predicting satisfaction with AI tools among management education researchers remains limited. Existing studies have focused largely on conceptual frameworks, ethical implications, often relying on student samples or cross-sectional studies. Consequently, little is known about the specific determinants of AI satisfaction among researchers. To address this gap, the present study investigates the determinants of user satisfaction with AI technologies within a management education context and develops a predictive framework to inform institutional decision-making. The study, based on a sample of 260 respondents, examined 9 key constructs. The Random Forest (RF) model was trained by running the bagging procedure on a dataset, and its performance was validated using out-of-bag error estimation to assess predictive accuracy. Structural Equation Modelling (SEM) findings reveal that perceived ease of use significantly enhances perceived usefulness, which in turn drives satisfaction with AI tools. Ethical concern attitudes are negatively associated with perceived usefulness, underscoring the managerial and pedagogical trade-offs inherent in AI adoption within business schools. The RF model complements the explanatory analysis by demonstrating strong predictive performance ($R^2 = 0.73$) and identifying perceived ease of use, access to AI technologies, and perceived usefulness as the most influential predictors of satisfaction. The convergence of theory-driven and machine learning results enhances the robustness and practical relevance of the findings. By integrating explanatory and predictive modelling, this study contributes to management education literature on digital transformation and responsible innovation. The findings offer actionable insights for business school leaders, curriculum designers, and policymakers seeking to support ethically-grounded, strategically-aligned AI integration in management research and education.

Introduction

Artificial intelligence is becoming an essential technology, with the fastest rate of development, revolutionising research methodologies and teaching procedures. In management education research, Artificial Intelligence (AI) is extensively used to analyse large-scale learning analytics data to predict student performance and engagement, and to support the design of adaptive learning systems that personalise case-based and simulation-based instruction. Advances in AI have enabled it to reproduce human intelligence, solving complex problems of deep learning, adaptation, and articulating human language (Tan, 2025). Scholars around the world are now using these technologies to enhance

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their learning outcomes, although challenges remain as how to use them appropriately. Despite the benefits of AI tools in management education research, challenges like plagiarism remain and they may reduce critical thinking skills amongst students (Deep and Chen, 2025). This study examines the factors influencing user satisfaction with AI, emphasising its importance in improving educational quality in institutions while addressing ethical considerations. Examining these factors not only contributes knowledge in this field but also practical guidelines to policymakers seeking to improve the status of AI, especially in management education research. Ultimately, the goal is to reconcile the gap between user experience and technological progress in academia.

In academia, AI improves management education research effectiveness, especially in gathering literature reviews, data analysis processing, enhancing researcher capabilities (Kondaveeti et al., 2024). Various types of AI tools have the potential to bring innovative ideas to management education research, as evidenced by Formanek (2025), who acknowledged the use of Scie and Elicit in gathering and processing large amounts of information, optimising the research process. Despite the growing need for research, AI tools raise ethical issues, necessitating the meticulous evaluation of their effects on research integrity and data confidentiality (Pigola et al., 2025). In higher tertiary education, the use of AI tools has facilitated customised educational experiences, helping management education researchers to identify at-risk students and adapt instructional strategies accordingly (Doğan et al., 2024). Moreover, it has enhanced administrative efficiency by automating tasks, alleviating the burden on faculty and leading to more focused research and teaching (Ahmad et al., 2022). Although AI is appreciated in higher and tertiary education, challenges of overdependence have led to reduced interpersonal relationships and concerns about equity in technological access. Dependence on AI may result in diminished interpersonal relationships and raise questions about equity in technological access (Doğan et al., 2024).

The vast growth of AI tools such as ChatGPT and Scite.ai has changed the shape of management education research, which entails writing, presenting a literature review and analysing data. The tools improve accuracy and efficiency, leading to deeper exploration in many fields. Writing manuscripts requires more time and innovative minds, and the use of AI tools therefore assists significantly in their drafting and editing, minimising the time spent in doing these tasks (Biondi-Zoccai et al., 2025). Each AI tool performs the specific tasks for which it was designed: tools like Grammarly help in improving grammar, whilst ChatGPT assists in drafting and improving overall writing quality (Khalifa and Albadawy, 2024). Organising different sources of management education research can be tedious, such that AI can help in rapid literature review by finding gaps, facilitating a thorough synthesis of existing research (Agrawal et al., 2024). In addition, the use of AI improves accuracy in data analysis and efficiency, leading to substantial findings (Abdollahi et al. 2021). Some authors, like Muwagunzi et al. (2024), noted that overreliance on AI can lead to skewed management education research outcomes, compromising its credibility. The research by Biondi-Zoccai et al. (2025) has indicated that the use of AI raises ethical concerns in academic integrity, creativity and misuse, which include the generation of deceptive content.

During the COVID-19 period, the use of AI contributed immensely to education and academic research. Since restrictions on movement were set to manage the pandemic, remote learning was enforced and the inclusion of AI in this regard brought about some improvements. Dong (2025) found that bibliometric analysis has indicated that AI applications have registered a growth rate of 4.59 % annually from 1975 to 2024. This tremendous growth is attributed to the growing demand, especially in the fields of social science, computer science and engineering, with Spain, USA, China and Taiwan emerging as the leading countries (Jia and Looi, 2024). The advent of AI chatbots like ChatGPT around November 2022 initiated the transformative phase in scientific writing, and this has seen an increase in the use of AI-related words such as ‘delve’ and ‘underscore’ in the field of academia between 2023 and 2024 (Masukume, 2024). The study by Masukume (2024), bibliographic databases such as PubMed and Scopus indicated that AI-related words have increased 85-fold in 2023 compared to previous years. This geometric increase highlights the need for a robust exploration of the implications of AI-generated material in management education research practices.

AI contributed to knowledge expansion, especially during COVID-19, where most new vaccines were developed in a short period. Research trends, student performance prediction and enhancement of intellectual integrity have been identified in management education research through the inclusion of AI (Hussain and Anwar, 2024). This has resulted in faster data analysis in management education research and improved decision-making. Many statisticians and data scientists relied on data analysis packages such as R and Python but the use of AI has brought some innovations, optimising research designs, managing large datasets and improving decision making in education. The Use of AI has been further augmented by the incorporation of machine learning algorithms, which have improved the precision and efficacy of research processes. Research conducted by Luo & Hsiao-Chin (2023) observed the contribution of AI-powered tools in predicting management education research student performance, resulting in the discovery of learning patterns and enhancing educational resources. Notwithstanding the benefits of AI tools in the academic field, ethical concerns such as plagiarism, accuracy of content and overdependence on AI-generated content (Harati, 2024), remain critical.

Zimbabwe’s environment is particularly relevant from the perspective of examining the adoption of AI in management education, given that it is a developing higher education setting, characterised by rapid digital transformation, infrastructural, institutional, and capacity constraints that influence the acceptance of technology, which is a key determinant of the success of a technological system. In Zimbabwe, higher education institutions have increasingly been embracing digital learning, data-based research, and AI, among other emerging digital technologies, with the overall objective of developing the country through innovation and knowledge-based economic development. The country is developing a national strategy that is aimed at improving technology, but, the challenges in Zimbabwe, includes lack of access to advanced digital technologies, training (Nherera et al. 2024) and funding, among others, create a unique setting, given that access, training, and awareness of AI-related issues, among others, play a critical role in determining satisfaction. From existing literature, it is evident that the adoption of technology is significantly influenced by contextual factors, including infrastructure, digital skill gaps, and institutional support systems (Omweri 2024), within higher education institutions that are located within Sub-Saharan Africa. The study is important, therefore, in that it will generate insights that can be transferred to other developing countries' education management systems.

Trust in AI technologies influences user satisfaction since users are inclined to engage with AI systems when they are assured of their accuracy and reliability (Xing, 2024). Despite the immense contribution of AI to improving user satisfaction, challenges associated with it include ethical considerations and effective adoption. There have been many debates in the management education research field regarding the ethical use of AI, especially concerning issues like plagiarism and over-reliance. Although AI can improve academic work, it also carries risks that could compromise academic integrity and critical thinking abilities.

The current study seeks to employ a hybrid structural equation modelling in predicting user satisfaction in AI. Relatively few studies have utilised hybrid models like SEM-RND to explain and predict satisfaction levels. This methodological gap highlights the need to model the complex interaction of factors that relate to AI satisfaction across management education researchers. Few studies have employed perceived usefulness as a mediator variable. In the study by Kashive et al. (2020), for example, perceived usefulness influences user satisfaction in many AI applications, such as AI image generators and

e-learning websites. Notwithstanding the deployment of perceived usefulness as a mediator variable in many instances, a comprehensive study is needed to fully understand the nuances of perceived usefulness in many circumstances.

Although previous studies have examined the adoption of AI technologies in management education research settings, there is a noticeable gap in understanding of the mediating role of perceived usefulness in shaping user satisfaction. Most existing management education research relies heavily on either purely statistical models or qualitative insights, accounting for the lack of a comprehensive, theory-based analysis of the causal relationships between user experience factors and satisfaction outcomes. Moreover, there is a scarcity of hybrid methodological approaches that integrate Structural Equation Modelling (SEM) with machine learning techniques such as Random Forest, which can enhance both the explanatory and predictive power of the analysis. This leaves a gap in effectively identifying and prioritising the most influential factors affecting satisfaction with AI tools in management education research, particularly in the terms of ethical awareness, tool accessibility, and perceived accuracy. Given these considerations, the objectives of this study are:

a) *To examine the structural relationships among the determinants of satisfaction with AI technologies in management education research, explicitly assessing the mediating role of perceived usefulness within the proposed theoretical framework.*
b) *To develop and validate an integrated explanatory–predictive model that supports management educators and institutional policymakers in identifying, prioritising, and strategically managing the key factors influencing satisfaction with AI tools in management research environments.*

The structure of this paper is as follows: Section 2 presents a theoretical model and hypothesis. Section 3 focuses on materials and methods, while Section 4 presents the results. Section 5 contains the discussions and the implications of the findings, while Section 6 presents the conclusions and future directions.

Literature review and hypotheses development

In the current study, the model seeks to assess the impact of perceived usefulness on user satisfaction with artificial intelligence tools in management education research in Zimbabwe. The theoretical foundations undergirding the conceptual framework will be explained first to understand how the model was created. Each variable in the conceptual model, as well as its hypothesis, will be explained.

Theoretical foundations supporting the conceptual model

The proposed conceptual model investigating the impact of Perceived Usefulness on User Satisfaction with Artificial Intelligence (AI) tools in management education research is grounded in several key theories that allow for an understanding of it. These theories provide a basis for selecting variables and their interrelations.

Technology acceptance model (TAM)

The TAM theory was first introduced in 1989 and is considered to be one of the most widely used frameworks to explain how people learn to use and accept new technology. TAM is centered on two principles, namely the perceived ease of use and the perceived usefulness of technology (Maharani and Usman, 2021). These two principles influence people's attitudes towards technology, including training, support, and design features, and may indirectly affect the adoption of these main beliefs. In reality, TAM has proven to be useful and adaptable across various technologies, highlighting its efficacy in this research. Researchers are more likely to be satisfied with AI tools if the tools significantly improve quality and efficiency, strengthening their adoption in management education research. TAM's primary driver for individual technology acceptance is based on cognitive evaluations of ease of use and usefulness, which affect behavioural outcomes. Ease of use of AI tools and the facilitatory factors of access to AI technologies, training and support availability, and time-saving benefits affect perceived usefulness of AI, which is the primary mediator in the research model.

DeLone and mclean information systems success model (ISSM)

Quality is an essential component when considering the success rate of technology, especially in AI adoption. The ISSM was proposed in 1992 and later updated in 2003. The framework focuses on system quality, information quality and service quality. System quality refers to the reliability of technology in meeting customer satisfaction requirements, while information quality relates to the accuracy and relevance of output. Service quality is about the support given to users (Lutfi et al. 2022). These quality issues are vital, especially in this era where AI is dominant in almost all sectors and could lead to user satisfaction. In the current study, the perceived accuracy of AI is closely linked to information quality, while training and support align with service quality. Including the ISSM model highlights the significance of considering quality and service in AI systems. ISSM theory centres on the outcomes of system success, which include the relationship between system quality, information quality, and support services and their impact on user satisfaction and system performance. Perceived Accuracy of AI Output, Research Quality Improvement, and Awareness of Ethical Concerns are factors related to information quality and support services, and which affect User Satisfaction with AI in Research (USR). TAM theory explains the cognitive process of acceptance and its effect on usefulness, while ISSM theory explains the process of evaluating system and information quality and their effect on acceptance and satisfaction outcomes. This hybrid model enables the research to examine AI usefulness and satisfaction from both behavioural acceptance and system success evaluation perspectives, which is theoretically sound for the SEM–Random Forest model for data analysis.

Access to AI technologies

Access to AI tools has a role to play in management education research. Some users may, for example, not be able to access these tools, which reduces satisfaction. Despite the accessibility of AI tools as an important factor, proficiency in utilising them should be considered. Several studies have shown the link between access to AI tools and satisfaction. A study conducted by Rodway & Schepman (2023), for example, found that the satisfaction levels of students and scholars with easy access to AI technologies, rise due to improved learning outcomes and productivity. Proficiency and training also play an essential role despite the accessibility of these tools. Users should be adequately trained to deploy these tools effectively, which is directly linked with their satisfaction and perceived utility (Wang et al., 2023). Integrating AI tools into the curriculum could have a positive effect. The inclusion of AI tools into the curriculum influences the perceived usefulness, leading to increased user satisfaction (Aldraiweesh and Alturki, 2025). Institutions should prioritise equality of access and training to enhance the advantages of AI in management education research. In light of the aforegoing, the following hypothesis was made:

H1. *Access to AI technologies positively influences the perceived usefulness of AI technologies in management education research.*

Research quality improvement

Despite the disadvantages of using AI tools in management education research, these tools have contributed to quality improvement, and their use has been increasingly recognised. Academics have different views – positive and negative – on the benefits of AI, especially in management education research. AI tools have facilitated personalised learning by

adapting to the specific needs of students, thereby resulting in improved engagement and understanding (Kaswan et al. 2024). A strong association of 0.719 was found in incorporating AI tools in the educational setup from this study, which included pharmacy students (Farhan et al., 2024; Nyagadza *et al.*, 2025). This highlights the advantages of AI in enhancing the quality of research. The use of AI has, moreover, reduced administrative work, enabling students to focus on teaching and less on bureaucratic duties, thereby improving the entire educational experience (Ahmad et al. 2024). The use of AI tools has improved efficiency, as is seen in the research by Fu et al. (2024), where they were observed in contributing to literature reviews and data analysis. and consequently, leading to quality outputs (Shahzadi et al. 2024; Rambe and Nyagadza, 2026). Tools such as ChatGPT have been widely used and can provide timely and relevant information, which is vital for management education research (Fu et al., 2024). Notwithstanding the benefits of AI tools in the education setup, issues relating to academic integrity and innovation have been noted and could compromise the quality of education. Accordingly, it is worth pointing out the following hypothesis:

H2. *Perceived quality improvement in research quality positively influences perceived usefulness of AI technologies in management education research.*

Awareness of ethical concerns

Ethical awareness in using AI tools is vital as it contributes to integrity and satisfaction. Principles such as data privacy and algorithmic bias are important considerations when using AI tools, as they significantly contribute to user satisfaction (Williamson and Prybutok, 2024). A study conducted by Razaky (2025) highlights how, of 86 % of students were using AI tools, only 5 % were aware of their institutional guidelines. These results highlight the need to educate management students about the school's guidelines on the use of AI tools to ensure the quality of management education research. In another study carried out on data privacy, 55 % expressed concern about data privacy and job loss (Fabrègue and Bogoni, 2023), highlighting that they were aware of the increase of AI tools. The use of AI tools in schools requires clear ethical guidelines, and students need more AI literacy classes to learn how to deal with AI problems in a responsible manner. Research has shown that overuse of AI tools can result in procrastination (Lahmer, 2025), and that ethical issues may affect students' satisfaction and engagement due to trust issues. Institutions should therefore engage in training and interdisciplinary collaboration on a continuous basis to address ethical challenges and improve user satisfaction. Even as they acknowledge ethical awareness as a critical issue for user satisfaction, some researchers observe AI as a tool that improves efficiency and academic performance. Accordingly, the benefits may overshadow ethical concerns. The following hypotheses are formulated:

H3. *Ethical concerns and attitudes towards AI use negatively influence perceived usefulness of AI technologies in management education research.*

Ease of use of AI tools

Ease of use of AI tools significantly influences the perceived usefulness of AI tools in management education research, as it directly influences the ability to interact effectively with technology. This factor is decisive in determining user satisfaction and the acceptance of these technologies. A friendly interface potentially increases the likelihood of a positive user experience, enhancing satisfaction and promoting ongoing usage. User-friendliness reduces cognitive and operational obstacles, enabling users to focus on attaining their objectives instead of grappling with complex or technological difficulties. The study by Chenchu et al. (2025), for example, demonstrates that a well-crafted interface minimises the learning curve, facilitating user navigation of AI products. In addition, the study by Gao et al. (2023) has shown that perceived ease of use positively influences perceived usefulness, as users tend to value the benefits of products they consider easy to operate. Notwithstanding the advantages of ease of use, it is important to note that some users may prefer advanced features and capabilities over simple ones.

It was therefore postulated that:

H4. *Perceived ease of use of AI tools positively influences perceived usefulness of AI technologies in management education research.*

Time-Saving benefits

The use of AI has contributed immensely to reducing the time spent doing a task, as it processes instructions in seconds. Despite the quality produced by AI tools, they have the potential to execute tasks and streamline various management education research academic tasks. The use of AI tools has enhanced efficiency, leading to the timely completion of activities (Kumar 2024). Greater satisfaction is obtained when AI automates repetitive tasks, reducing the time spent completing a task (Singh 2024). Moreover, automation can manage repetitive tasks such as data entry, document organisation and literature reviews, allowing valuable time for academics to focus on critical thinking and analysis (Aslanyan-rad 2024). Students can manage assignments and activities by using AI tools to enhance their output, but without copying. AI tools have improved time management (Saardloun et al. 2024), especially among students, since they can check for grammar, organise schedules and dedicate more time to essential learning activities and personal growth. Research has demonstrated that the use of AI tools can help manage stress levels, especially when these tools streamline activities such as management education research assignments, enabling individuals to comfortably meet deadlines (Li et al., 2023). Despite the positive benefits of AI, however, it has led to overdependence, which may consequently hinder critical thinking. Accordingly, it was therefore posited that:

H5. *Perceived time-saving benefits positively influence perceived usefulness of AI technologies in management education research.*

Perceived accuracy of AI output

Artificial intelligence provides users with varied and dependable information in management education research. Perceived accuracy of AI output refers to the extent to which potential users have confidence that the output produced by AI is correct, trusted and reliable. Factors such as prior knowledge and clarity are crucial in this regard, since they directly influence how users understand and trust AI systems (Lu *et al.*, 2026). The study conducted by Vizconde & Caguiat (2024) demonstrated that high perceived accuracy fosters trust in AI solutions, leading to enhanced user happiness and sustained usage. The accuracy of AI tools impact on learning outcomes, as suggested by Wang et al. (2025), and AI technologies can improve learning experiences, as users have greater confidence in the information provided (Chikazhe *et al.*, 2023). Despite the importance of perceived accuracy in AI outputs, challenges such as biases and inaccurate outputs can potentially erode their trust and satisfaction in management education research (Zhao and Xu, 2025). Moreover, since users have high expectations relating to accuracy, any inconsistency found may result in dissatisfaction, highlighting the necessity for reasonable user expectations (Vizconde and Caguiat, 2024). Based on the aforegoing, the following hypothesis was formulated:

H6. *Perceived accuracy of AI-generated outputs positively influences perceived usefulness of AI technologies in management education research.*

Training and support availability

Users of AI tools may lack the prerequisite management education research skills to use these tools. Training and support are therefore important to enhance understanding and skills, leading to increased

satisfaction. Studies have shown that when students and educators receive proper training, this boosts their trust in using AI tools, improving their satisfaction levels. Training in the use of AI tools can improve skills, enabling teachers who have received training to develop AI-based applications, thereby enhancing their interaction with students (Pillai et al. 2024). Moreover, training and support can lead to increased acceptance in using AI tools, as evidenced by the study by Rodway & Schepman (2023), which found that over 69 % students showed interest in using AI tools if adequate support is offered, highlighting the need for investing in training to improve satisfaction. Training and support can therefore lead to collaborative development, which can improve the relevance and effectiveness of AI training programmes. While training is important, such initiatives may fail because of the costs involved in facilitating them and may not therefore be effective in some situations. Accordingly, we propose the following hypothesis:

H7. *Perceived availability of training and institutional support positively influences perceived usefulness of AI technologies in management education research.*

Perceived usefulness of AI

Perceived usefulness of AI refers to the extent to which users believe that utilising AI can improve performance, decision-making and productivity. Users can embrace AI in their work, especially when they perceive AI to be beneficial and this can automatically improve their confidence in it. The study by Alshammari & Babu (2025) has shown that perceived usefulness in AI can have an impact on user satisfaction, achieving higher satisfaction. Perceived usefulness as a mediator variable plays a crucial role, and in the study by Alsulami et al. (2024), it successfully acted as a mediator between the effects of system quality, information quality, and service quality whilst student satisfaction was the dependent variable. In another study, perceived usefulness has been found to influence satisfaction when factors like content quality and emotional well-being were used for modelling (Yang 2024). Despite the significant role of perceived usefulness in AI, it should be acknowledged that other factors, such as emotional well-being and quality of the system, contribute to user satisfaction. The following hypothesis is framed based on previous literature:

H8. *Perceived usefulness of AI technologies positively influences user satisfaction with AI tools in management education research.*

User satisfaction with AI in management education research

User satisfaction with AI in management education research refers to the contentment of users when using AI technologies. Satisfaction is influenced by factors such as reliability, accuracy and relevance in facilitating tasks like data analysis, predictive modelling and literature review (Xie et al. 2024). Users have derived satisfaction from using tools like ChatGPT since they can enhance research topics and refine writing skills in postgraduate students (Chauke et al., 2024; Nyagadza, 2021). Research has shown that an estimated 78.7 % of students cited such benefits of using AI tools as ease of access and minimising time to complete a task, highlighting that AI can enhance users' satisfaction despite their advantages. Moreover, a strong correlation was found between user satisfaction and utilitarian gratification, illustrating the positive benefits of AI despite criticism of it. Notwithstanding the benefits to users of deploying AI in management education research, ethical considerations and accuracy are vital. Addressing these concerns is important in enhancing the benefits of using AI tools in management education research. Fig. 1 summarises the conceptual model to be used in this management education research.

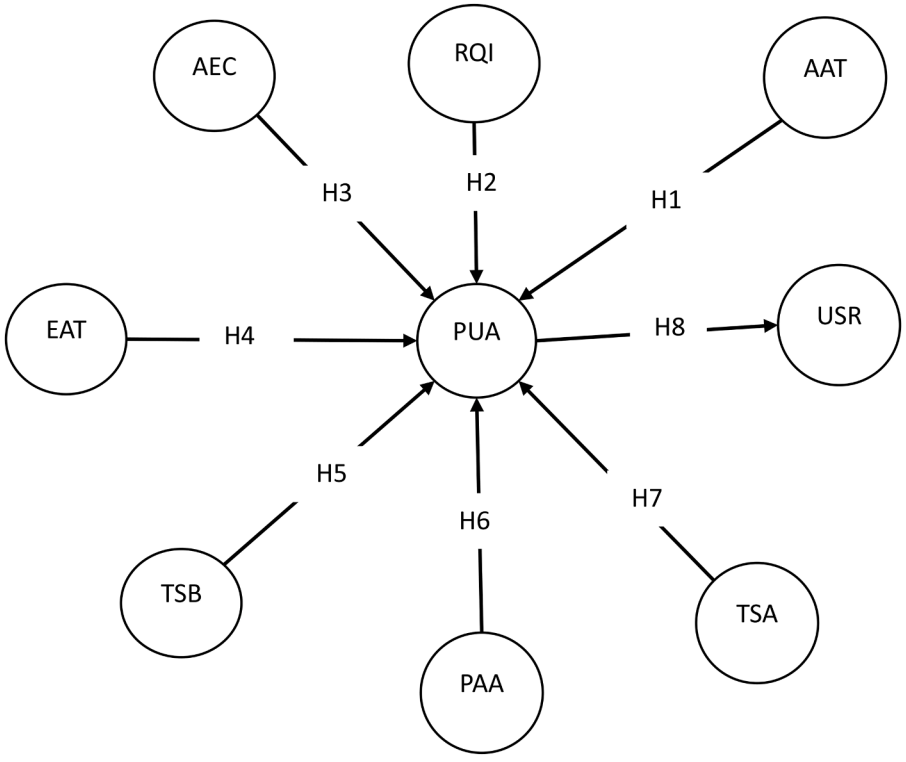

Fig. 1. The conceptual model.
Key: Ease of Use of AI Tools (EAT), Access to AI Technologies (AAT), Perceived Accuracy of AI Output (PAA), Time-Saving Benefits (TSB), Research Quality Improvement (RQI), Training and Support Availability (TSA), Awareness of Ethical Concerns (AEC), Perceived Usefulness of AI (PUA), User Satisfaction with AI in Research (USR).

Materials and methods

Research design & sampling strategy

The current study employed a cross-sectional quantitative approach, where the data were collected using a closed questionnaire distributed amongst 260 male and female participants. Data collection took place in Marondera and research included both management education research students and lecturers to allow for diverse answers about perceived usefulness on user satisfaction with artificial intelligence. The respondents were selected using a stratified random sampling where the sampling frame was obtained and divided into two strata (lecturers and students) since this technique has greater precision and there is a fair representation from each group. The simple random sampling was then utilised to select the respondents from each stratum.

Data collection, instrumentation, and measurement scaling

The data was collected using a structured, closed questionnaire, which respondents completed. Each respondent was required to express their perceptions on the usefulness of AI within the institutional environment. The instrument used was divided into two sections and the constructs were organised into 5 Likert scales, strongly disagree to strongly agree, to allow them to choose from a wide range of views, thereby promoting a quantitative approach. Pilot testing was conducted to allow for refinements were made before the final survey. To avoid confusion, respondents were alerted before the data collection commenced so that they would commit themselves or withdraw. A total of 275 questionnaires were distributed across the university, but 260 respondents completed and returned the questionnaire, translating to a return rate of 94.5 %, which is considered desirable (Murshad 2025). According to Hair et al. (2017), moreover, a sample of 200 would be suitable for an SEM method.

Estimation methodologies

The data was analysed using SmartPLS v.4.1.0.9, SPSS 26, and the R package. Firstly, the demographic datasets were analysed to enable a clear understanding of the composition of the respondents. The descriptive statistics were then done to examine the characteristics of the constructs and this was done using mean, standard deviation, skewness and kurtosis. The data was considered normal if it had skewness values between ±1.50 and kurtosis values between ±3.0 (Demir 2022). The exploratory factor analysis (EFA) was then utilised to improve measurement validity and ensure a more reliable instrument. The EFA was performed using a rotated component matrix, Kaiser–Meyer–Olkin (KMO), Bartlett's analyses, Cronbach's alpha, factor loading, composite reliability, and average variance extracted. These tests ensure that the constructs and items were validated to ensure dependable results. Hereafter, a hybrid SEM-random forest was used, the SEM approach was deployed to examine the measurement model. Under the SEM approach, exploratory factor analysis and confirmatory factor analysis are used to validate the measurement model and examine the observed and unobserved variables, respectively. The hypotheses in the model were examined through structural equation modelling (SEM), as demonstrated by Ahmed et al. (2024). Moreover, the fit indices were utilised to validate the hypothesised measurement model, as recommended by Hair et al. (2020). Machine learning was then used in the form of a random forest, since it provides high predictive accuracy without underlying assumptions about data distribution.

Structural equation modelling (SEM) analysis

The PLS-SEM method is to first be used to assess the proposed hypothesis. When using a small dataset, PLS-SEM is very suitable and can show the causal predictive relationship among the variables in the model (Kock, 2015). To test the path model, t-values, p-values and confidence intervals are used (Hair et al., 2019). In comparison with the Covariance-Based-SEM (CB-SEM), the PLS-SEM is considered the most suitable method for many reasons, including, for example, its ability to reveal complex interactions of higher models (Hair et al., 2019). The PLS-SEM focuses on testing the structural relationship of variables, specifically focusing on associations between the constructs (Ramayah et al., 2018).

To illustrate the PLS-SEM, it is assumed that there are p groups of latent variables, with each containing q variables and this implies that each group of latent variables can be formulated as:

$$Y_j = \left\{ y_{i1},\ y_{i2}, \ldots\ldots, y^{i}_{iq} \right\} i = \{1, 2, 3, 4, \ldots., p\} \tag{1}$$

Following Eq. (1), it is estimated that there is a linear combination of latent variables and observed variables. The observed variable is related to each unique latent variable and thus the equation of the measurement can be written as follows:

$$y_{ik} = \lambda_{ik}\ \zeta_i + \ \sigma_{ik} + (i = 1, 2, \ldots., p; k = 1, 2, \ldots., q_i \tag{2}$$

From Eq. (2) the symbol y_{ik} represents the observed variables, while i and k represent the number of latent variables and the number of observed indicators, respectively. The symbol ζ_i denotes the factor loading, which represents the strength between the latent variable and the observed indicator. Finally, σ_{ik} represents the measurement error.

The equations of the structural model are:

$$\zeta_i = \sum_{i \neq k} \beta_{ik} \zeta_i + \ \varepsilon_i$$

Random forest

RF is an ensemble machine-learning technique that employs the bagging technique. Despite its bias towards the classification of high-level categorical features of datasets, including varying quantities of categorical data, the random forest algorithm is now regarded as highly rigorous learning (Hancock et al. 2020). The technique works by first gathering random samples from the provided dataset. Therefore, each sample is used to construct a decision tree. The predicted outcomes are then voted on to determine which classification receives the most votes. The trees are trained by running the bagging procedure on a dataset of N items. The Random Forest method is expressed as follows:

$$f = \frac{1}{f} \sum_{i=1}^{p} g_i(x^1), \tag{3}$$

where f represents the predicted value whilst x^1 is the unseen sample. Moreover, g_i is the trained decision tree on data sample i, and p is the number of iterations required to repeat the process.

Evaluation of the random forest model. To assess the performance of the Random Forest model for AI user satisfaction, many evaluation metrics were utilised, and these included the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Moreover, the coefficient of determination (R^2) was used to assess the contribution of the independent variables in AI user satisfaction. Accordingly, the use of these metrics will ensure accuracy and reliability in AI user satisfaction.

Results

Demographic analysis

The results demonstrate a moderate imbalance in representation, where 60.8 % (158) of females and 39.2 % (102) of males participated in user AI satisfaction levels. Female participants were slightly more in number than their male counterparts and this could be attributed to the dominance of females at the university and management education research shows that females tend to be more responsive to academic

surveys. The study also took age into account, with many respondents falling into the age range 17 to 25, which is relatively young, suggesting the dominance of undergraduate students as compared to postgraduate ones. The age range 26 to 35 accounted for 21.5 % of participants and those above 50 years were fewest, which is to be expected in a university setting, since this group mainly comprises university workers. The Faculty of Applied Science and Technology had the lowest representation of participants, and this could be attributed to the fact that there is a lower uptake of applied science degree programmes as compared to others. Moreover, the study also took into account participants' roles at the university: 64.6 % were undergraduate students, who fall into the age 17 to 25 age group, which constituted the majority of participants. The administrative staff represented the lowest percentage at 5.8 %, highlighting that they are normally fewer than other groups. AI experience length was also considered, since it impacts on the nature of this research. Many participants (65 %) reported having more than two years of experience, which is skewed towards more advanced users, and this can facilitate proper findings. Lastly, the study included digital literacy self-rating, which forms the basis of this research and 77.7 % of participants indicated that they were able to use digital technologies for their academic purposes. Only 1.2 % indicated that they had a low digital literacy rate, highlighting that the study comprises many people who can use AI tools, making the results of this study dependable. In conclusion, the study suggests a demographic profile of primarily young people, experienced participants and digitally literate people, forming a strong foundation in examining the satisfaction of AI tools in management education research.

Descriptive statistics

The descriptive statistics in Table 1 demonstrate important insights into the variables used in this research. Variables such as the mean, standard deviation, kurtosis, and skewness were used. The results revealed that both the skewness and kurtosis were between ±1.50 and ±3.0, respectively, as stated by Singh & Murthy (2023), and thus the normality assumption was satisfied. The standard deviation also illustrates that the observations were close to each other and this is, therefore, desirable. Moreover, the mean values suggested that most respondents agreed on the questions asked and except for the one relating to awareness of ethical concerns.

Exploratory factor analysis (EFA)

Exploratory Factor Analysis is a statistical technique that seeks to reduce many variables into fewer ones, and in this scenario, the researcher has no information about the nature of factors being used and thus allows exploration. Table 2 shows the Cronbach's alpha (CA) and composite reliability (CR) validated the reliability of constructs, since the values were higher than 0.70, as recommended by Haji-Othman & Yusuff (2022). Moreover, factor loading (FL) was used and the values were within the range 0.805 and 0.967, which confirmed the convergent validity of having each loading value greater than 0.7(Ahmed et al. 2022). Discriminant validity was examined through the average variance extracted (AVE) and all the constructs had values of over 0.5 (Cheung et al. 2024). Consequently, the items and constructs in this study can be considered reliable and our proposed measuring methodology was proven and validated (Ahmed et al. 2022**).**

Table 2
Measurement model.

Factors	Items	FL	CA	CR	AVE
Ease of Use of AI Tools	EAT1	0.941	0.913	0.832	0.826
	EAT2	0.927			
Access to AI Technologies	AAT1	0.903	0.915	0.921	0.819
	AAT2	0.967			
Perceived Accuracy of AI Outputs	PAA1	0.915	0.902	0.895	0.825
	PAA2	0.923			
Time-Saving Benefits	TSB1	0.870	0.897	0.862	0.817
	TSB2	0.893			
Research Quality Improvement	RQI1	0.952	0.934	0.917	0.892
	RQI2	0.942			
Training and Support Availability	TSA1	0.905	0.90	0.873	0.833
	TSA2	0.917			
Awareness of Ethical Concerns	AEC1	0.805	0.806	0.828	0.801
	AEC2	0.828			
Perceived Usefulness of AI	PUA1	0.954	0.926	0.904	0.873
	PUA2	0.912			
User Satisfaction with AI in Research	USR1	0.924	0.913	0.860	0.821
	USR2	0.915			

Key: Ease of Use of AI Tools (EAT), Access to AI Technologies (AAT), Perceived Accuracy of AI Outputs (PAA), Time-Saving Benefits (TSB), Research Quality Improvement (RQI), Training and Support Availability (TSA), Awareness of Ethical Concerns (AEC), Perceived Usefulness of AI (PUA), User Satisfaction with AI in Research (USR).

Total variance explained

The Total Variance technique was also used to explain the variability in the datasets, enabling an understanding of the contribution of each variable to the overall variance. Table 4 shows the cumulative variance of 9 variables that stood at 67.17(67.17 %) as compared to the cut-off value of 50 %. Moreover, the eigenvalues for every item were constructed and the results were desirable. Accordingly, the reliability and suitability of data are safe for the SEM-based multivariate approach to be utilised (Hair et al. 2020).

Confirmatory factor analysis (CFA)

The results displayed in Table 2 show the hypothesised measurement model and 8 factors were considered, and all had 2 constructs. Access to AI Technologies, for example, had AAT1 and AAT2. Our study has one mediator variable, namely Perceived Usefulness of AI and user satisfaction with AI in research, representing the dependent variable. The hypothesised model had 9 constructs, including the mediator and the dependent variables. To assess whether the model represents the observed data, a model fit index, which includes an Incremental fixed

Table 1
Descriptive Analysis.

Variables	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Ease of Use of AI Tools	3.85	1.06	−0.76		0.24	0.066
Access to AI Technologies	3.72	1.09	−0.87		0.45	0.068
Perceived Accuracy of AI Outputs	3.89	1.24	−0.94		0.36	0.077
Time-Saving Benefits	3.64	1.28	−0.81		0.37	0.079
Research Quality Improvement	3.82	1.12	−0.72		0.42	0.069
Training and Support Availability	3.83	1.04	−0.91		0.51	0.063
Awareness of Ethical Concerns	2.58	1.14	0.23		0.15	0.071
Perceived Usefulness of AI	3.86	1.10	−0.85		0.46	0.068
User Satisfaction with AI in Research	3.88	1.19	−0.93		0.38	0.074

Table 4
Total Variance Explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cum %	Total	% of Variance	Cum %	Total	% of Variance	Cum %
1	5.88	25.33	25.33	5.88	25.33	25.33	5.06	24.21	24.21
2	3.84	15.32	40.65	3.84	15.32	40.65	3.25	14.27	38.48
3	2.73	12.24	52.89	2.73	12.24	52.89	2.36	12.07	50.55
4	2.06	7.25	60.14	2.06	7.25	60.14	2.01	7.23	57.78
5	2.01	5.73	65.87	2.01	5.73	65.87	2,00	5.13	62.91
6	1.91	4.28	70.15	1.91	4.28	70.15	1.64	4.26	67.17

index, Comparative fit index, Normed fixed index and Parsimony-adjusted normed fit index, was used. Since the results shown in Table 5 are within the expected range, our hypothesised measurement model was validated.

Structural equation modelling results

To test the hypotheses in the model, SmartPLS v.4.1.0.9 was utilised. The path analysis for the final model used in this study is displayed in Fig. 3, where the bold lines represent the relationships between variables. The standard errors (SE), t-statistics, and p-values were used to assess the nature of the relationship. Access to AI technologies and research quality improvement exerts a substantial positive influence on perceived usefulness of AI, with path coefficients of 0.145 and 0.146, respectively and their p values were zero, as shown in Table 6 time-saving benefits also exhibited a significant positive relationship with perceived usefulness of AI(*H5*: $\beta = 0.160$, SE = 0.025, $p < 0.01$, $t = 4.46$) and with perceived Accuracy of AI outputs (*H6*: $\beta = 0.120$, SE = 0.019, $p < 0.01$, $t = 3.87$). Moreover, ease of use of AI tools shows a strong positive impact on perceived usefulness of AI (*H4*: $\beta = 0.637$, SE = 0.021, $p < 0.01$, $t = 5.34$) and training and support availability also show a positive, albeit weak, relationship (*H7*: $\beta = 0.025$, SE = 0.02, $p < 0.01$, $t = 3.08$). Furthermore, the perceived usefulness of AI exhibits a strong positive association with user satisfaction (*H8*: $\beta = 0.791$, SE = 0.014, $p < 0.01$, $t = 6.23$). Despite having many constructs showing a positive link, awareness of ethical concerns had a negative link with the perceived usefulness of AI (*H3*: $\beta = -0.178$, SE = 0.064, $p < 0.01$, $t = 1.35$).

Mediation effect analysis (Sobel's test)

The Sobel's Test for the mediation analysis is presented in Table 7, where specific indirect effects reflect the hypothesised indirect relationships. From the analysis in Table 7, the path AAT → PUA→USR, there is the product of 0.145 and 0.791, which are beta values for AAT → PUA and PUA→USR, respectively, that is, 0.237 × 0.507 results in 0.120. In addition, the relationship between access to AI Technologies and user satisfaction with AI in research is significantly mediated by the perceived usefulness of AI (β=0.114, $p = 0.000$). The mediation effect has some limitations, since it can change the direction of some relationships. In this research, there was no change in either the direct and indirect relationships. To confirm the results, the confidence interval was used.

Evaluation of the model

After the model and its hypothesis were tested, the contributions of the dependent variables(s), and the size and relevance of the effect were further examined via the coefficient of determination(R^2), effect size (f2) and predictive relevance (Q2). According to Schumacher et al. (2016), R^2 is the amount of variance in the dependent variable that is explained by the relationship in the independent variable categories. According to Dawar et al. (2021), R2 values of 0.25, 0.5, and 0.75 indicate weak, moderate, and strong effects, respectively. For the perceived usefulness of AI in the present study, the R2 value of 0.752 contributed by all the predictors in the model and is classified as strong. The User Satisfaction with AI in Research had an R2 value of 0.625 (moderate to strong). In some cases, very high R2 values are not desirable as they can lead to spurious relationships that can be misleading. The model was also evaluated through predictive relevance and according to Fauzi (2022), the Q2 is classified as small (0.02), medium (0.15) and large (0.35). The results displayed in Table 8 show medium to large classification and, therefore, the predictive relevance of this study was acceptable for all endogens constructs. According to Barnett and Salomon (2006), an effect size of ≤ 0.30, $0.3 < f2 \leq 0.50$ and $f2 > 0.50$ means weak, moderate and strong, respectively. For this study, the effect size is generally moderate. It can be concluded that the effect of the independent variable on the dependent variable is moderate in effect size. This study reveals an effect size that is weak to moderate and it can be stated that the impact of independent variables on the dependent variables has a weak to moderate effect size.

The random forest results

The prediction of user satisfaction in AI use among management education researchers in Zimbabwe is very critical. When the model was run, the dataset was split randomly into training and testing sets, which ensured that model evaluation was not biased. A data split ratio of 70:30 was used: 70 % of the data was used to train the Random Forest model, while 30 % of the data was set aside as testing data. Stratified random sampling was used when necessary to maintain response variable balance in the data set. Before data splitting, data pre-processing was

Table 5
Model Fit Indices.

The Goodness of Fit Measures	Absolute Fit Indices			Relative Fit Indices			Non-Centrality-Based Indices			Parsimonious Fit Indices	
	χ2/df	Prob	GFI	NFI	IFI	TLI	CFI	RMSEA	RNI	PCFI	PNFI
Measurement Model	2.21	0.02	0.97	0.93	0.98	0.97	0.98	0.031	0,97	0.84	0.87
Structural Model	3.04	0.01	0.96	0.91	0.96	0.98	0.97	0.034	0.96	0.82	0.84
Criterion (Threshold values)	<5.0	<0.05	>0.95	>0.90	>0.95	>0.95	>0.95	<0.05	>0.95	>0.75	>0.75

Note: IFI = Incremental fixed index; TLI = Tucker-Lewis Index; χ2/df = Relative Chi-square; RMSEA = Root mean squared error of approximation; CFI = Comparative fit index; GFI = Goodness of Fit Index; NFI = Normed fixed index; RNI Relative Non-centrality Index; PNFI = Parsimony-adjusted normed fit index; PCFI = Parsimonious adjusted fit index.

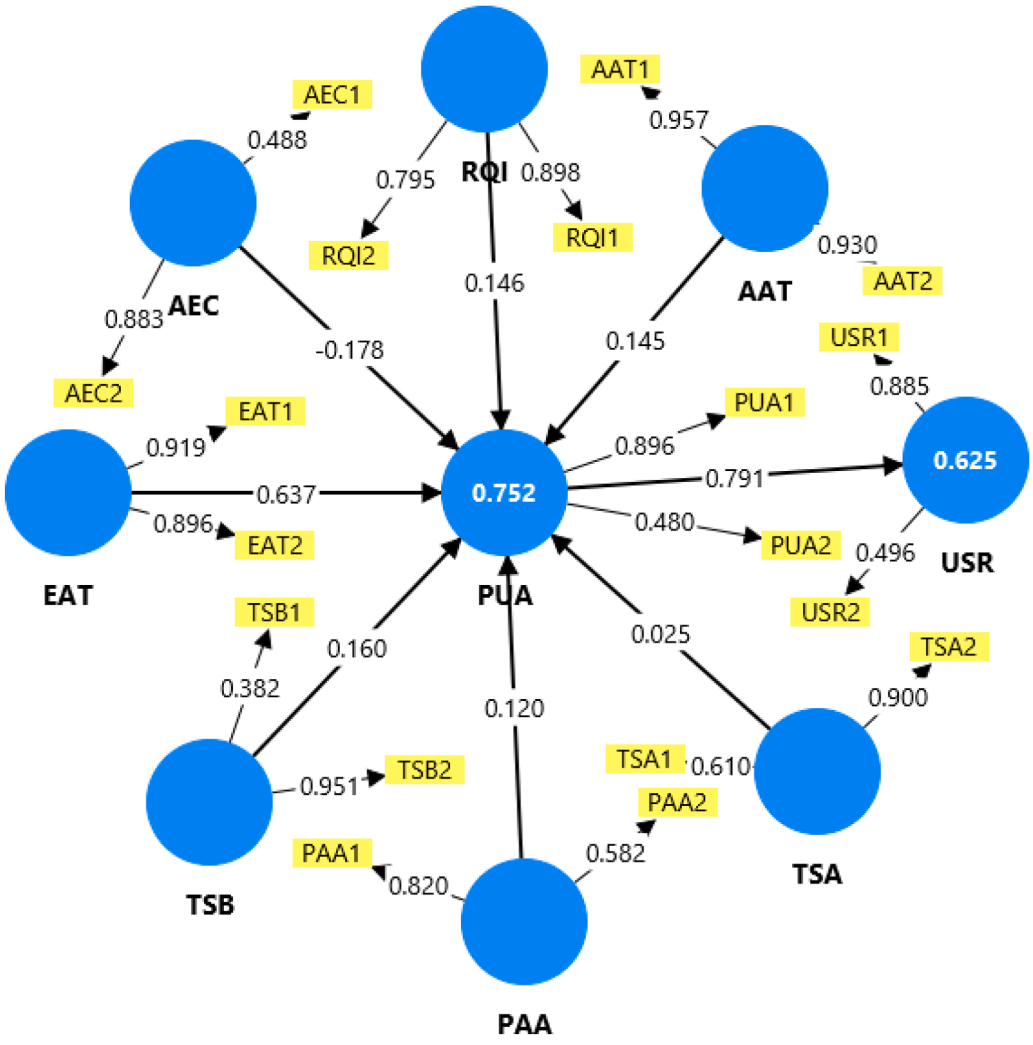

Fig. 3. The SEM path diagram.
Key: Ease of Use of AI Tools (EAT), Access to AI Technologies (AAT), Perceived Accuracy of AI Outputs (PAA), Time-Saving Benefits (TSB), Research Quality Improvement (RQI), Training and Support Availability (TSA), Awareness of Ethical Concerns (AEC), Perceived Usefulness of AI (PUA), User Satisfaction with AI in Research (USR).

Table 6
The SEM Results.

Hyp	Regression Paths	Standardised Regression Weights (β)	SE	T	p	Decision
H1	AAT → PUA	0.145	0.038	4.09	0.00	Supported
H2	RQI →PUA	0.146	0.027	4.27	0.00	Supported
H3	AEC →PUA	−0.178	0.064	1.35	0.16	Unsupported
H4	EAT → PUA	0.637	0.021	5.34	0.00	Supported
H5	TSB →PUA	0.160	0.025	4.46	0.00	Supported
H6	PAA → PUA	0.120	0.019	3.87	0.00	Supported
H7	TSA → PUA	0.025	0.02	3.08	0.00	Supported
H8	PUA →USR	0.791	0.014	6.23	0.00	Supported

Source: Field Data (2025).
Key: Ease of Use of AI Tools (EAT), Access to AI Technologies (AAT), Perceived Accuracy of AI Outputs (PAA), Time-Saving Benefits (TSB), Research Quality Improvement (RQI), Training and Support Availability (TSA), Awareness of Ethical Concerns (AEC), Perceived Usefulness of AI (PUA), User Satisfaction with AI in Research (USR).

Table 7
Mediation Analysis (Sobel's Test).

Relationship	B	P-value	95 % CI LL	95 % CI UL	Comment
AAT → PUA→USR	0.114	0.000	0.106	0.124	Supported
RQI →PUA→USR	0.115	0.000	0.112	0.159	Supported
AEC →PUA→USR	−0.141	0.13	−0.025	−0.156	Unsupported
EAT → PUA→USR	0.504	0.000	0.216	0.615	Supported
TSB → PUA→USR	0.127	0.000	0.110	0.202	Supported
PAA → PUA→USR	0.094	0.000	0.044	0.256	Supported
TSA → PUA→USR	0.020	0.000	0.011	0.107	Supported

conducted, which included handling missing values and standardising variable formats. The training data set was used for model learning and hyperparameter tuning, while the testing data set was used exclusively for model testing and evaluation. To make the model more robust and prevent overfitting, k-fold cross-validation was incorporated into model training. In this case, 10-fold cross-validation was used, with the training data set split into ten equal-sized data sets or folds. In each iteration of model training, nine data sets were used for model training, while one

Table 8
Model Evaluation.

Endogenous Construct	R2	Q2	Relationship	f2	Decision
PUA	0.752	0.386	AAT → PUA	0.261	Weak
			RQI →PUA	0.304	Moderate
			AEC →PUA	0.101	Weak
			EAT → PUA	0.362	Moderate
			TSB → PUA	0.312	Moderate
			PAA→PUA	0.201	Weak
			TSA → PUA	0.195	Weak
USR	0.625	0.431	PUA→USR	0.409	Moderate

Source: Field Data (2025).

data set was set aside as validation data. The model was trained and validated ten times until each data set had been used as validation data once.

The results displayed in Table 9 showed that the model demonstrates high precision with an R^2 value of 73 %, meaning that the total amount of variation in user satisfaction in AI is explained by ease of use of AI tools, access to AI technologies, perceived accuracy of AI outputs, time-saving benefits, research quality improvement, training and support availability, awareness of ethical concerns and perceived usefulness of AI. The model plot is indicated in Fig. 4, which shows how the inputs, outputs and hidden interact with each other. Evaluation metrics such as RMSE, MAPE, MSE and MAE were also used to evaluate the model. The low values of RMSE (0.744), MSE (0.553), and MAE (0.467) indicate the model's ability to predict user satisfaction in AI, with small deviations between the predicted value and actual values. These results show that the factors under this model can influence the use of digital tools in entrepreneurship activities. The low values of the evaluation metrics (RMSE, MSE and MAE) mean that the model is reliable in devising new policies aimed at promoting satisfaction in AI use.

Variable importance

Feature importance was calculated using the Random Forest Variable Importance approach to determine the key predictors contributing to User Satisfaction with AI in Research outcome. The primary method used was the "Mean Decrease in Accuracy (permutation importance)" approach. Each predictor was randomly permuted, while holding other predictors constant to measure the increase in the error rate for the model. A larger error rate was associated with the importance of the predictors. The "Mean Decrease in Gini impurity" was used as an alternative method for measuring the improvement in node impurity for the model. The variable importance plot from the Random Forest model indicates ease of use of AI tools as the most influential predictor by a significant margin in both %IncMSE and IncNodePurity metrics, demonstrating their dominant role in driving model performance. Access to AI technologies and perceived usefulness of AI were the second-best variable in both %IncMSE and IncNodePurity metrics. Other variables, such as research quality improvement and training and support availability, also contribute notably, but their impact is much less pronounced than access to AI technologies. The remaining variables, time-saving benefits awareness of ethical concerns, display lower importance in both metrics, suggesting a weaker association with the model outcome. Overall, these results highlight a marked disparity in predictor importance, with access to AI technologies being consistently paramount in management education research, irrespective of the metric used.

Table 9
RF Model results.

Metrics	Value
MSE	0.553
MAE	0.467
RMSE	0.744
MAPE	0.67
R2	0.73
Hyperparameters	
number of trees (ntree)	501
minimum size of terminal nodes (nodesize)	6

Discussion

The results of this study provide strong support for the causal relationship between perceived usefulness of AI and user satisfaction in the management education research context, aligning with the Technology Acceptance Model and DeLone and McLean Information Systems Success Model. Structural equation modelling revealed that ease of use of AI tools came as the most powerful predictor of perceived usefulness. At the same time, access to AI technologies, training and support availability, and research quality improvement exert significant positive direct effects. On the other hand, an ethical concern attitude was negatively related to perceived usefulness, which emphasises the conflict between technology adoption and ethical considerations in management education research. Moreover, the results from the mediation analysis also supported the idea that perceived usefulness significantly mediates the effects of key predictors, such as AI access, on user satisfaction, demonstrating that usability and access improvements lead to acceptance.

The results of the present study support previous studies, which discuss the important role of usability and access in shaping attitudes towards emerging technologies in management education research, but also add a twist by showing how ethical awareness could reduce perceived benefits. The results of the Random Forest complemented the SEM efforts by achieving high predictive efficiency ($R^2 = 73$ %), and low error metrics (RMSE = 0.744, MSE = 0.553, MAE = 0.467). The variable importance revealed that ease of use of AI tools was the most important factor, followed by access to AI technologies and perceived usefulness, consistent with structural equation modelling results and findings from machine learning. These findings demonstrate that both explanatory (SEM) and predictive (RF) approaches agree with each other, indicating that practical usability and accessibility are determinants of satisfaction with AI tools in management education research. The results further support the notion that universities and policymakers should prioritise concerns associated with ease of use, accessibility, and training alongside addressing ethical issues for the sustainable adoption of AI in management education research.

The negative correlation between awareness of ethical concerns (AEC) and perceived usefulness of AI (PUA) suggests that an increased level of awareness of ethical concerns may reduce or moderate the cognitive judgment of the benefits that an individual may derive from AI, and this may be seen from the recent research on the ethics of AI, emphasising trust, risk, and AI adoption. Ethical concerns such as data privacy, bias, academic integrity, authorship, and transparency may lead to a level of uncertainty regarding the legitimacy and/or validity of research results produced by AI, affecting its usefulness, even when there is efficiency. Responsible AI adoption literature suggests that a heightened awareness of AI ethics could create a level of critical scrutiny, especially in the academic environment, since academic integrity, credibility, and originality are essential components of a researcher's professional integrity. In the academic environment, issues of plagiarism, over-reliance on AI reasoning, and the consequences of AI-generated content could create some doubt in the user's mind as to whether AI is a force that enhances or undermines the quality of research. From a Technology Acceptance Model perspective, the perceived risks could undermine the positive cognitive judgement of the usefulness of AI, while the Information Systems Success Model suggests that the success of the system in satisfying the user is dependent on the trust and governance structures in place. In a resource-constrained environment such as Zimbabwe, the absence of AI governance frameworks could create a heightened level of concern. The study, therefore, shows that there is a significant emphasis on integrating ethical

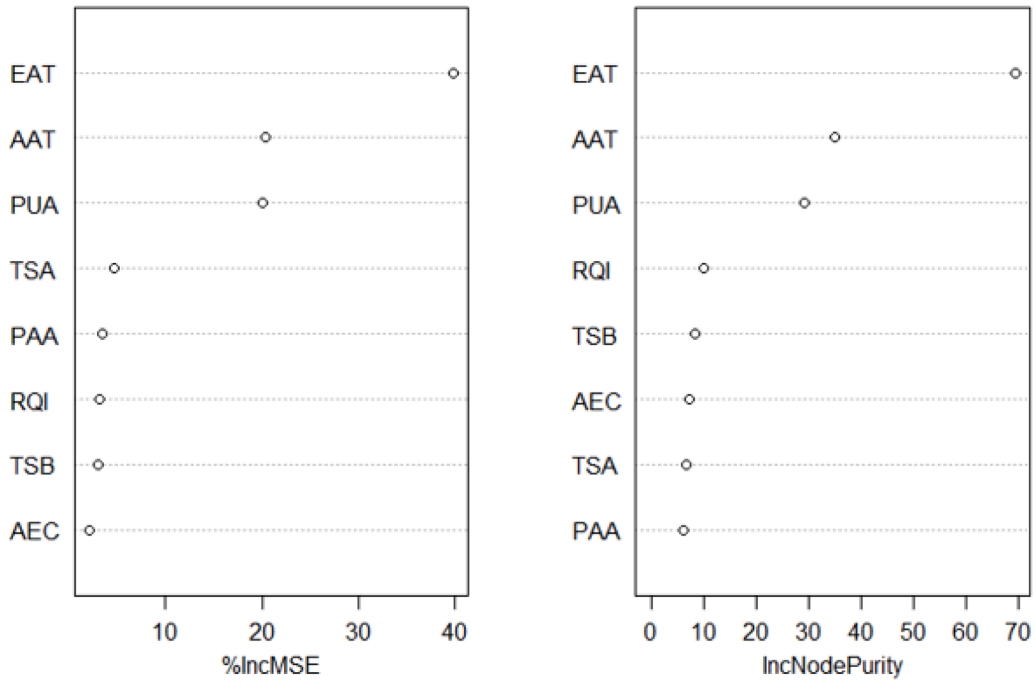

Fig. 4. The Variable Importance plot.

governance and transparency, such that awareness of ethical concerns does not reduce its usefulness.

The comparison between the results obtained by the Structural Equation Modelling technique and those obtained by the Random Forest technique goes beyond the simple agreement in results. It also underscores the advantages offered by explanatory analysis versus those offered by predictive analysis. The results relating to the SEM technique offered a theoretical basis that could be used in formulating causal explanations, as they confirmed the role played by the constructs developed based on the TAM and ISSM theories in determining the Perceived Usefulness of AI and the User Satisfaction with AI in Research constructs. The results relating to the RF technique, on the other hand, focused on the prediction, as it identified the variables that most contributed to the prediction, regardless of the theoretical basis on which this is formulated. The agreement between the results yielded by the SEM technique and those yielded by the RF technique underscores the robustness of those obtained in determining the Ease of Use of AI Tools and the Access to AI Technologies constructs. The results relating to the RF technique, on the other hand, help institutional decision-makers to identify the areas needing investment, as these results could be used in formulating an investment strategy, even in cases where results relating to the SEM technique indicate indirect relationships or mediation.

The findings of this research are very consistent with the TAM, which identifies perceived usefulness as the most important predictor of technology adoption and satisfaction. Consistent with findings of Davis (1989) and Venkatesh & Davis (2000), this research validated the fact that ease of use significantly increases perceived usefulness, which in turn influences user satisfaction with AI tools. The results of the mediation analysis, specifically those relating to perceived usefulness, also support the findings of Tao et al. (2022) that this construct is a key determinant in explaining the adoption of technology used in management education research and professional practice. This alignment suggests that the TAM theory remains essential, especially when applied to advanced technologies like AI in Zimbabwe's higher education system, thereby propagating the generalisability of these constructs across varying technological and cultural contexts.

Institutional infrastructural limitations had a significant contextual influence on several research results. The scarcity of high-performance computing, unreliable internet connectivity, and uneven availability of licensed AI tools affected the strength of Access to AI Technologies as a significant predictor of User Satisfaction with AI in Research. These limitations may have contributed to the identification of Ease of Use as the most significant predictor, with users preferring tools with reliable performance in infrastructurally limited environments. Training and support availability were also affected, with institutions with weak digital infrastructures hindering users' optimal usage of AI tools. These limitations may have contributed to Training and Support Availability being less significant in determining users' perceptions of AI output accuracy, owing to unreliable tool performance. Ethical awareness was generally low, given that AI governance structures within institutions are still in their infancy. These results, therefore, reflect adaptive AI use in infrastructurally constrained academic environments.

The positive effect of the role of access to AI technologies and research quality improvement provides new findings, where studies previously published focused on usability or training, with less attention paid to infrastructure and outcome-related aspects. The study conducted by Rana et al. (2024), for example, concluded that system quality and access had a strong impact on perceived usefulness of educational technology in emerging nations, which the authors found to be similarly true here in the context of AI. However, in contrast to the earlier research that presented infrastructural access as a less important factor in AI adoption (Thavi, 2022), our findings emphasise its centrality to an even greater extent, especially within low-resource countries like Zimbabwe, where the lack of access to AI tools can constitute a major impediment to adoption and satisfaction. This highlights the context-specific contribution of our study in that access is not only a background factor but significantly influences perceived usefulness in low-infrastructure settings. Conversely, the negative factor relationship between awareness of ethical concerns and perceived usefulness aligns partly with the study by Floridi et al. (2021), who found ethical considerations, such as fairness, transparency and accountability, can build trust in and further the adoption of AI systems. However, the negative relationship of ethical awareness on perceived usefulness highlights that when users are more sensitised to the potential risk of AI in management education research, in terms of overreliance on automation and reduced critical thinking, their perception of AI benefits may decrease. Further

research on the influences of socio-cultural and regulatory contexts on ethical dimensions of AI acceptance may be required to fully understand these dynamics.

Implications of the study

Academic implications

The results of this study contribute to academic knowledge on technology adoption by incorporating the Technology Acceptance Model (TAM) and DeLone and McLean Information Systems Success Model (ISSM) in the field of AI in management education research. The use of the hybrid SEM–Random Forest approach constitutes a methodological innovation as it integrates causal inference and prediction in order to better understand factors influencing user satisfaction. This integration contributes to the literature by further substantiating the role of perceived usefulness, ease of use, and system quality in influencing technology acceptance. For management educators and researchers, the study underscores the critical role that AI tools can play in improving research efficiency and knowledge production, especially in resource-constrained environments.

Policy implications

The findings of this study also affect policy for universities and governments seeking to foster responsible and effective use of AI in management education research. The strong influence of ease of use, access to AI technologies and perceived usefulness in user satisfaction demonstrates that policies should be developed to expand digital infrastructure, make AI tools affordable for a broad number of users and include training on using AI in academic curricula. At the same time, the negative impact of ethical considerations draws attention to the need for a well-balanced regulatory framework and institutional instructions to defend academic integrity, address plagiarism and encourage the correct use of AI. Consequently, investment in AI technologies and management education research can be coupled with robust ethical and capacity-building policies by governments and universities.

Practical implications

The study results offer practical implications in terms of how universities, research institutions and educators might benefit from AI tools for management education research. From the findings, since ease of use and access to AI technologies were found to be the most significant factors driving user satisfaction, institutions should focus on ensuring user-friendly platforms and investing in digital infrastructure that offers both students and staff equal access to AI resources. Training workshops, practical courses and integration of AI tools into the current management education research infrastructure can contribute to increasing perceived usefulness and reduce barriers to adoption. Meanwhile, the results also show that there is a pressing need to manage ethical concerns and foster a culture of responsible AI use. Awareness campaigns should be conducted to shape student and staff attitudes towards plagiarism as one of the concerns related to intellectual property rights and breach of data.

Conclusion

This paper examined the critical issue of perceived usefulness on user satisfaction with artificial intelligence tools in management education research using structural equation modelling and a random forest algorithm. The main objective was to highlight the interrelationships of the variables that affect user satisfaction with artificial intelligence tools and create a prediction model that guides key stakeholders as they take corrective actions and rank the factors that affect user satisfaction**.** Key findings of the study include that ease of use of AI tools, access to AI technologies, and research quality improvement show positive links with the perceived usefulness of AI, as determined using structural equation modelling . Only awareness of ethical concerns exhibited a negative association with the perceived usefulness of AI. Despite the advantages of using SEM, the random forest model provides that variable importance and overall, ease of use of AI tools and access to AI technologies contributed significantly to user satisfaction. There was a close relationship between the SEM and random forest models, enabling the methodological limitations of each to be overcome. The results provided important insights that will assist policymakers and stakeholders in improving the use of AI tools, especially in management education research.

Limitations

Despite the valuable contributions of this study to understanding satisfaction with AI tools in academic research, certain limitations must be acknowledged. The study was carried out in Zimbabwean higher education institutions and, therefore, the generalisability of the findings to other contexts that might have different technology infrastructure or academic environments is limited. Ethical issues might, for example, appear differently to those working with well-developed countries in terms of access, and regulatory structures and this influences the applicability of this study in other environments. Notwithstanding the essence of the hybrid technique in this study, potential limitations relating to the use of self-reported data can lead to social desirability bias and potential biases in prediction.

Future studies

Future studies could investigate the application of AI tools in different academic fields and levels of education, such as secondary and postgraduate levels, in order to determine whether perceived usefulness and satisfaction differ across contexts. Moreover, research could be conducted on the long-term association of AI use with other outcomes such as research productivity, critical thinking and academic integrity, allowing for better causal inference. By incorporating these suggestions, the authors hope that the future of AI will shape the academic field without violating its intended use.

Ethics approval and consent to participate

The research received Ethical Approval from the Ethics Committee (08/07/2025) of the Marondera University of Agricultural Sciences & Technology (MUAST) Research Board as per the MUAST Research Ethics Policy (2020).

Consent for publication

All authors consented to the publication of the article.

Availability of data and material

Anonymised survey data generated during this study are available from the corresponding author on reasonable request, subject to ethical approval and data protection requirements.

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CRediT authorship contribution statement

Gideon Mazuruse: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Brighton Nyagadza:** Writing – original draft, Visualization, Validation, Supervision, Investigation, Funding

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Declaration of competing 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.

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