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AI-powered mixed reality acceptance in mining: A PLS-SEM and Bayesian Network modeling

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A B S T R A C T

Facilitating digital transformation and sustainable management in the mining industry requires a strategic understanding of how emerging technologies are perceived and adopted by the workforce. Given the sector's traditionally conservative culture and its resistance to change, there remains a pressing need for empirical investigations that illuminate the pathways toward successful innovation adoption. This study explores the acceptance of AI-powered Mixed Reality (AIPMR) technology among the mining workforce in Indonesia, focusing on its potential to revolutionize human-machine interaction and contribute to smart mining solutions. Drawing upon the Technology Acceptance Model (TAM), an extended conceptual framework was developed to examine the influence of six key factors on employees' intentions to adopt AIPMR technologies. Data were collected from 304 mining employees and analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM), further complemented by Bayesian Network analysis to enhance predictive robustness and uncover probabilistic interdependencies. The empirical results demonstrate that perceived usefulness, perceived ease of use, perceived novelty, top management support, and corporate culture significantly influence employees' attitudes toward adopting AIPMR technology, which subsequently impacts their acceptance of this innovation. The model in this research accounts for 72.6 % of the variance in intention to adopt AIPMR technology innovation. This research contributes to the literature by offering a data-driven foundation for developing decision support systems that align with the socio-technical dynamics of the mining industry. It also provides actionable insights for stakeholders seeking to implement technology acceptance strategies that facilitate sustainable digital transformation through the integration of AI-powered Mixed Reality in high-risk industrial environments.

1. Introduction

Innovation is crucial for overcoming productivity challenges, addressing environmental concerns, enhancing social awareness, and ensuring the continuity and sustainability of mining activities [1]. Despite broad consensus on the strategic value of technological advancement [2,3], the mining sector remains deeply entrenched in traditional operational paradigms, often exhibiting cultural inertia, organizational rigidity, and systemic resistance to change [4]. As a result, the industry lags behind other sectors in leveraging digital innovation as a catalyst for competitive advantage and sustainable growth.

Against this backdrop, the integration of Artificial Intelligence (AI) and Mixed Reality (MR) technologies, presents a transformative opportunity for redefining mining practices [1]. AI enables machines to process large volumes of data, learn from patterns, and make autonomous decisions [5,6], while MR facilitates the seamless blending of physical and digital environments, allowing mining professionals to visualize geological structures, simulate hazardous scenarios, and collaborate in real-time [7,8]. The constructive collaboration of AI and MR (*forth* AIPMR) offers immense potential for optimizing mining processes and bolstering safety measures, positioning the sector at the forefront of technological innovation and digital transformation.

However, the seamless integration of these technological innovations (AIPMR) is heavily dependent on the acceptance of mining industry employees. While immersive technologies like AR and VR have been extensively researched [9,10], empirical evidence on the determinants of AIPMR acceptance remains limited, particularly in the mining sector [8,11]. This research, therefore, addresses a timely and underexplored question: What are the key factors that influence mining employees' acceptance of AIPMR, and how do these factors ultimately impact on the intention to adopt such innovations?

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The significance of this research lies in its capacity to fill this critical knowledge gap [8,11], offering both a conceptual and empirical framework to understand how cognitive, organizational, and cultural factors interact in shaping the acceptance of AIPMR innovations among the mining workforce. Furthermore, the contribution of this research is threefold. First, it represents one of the earliest empirical investigations into AIPMR acceptance in the mining sector, particularly within the context of a developing country. Second, it employs a hybrid methodological approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) for theory testing and Bayesian Network (BN) analysis for probabilistic inference, thereby offering both statistical rigor and analytical depth. Third, it emphasizes not only the human–machine interaction dimension but also organizational aspects of technology adoption, a vital component for the advancement of intelligent mining systems, decision-support infrastructures, and the broader agenda of sustainable digital transformation in the mining industry.

2. Review of literature and hypotheses formulation

2.1. Review of literature

In this research, innovation is defined as any novel idea or method requiring knowledge, ingenuity, focus, and perseverance, with a dedicated effort to generate profits as a reward for its success [12]. This conceptualization aligns with the transformative potential of AIPMR in enhancing productivity, reducing operational costs, and improving safety standards within the mining industry [1]. Empirical evidence suggests that the implementation of intelligent digitalization technologies can elevate profitability in mineral extraction enterprises by up to 20 percent [13].

Nevertheless, the integration of such innovations continues to present substantial challenges, particularly in developing economies, which, despite their considerable mining output, exhibit limited technological advancement [14]. These nations, including Indonesia, are confronted with the dual imperative of importing advanced technologies while simultaneously fostering endogenous innovation to optimize their utility [13,15,16]. This research, therefore, focuses on examining the intention to adopt AIPMR within Indonesia's mining sector, advancing contextually relevant hypotheses and extending theoretical insights from prior studies on immersive and artificial intelligence technologies [10,11,17,18]. To distinguish AIPMR from other immersive technologies (Fig. 1), it is imperative to delineate the spectrum between Augmented Reality (AR) and Virtual Reality (VR). Mixed Reality (MR), as a convergence of AR and VR, enables seamless interaction between real world and virtual environments [19]. While AR overlays virtual elements onto real-world views through devices such as smartphones or smart glasses, MR delivers a more immersive and autonomous experience via pixel-based displays controlled by voice or gestures [8]. When augmented by AI, MR evolves into AIPMR, incorporating capabilities such as head tracking, depth sensing, and gesture recognition, thus rendering it particularly suitable for complex mining operations. AIPMR represents a significant enabler of sustainable digital transformation by facilitating enhanced training, operational efficiency, safety, and collaborative practices in the mining industry [1,7].

Furthermore, in light of the evident literature gap concerning the acceptance of AIPMR within the mining sector [8,11], the present study is undertaken to address and fill this critical void. As illustrated in Table 1, prior research has been predominantly concentrated on industries characterized by more structured and controlled environments, including but not limited to retail, services, education, manufacturing, marketing, information technology, and tourism [10,20,29,21–28]. These sectors differ substantially from the mining industry in terms of operational complexity, environmental unpredictability, safety considerations, and workforce dynamics. Consequently, existing findings may not be directly transferable or adequately reflective of the challenges and enablers associated with AIPMR adoption in the mining context. This research, therefore, contributes to advancing scholarly understanding by offering empirical evidence specific to a traditionally conservative and high-risk industry, thereby enriching the discourse on technology acceptance in complex industrial settings.

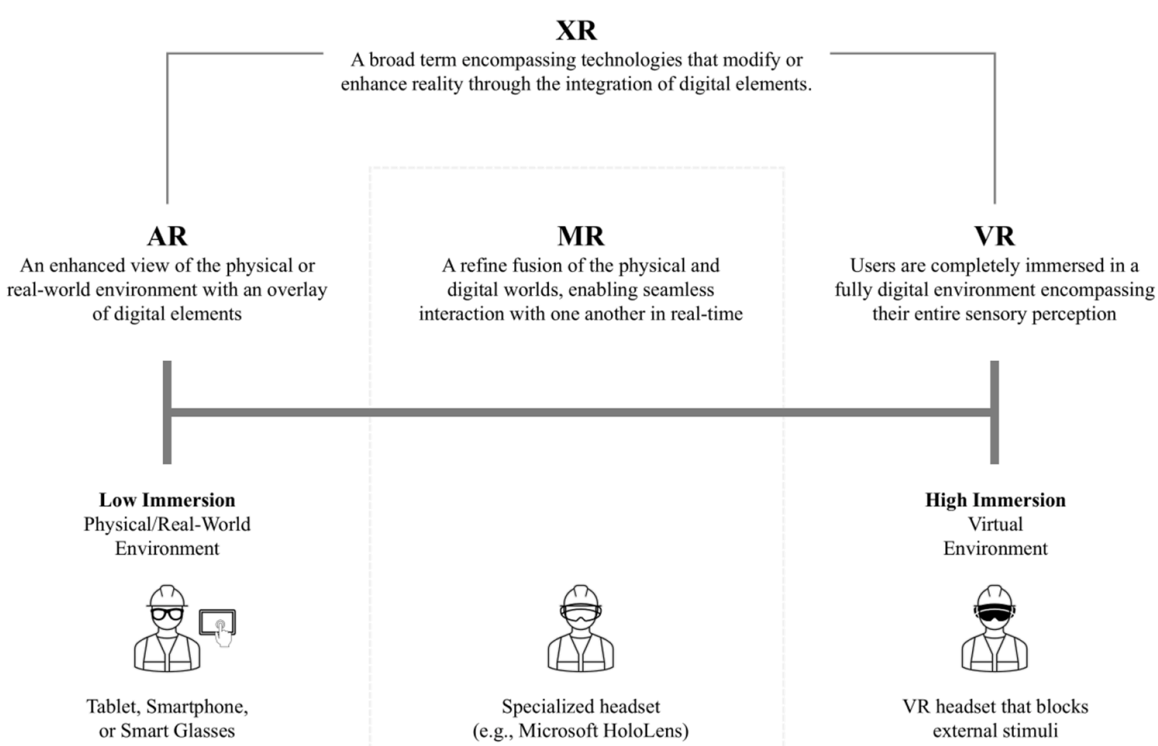


Fig. 1. Distinction between AR, VR and MR.

Table 1
Overview of previous research on extended reality or contemporary artificial intelligence adoption.

Author(s)	Objective(s)	Major Finding(s)	Industry	Research Location
Jang et al. [10]	Examine teachers' readiness to adopt AR and VR in educational practices.	Technological pedagogical and content knowledge influence perceived usefulness and ease of use which ultimately affect positive attitude	Education	Republic of Korea
Holdack et al. [20]	Proposing an enhanced TAM to forecast future adoption of AR.	Joy-related factors substantially impact the acceptance of AR in retail environments	Retail	Federal Republic of Germany
Schuster et al. [21]	Investigating the acceptance of AR in manufacturing to bolster the smart factory concept for intelligent production	Image and social influence are factors that affect the intention to use AR, ultimately influencing its actual usage. Conversely, computer anxiety negatively impacts the intention to use AR.	Manufacture	Federal Republic of Germany
Shen et al. [22]	Investigating factors influencing the acceptance of AR and VR.	Perceived usefulness, hedonic motivation and price value are key predictors of the acceptance of AR and VR	Tourism and Hospitality	People's Republic of China
Huang et al. [23]	Developing a theoretical framework to explain the intention to use VR for surfing experience.	Hedonic factors and utilitarians factors significantly influence the intention to adopt VR for virtual surfing.	Tourism and Hospitality	Republic of China
Koutromanos et al. [24]	Extending TAM for mobile AR in education.	The intention to use mobile AR was influenced by attitude, perceived usefulness and facilitating conditions.	Education	Greece
Saif et al. [25]	Integrating TAM with behavioral concerns: stress and anxiety arising from the utilization of Chat-GPT.	Individual stress leads to anxiety, which subsequently motivates the adoption of Chat-GPT to efficiently complete tasks within deadlines, using any device from any location	Education	Islamic Republic of Pakistan
Chatterjee et al. [26]	Identifying factors influencing the adoption of AI-integrated CRM systems in organization.	Perceived ease of use and trust influence attitude. Perceived usefulness and attitude impact the intention to use AI CRM systems, ultimately affecting their adoption.	Manufacture and Services	Republic of India
Baabdullah [28]	Validating the integrated AI acceptance-avoidance model in organizations.	Performance expectancy, effort expectancy, facilitating conditions, personal well-being concerns, and attitude influence either the attitude towards or the adoption of AI.	Marketing, Finance, IT, and Manufacture	Saudi Arabia
Chatterjee et al. [27]	Identifying how environmental, technological, and social factors influence the adoption of AI in digital manufacturing.	All relationships, except organizational readiness, compatibility, and partner support on perceived ease of use, are significant factors in AI adoption within digital manufacturing.	Manufacture	Republic of India
Hadi et al. [29]	Utilizing the TAM to assess user acceptance of AR-based learning media.	The results show that potential users' intention to use the application is influenced by perceived ease of use, perceived usefulness, and attitude.	Education	Republic of Indonesia

2.2. Theoretical background and hypotheses formulation

The hypotheses for this research were grounded in the well-established Technology Acceptance Model (TAM) [30,31] and its extensions [8,10], which offer a robust, user-centered framework for examining the adoption of emerging technologies across diverse sectors. Given the limited investigation on the adoption of innovative technologies (i.e. AIPMR) within the mineral-extracting industry, a sector characterized by arduous working conditions, low prioritization of innovation, and a generally conservative outlook toward change, particularly in developing nations [11], TAM was selected for its theoretical clarity, practical relevance, and adaptability. In contrast to more complex models, TAM's parsimonious structure aligns well with the contextual realities of the Indonesian mining sector [8]. By applying this model, the research aims to generate novel understandings into the determinants of technology acceptance in a traditionally resistant industry, thereby extending the applicability of TAM and contributing to the broader literature on digital transformation in resource-intensive environments.

The TAM framework [30,31], along with its widely adopted extensions [10,25], identifies perceived usefulness and perceived ease of use as foundational predictors of users' attitudes and intentions toward the adoption of emerging technologies. These models suggest that when a technology is perceived as highly useful in enhancing performance and efficiency, and is considered easy to use, it is more likely to cultivate a positive attitude, thereby increasing the probability of its acceptance [10,30–32]. Moreover, individuals are generally more inclined to adopt IT innovations that they perceive as "new," "neat," and "refreshing" alternatives to existing service channels [9]. Heightened curiosity toward a novel stimulus can trigger states of arousal and positive attitude, motivating individuals to seek out more information and explore the innovation further [8,33].

Nevertheless, empirical evidence on the consistency of these relationships across industries remains inconclusive [20,22,24,25]. While perceived usefulness, ease of use, and novelty have demonstrated strong predictive power in technology-rich sectors [9,23,29,33], their influence may vary in more traditional, conservative domains such as mining [8]. In this regard, the present research positions AIPMR as a cutting-edge innovation offering immersive, intuitive, and highly functional capabilities that can transform operational workflows within the mining industry. AIPMR is theorized to be not only useful and accessible but also experientially novel, introducing dynamic interaction models that enhance worker understanding, situational awareness, and productivity. Accordingly, to empirically validate the relevance of these factors within the mining industry, where the acceptance of advanced technologies remains underexplored [8,11], the following hypotheses are proposed:

H1. Perceived usefulness positively influences attitude towards the adoption of AIPMR technological innovation.

H2. Perceived ease of use positively influences attitude towards the adoption of AIPMR technological innovation.

H3. Perceived novelty positively influences attitude towards the adoption of AIPMR technological innovation.

In addition, top management support and corporate culture are widely acknowledged as fundamental enablers of technology acceptance within organizational contexts. Senior executives, particularly those who exhibit strategic vision and actively champion innovation, play a decisive role in shaping organizational readiness and employee receptivity toward technological transformation [34]. Their endorsement is essential not only for fostering a conducive environment for change but also for ensuring the availability of critical resources, legitimizing the adoption process, and driving successful implementation outcomes [17,35,36].

Simultaneously, corporate culture functions as both a facilitator and a potential constraint in the adoption of emerging technologies [37]. A culture that prioritizes innovation, adaptability, and continuous learning serves as a key determinant of whether employees develop a positive orientation toward new technologies [38]. Conversely, organizational cultures characterized by rigidity, hierarchical resistance, or limited openness to experimentation may impede the realization of technological benefits [4]. As such, corporate culture shapes not only the behavioral intentions of individuals but also the broader institutional capacity to embrace and integrate innovation effectively [35,37].

Given the critical role these organizational dimensions play in advancing sustainable digital transformation, especially within sectors such as mining, where structural conservatism and operational complexity often pose unique challenges, this research examines the extent to which top management support and corporate culture affect the adoption of AIPRM by mining industry employees. Accordingly, the following hypotheses are proposed to guide this research:

H4. Top management support positively influences the intention to adopt AIPMR technological innovation.

H5. Corporate culture positively influences the intention to adopt AIPMR technological innovation.

Furthermore, attitude is conceptualized as a learned predisposition that reflects an individual's tendency to respond favorably or unfavorably to a particular behavior or innovation. Within the context of technology acceptance, attitude has been consistently identified as a central factor influencing users' behavioral intentions to adopt new technologies [10,20,25,28,29]. Numerous empirical studies affirm that attitude not only serves as a direct predictor of technology adoption [20,25,28,29], but also as a critical mediating variable linking antecedent factors (perceived usefulness, ease of use, novelty and organizational aspects) to behavioral intention [8,10,26,34]. This is particularly relevant in the mining sector, which is often characterized by conservative operational paradigms and cautious approaches to innovation [4,11]. The success of advanced solutions (i.e. AIPMR) in promoting sustainable digital transformation depends substantially on the attitudes of mining industry employees [8]. In these high-risk, data-intensive environments, the integration of AIPMR not only enhances productivity and safety but also transforms the nature of human-machine interaction, thereby redefining the operational landscape of mining.

As mentioned previously, prior research has underscored the influential role of attitude in guiding technology-related decisions across sectors. For instance, Jang et al. (2021) demonstrated that educators' attitudes significantly influenced their behavioral intentions toward adopting AR and VR technologies, reinforcing the importance of attitude in shaping digital engagement. Similarly, Chatterjee et al. (2021) emphasized that attitude is not only a predictor of future behavior but also a guiding force that directs individuals' willingness to adopt and utilize innovative technologies. In light of these insights, this research highlights attitude as a decisive factor in the acceptance and implementation of AIPMR technology in the mining sector. Accordingly, the following hypotheses are proposed:

H6. Attitude positively influences the intention to adopt AIPMR technological innovation.

H6. (*a-c*) Attitude mediates the relationships between perceived usefulness, perceived ease of use, perceived novelty, and the acceptance of AIPMR technological innovation.

Moreover, Fig. 2 depicts the conceptual model along with all related hypotheses.

3. Methods and Materials

3.1. Methods

Due to the research's objective of investigating the elements affecting the acceptance of AIPMR among employees working in the mining sector, a positivist paradigm is deemed the most suitable approach [39]. Widely used in business research [8,40], this paradigm involves quantitative methodologies, including controlled experiments on representative population samples. In addition, data analysis was carried out using a hybrid approach of PLS-SEM and BN algorithms [41].

PLS-SEM was selected due to its robustness in analyzing structural models that involve multiple constructs and indicators, making it

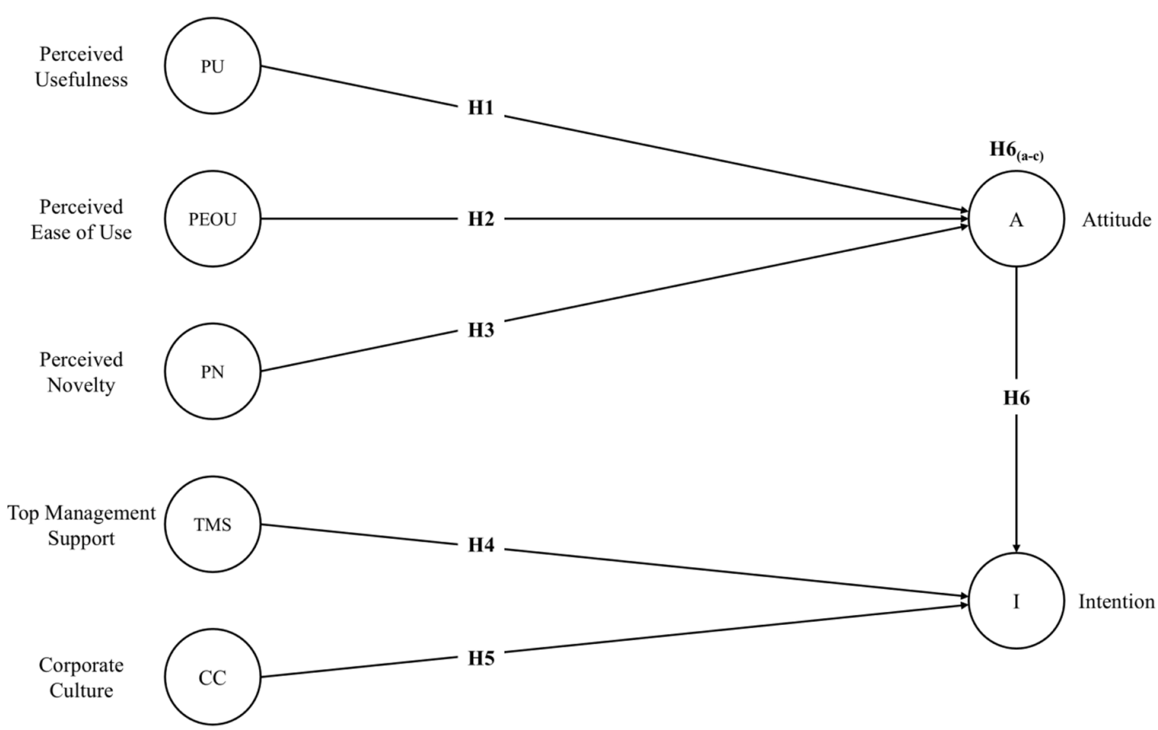


Fig. 2. The conceptual model.

particularly suitable for hypotheses testing in exploratory research contexts with limited sample sizes or non-normally distributed data [42,43]. As PLS-SEM requires the researchers to actively explore all potential model configurations, a process that is often both time-consuming and demanding, there has been a rising interest in leveraging data science to extract valuable insights from complex datasets [44]. This shift has fostered the adoption of machine learning techniques as powerful approach in research on technology acceptance [41,44]. In this regard, BN algorithms have emerged as particularly effective complementary tools. They enhance the predictive accuracy of the conceptual model, deepen the understanding of relational dynamics, and identify new relationships [41]. In this research, Grow-Shrink (GS) and Hill-Climbing (HC), the prominent algorithms in BN, were employed.

The GS algorithm focuses on identifying relevant variables through conditional independence, while HC seeks to optimize existing structures through iterative improvement. In GS algorithm, it is designed to discover Markov blanket of a target variable [45]. The *growing* phase attempts to add variables E' to the current structure variables E based on independence tests. In mathematical representation is described as follows:

$$E' = E \cup \{(a,\ b) | I(X_a,\ X_b | X_{MB(a)}) \text{ is false}\}$$

where E' is the updated set of variables, E is the current set of variables, $I(X_a,\ X_b|X_{MB(a)})$ indicates whether X_a and X_b are independent given the Markov blanket $MB(a)$. After growing the structure, the algorithm removes variables that do not satisfy the independence constraints, where in the following equation E'' represents the final set of variables after the *shrink* phase.

$$E'' = E' \cup \{(a,\ b) | I(X_a,\ X_b | X_{MB(a)}) \text{ is true}\}$$

Meanwhile, in the greedy HC procedure, the iterative optimization algorithm initiates with an initial network structure x, iteratively making small, localized changes to optimize it according to a specific scoring criterion. A heuristic function $f(x)$ evaluates the quality of each adjustment, guiding the algorithm in refining the solution. This process continues until a local maximum is reached, where no further improvement is possible with the existing set of adjustments [46]. The HC algorithm can be mathematically represented as follows:

$$\text{If } f(x_{new}) > f(x_{current}) \text{ then set } x_{current} = x_{new}$$

This process repeats until no neighboring provides better value for $f(x)$. With these methods, the GS and HC algorithms produce visual depiction for the models, with arrows depicting directed relationships between variables and lines indicating undirected relationships. These visual representations assist in validating existing relationships, uncovering missing links, and revealing new associations that may highlight areas for enhancing the benchmark model within the PLS-SEM [41].

3.2. Research instruments

The validation process for the conceptual model and hypotheses involved conducting quantitative research through surveys, which required the creation of a questionnaire. The research questionnaires were specifically designed to capture the core elements and context of the factors and underwent rigorous validation through pretesting. Initially reviewed by industry experts from diverse fields [26], the questionnaire was interpreted from English to Indonesian language by the authors, with a qualified linguist verifying its accuracy. Further refinement was achieved through pilot testing with several mining industry employees to ensure clarity and appropriateness of responses.

Data collection employed a 5-point Likert scale [26], ranging from '1' (strongly disagree) to '5' (strongly agree), to measure the core elements regarding the acceptance of AIPMR. To ensure transparency and replicability, comprehensive definitions of all constructs, along with the questionnaire items in both English and Indonesian, are provided as supplementary material. This meticulous validation and refinement process was essential to guarantee the reliability and validity of the data collected for testing the conceptual model and hypotheses.

3.3. Approach to gathering data and selecting samples

Judgmental sampling was selected for this research, as it is frequently employed in exploratory research and valued for its efficiency compared to random sampling. This approach is particularly suited to specialized populations, such as mining industry employees, where random sampling may not be feasible [40]. The research was conducted in Indonesia and specifically targeted employees from large mining companies that meet specific criteria: being a legal entity, employing a substantial workforce, holding considerable assets, or being listed on the Indonesian stock exchange. These criteria were carefully selected to ensure that the sample aligns with the research's objectives and relevance. Additionally, an in-office intercept survey method was implemented in office areas to ensure both efficiency and a high response rate [40,47]. To enhance data collection efficiency, handheld computers, including laptops, notebooks, or tablets, were utilized in place of traditional paper surveys.

Prior to responding to the survey questionnaires, employees received a detailed overview of the research objectives and procedures, and their participation was contingent upon agreement with the terms and conditions of the research. Participants were then provided with an informational module and video on AIPMR technology and its potential applications to support their work. To encourage participation, respondents were offered a small benefit, valued between one and two dollars, upon survey completion. This research was conducted in accordance with ethical standards established by official committees in Indonesia (KE/079/UGM/EC/2024).

The survey finally received 304 valid responses from mining industry employees, with ages ranging from twenty to over 51 years. Following established guidelines for PLS-SEM and BN, which recommend an indicator-to-respondent ratio of 1:5 to 1:20, this study aligns with these standards [8,42,43], ensuring robust measurement and analysis. The sample was 57 percent male and 43 percent female, with most respondents holding a bachelor's degree, followed by those with a three-year diploma and master's degrees. Job tenure among participants ranged from under one year to over twelve years. Fig. 3 illustrates the research design and sampling procedures in this research.

4. Analyses and findings

4.1. PLS-SEM reflective measurement model

The conceptual model was developed based on a reflective construct framework, for which indicator loadings exceeding .708 are recommended [42]. This threshold suggests that the construct explains more than 50 % of the indicator's variance, thereby ensuring acceptable item reliability. The analysis yielded values ranging from .861 to .919, aligning with the aforementioned quality standards. Furthermore, internal consistency and construct reliability were assessed using Cronbach's Alpha (α), Rho A (ρA), and Composite Reliability (CR), all of which met the required quality criteria [42,48]. The results of Cronbach's Alpha produced values between .90 and .92, ρA values ranged from .90 to .92, and CR remained below .94. The use of bootstrap confidence intervals, which yielded values below .95, further substantiates that the constructs significantly surpass the recommended minimum threshold. In assessing convergent and discriminant validity, both the Average Variance Extracted (AVE) and the HeteroTrait-MonoTrait (HTMT) ratio of correlations were examined. AVE, which evaluates the extent to which a construct explains the variance of its items, generated values above the minimum requirement of .50 for each construct [42]. The HTMT ratio, which assesses the empirical

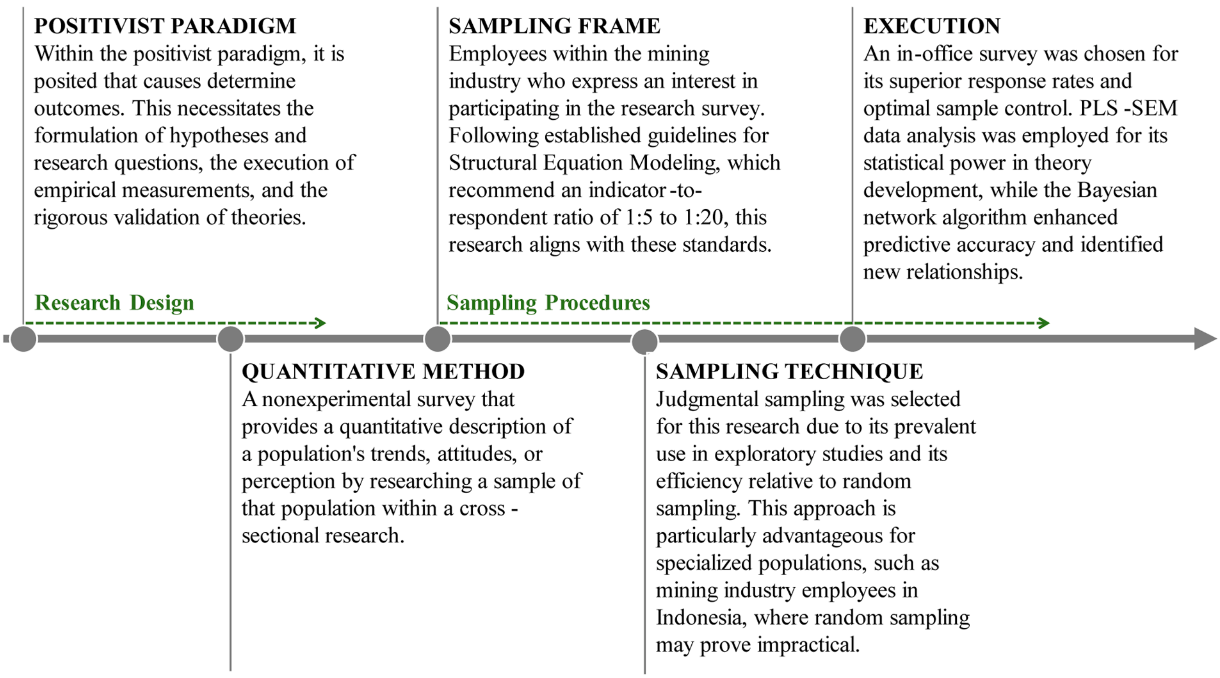


Fig. 3. Design of research and sampling procedures [39–41,43].

distinctiveness of constructs within the structural model, produced values below .85, meeting the necessary quality criteria [49]. Appendix A and Appendix B summarize the assessments of indicator loadings, internal consistency reliability, construct reliability, convergent validity, and discriminant validity.

In addition, the Confirmatory Tetrad Analysis (CTA-PLS) was employed to assess the structural integrity and reliability of the proposed model [42,50]. The results reinforced the reliability of the reflective measurement model, providing additional evidence of its validity and demonstrating consistency with its widespread application in previous research.

4.2. PLS-SEM structural model

The structural model assessment was conducted after confirming the satisfactory results of the measurement model. Prior to evaluating the structural relationships, collinearity was examined using the Variance Inflation Factor (VIF) to ensure that it does not distort the results. Ideally, VIF values should remain below 5 [51], and the analysis yielded values between 2.4 and 3.5, thus meeting the necessary quality standards. The R^2 values, representing the model's explanatory strength, show significant outcomes with 0.68 for both intention and attitude, with the rank order of the f^2 effect sizes aligning with the magnitude of the path coefficients. Moreover, the Q^2 statistic which evaluates the model's predictive accuracy, produced values of .688 for intention and .676 for attitude, reinforcing the model's predictive validity [52,53]. To further complement the insights from the R^2 values regarding predictive power, the PLSpredict assessment (Appendix C) confirmed that none of the Root Mean Square Error (RMSE) values surpassed those of the naïve Linear Regression Model (LM), further validating the model's strong predictive capability.

In addition, the overall model fit was substantiated by a Normed Fit Index (NFI) value of .901 and a Standardized Root Mean Square Residual (SRMR) of .032, both of which fall within the recommended thresholds, indicating a good fit of the model to the data [40]. Moreover, the bootstrapping method was employed to conduct hypothesis testing within the PLS-SEM framework, generating 10,000 resamples from the initial dataset of 304 samples [54]. This approach offers significant advantages by enabling hypothesis testing independent of parametric assumptions, thereby ensuring reliable results even under nonparametric conditions [55]. To evaluate significance at the 5 % level, the analysis utilized the percentile method to compute a 95 % bootstrap confidence interval. The outcomes disclosed that perceptions of usefulness ($\beta = .417$, $p < .001$), ease of use ($\beta = .300$, $p < .001$), and novelty ($\beta = .203$, $p < .01$) are significant determinants in forming attitudes toward the adoption of AIPMR technology, which subsequently influences the intention to use these innovations ($\beta = .442$, $p < .001$).

Additionally, top management support ($\beta = .338$, $p < .001$) and corporate culture ($\beta = .179$, $p < .01$) were found to have a substantial impact on the acceptance of AIPMR technologies. Further, attitude plays a crucial mediating role in the relationships among perceived usefulness ($\beta = .186$, $p < .001$), perceived ease of use ($\beta = .132$, $p < .001$), and perceived novelty ($\beta = .090$, $p < .01$) with intention. This mediation underscores the significance of attitude formation as an intermediary process, through which these perceptions affect the acceptance of AIPMR technology. A detailed summary of these results is presented in Table 2, while Fig. 4 provides a graphical representation of the structural equation model based on the proposed conceptual framework.

4.3. Bayesian Network machine learning algorithms

BN machine learning algorithms were utilized to confirm the causal structure of the model by leveraging latent variable scores obtained from the full PLS-SEM model, which connects all constructs through a factor weighting scheme [41]. Two notable BN algorithms, the Grow-Shrink (GS) and Hill-Climbing (HC) algorithms, were applied. These algorithms are well-regarded for their ability to identify optimal structural models, validate pre-existing causal relationships, and uncover potential new associations within the sample data sets. A constraint-based algorithm, GS, was first employed to identify the optimal structural model that best explains the data, thereby establishing the final BN framework. Subsequently, a score-based algorithm, HC, was used to select the model with the most favorable score. To maintain consistency with established technology acceptance literature [56], constructs such as attitude and intention were restricted from being linked directly to predictors (PU, PEOU, PN, TMS, and CC). This methodological approach enhances the

Table 2
Statistical significance and relevance of the path coefficients from the conceptual model.

Hypothesis	Path	Path Coefficient	P-Value	Result
H1	PU ⇒ A	.415	***	Supported
H2	PEOU ⇒ A	.303	***	Supported
H3	PN ⇒ A	.203	**	Supported
H4	TMS ⇒ I	.338	***	Supported
H5	CC ⇒ I	.179	**	Supported
H6	A ⇒ I	.442	***	Supported
H6a	PU ⇒ A ⇒ I	.183	***	Complementary (Partial Mediation)
H6b	PEOU ⇒ A ⇒ I	.134	***	Complementary (Partial Mediation)
H6c	PN ⇒ A ⇒ I	.090	**	Complementary (Partial Mediation)

Note: I = Intention; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PN = Perceived Novelty; TMS = Top Management Support; CC = Corporate Culture; A = Attitude; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$.

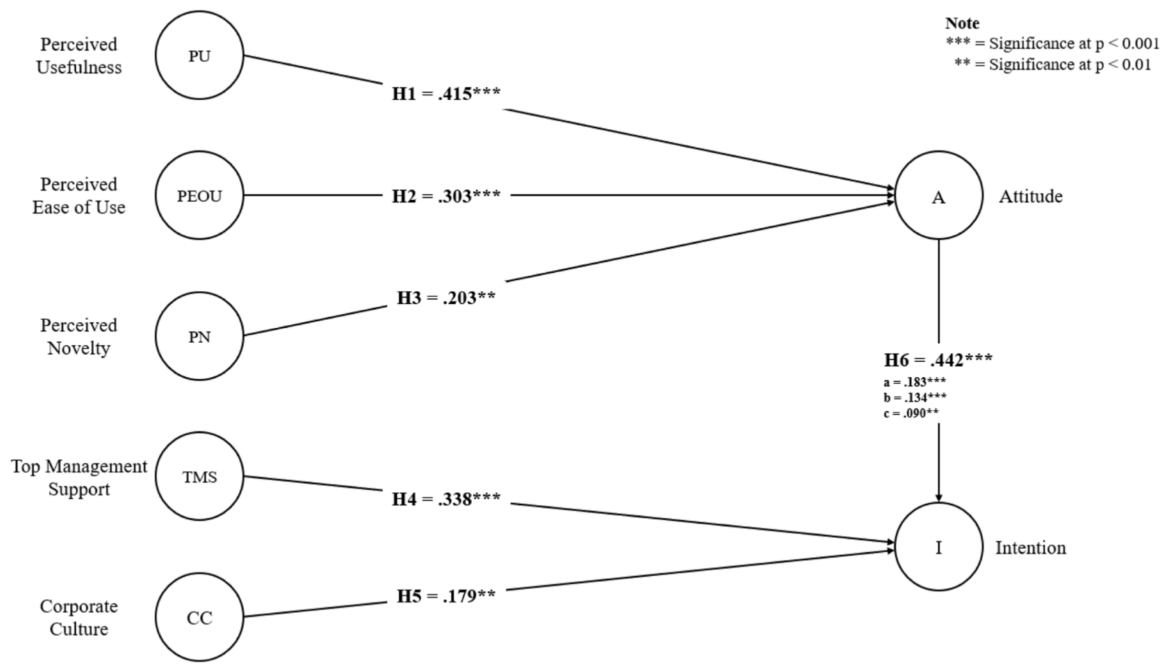


Fig. 4. Structural equation modeling (SEM) was utilized to assess the conceptual model through path weights and statistical significance.

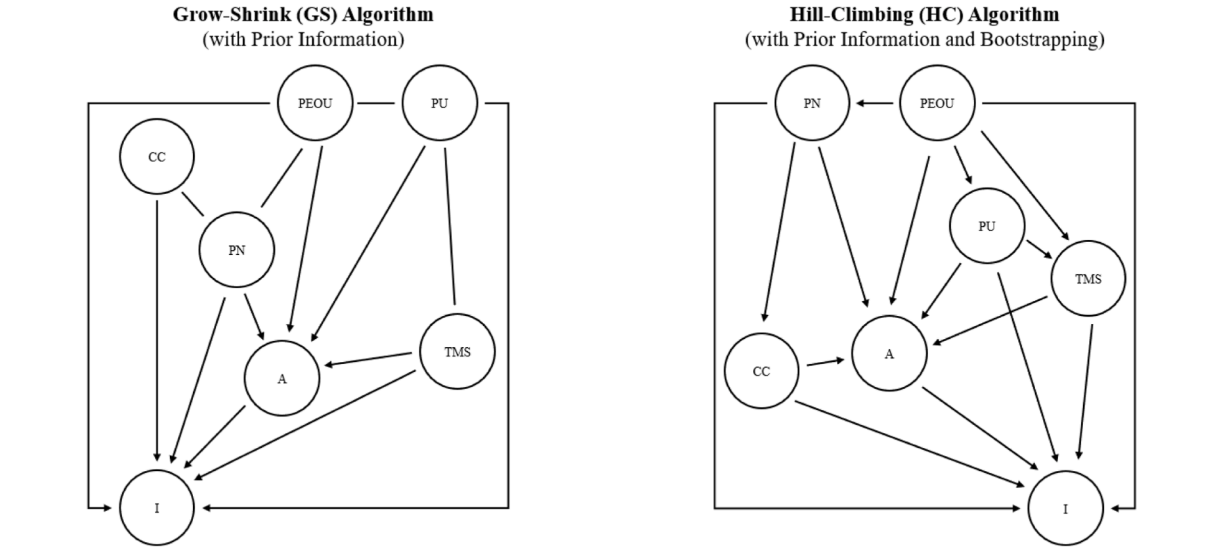
robustness of the findings and aligns with well-supported theoretical perspectives in the field [41].

Fig. 5 on the left-hand side illustrates the model structure derived from the GS algorithm. It identifies significant relationships at a 5 % threshold, represented by directional arrows from one construct to another, indicating a causal influence [41]. In addition, conditional dependencies between constructs are depicted with lines, showing the interdependent relationships that exist without direct causality [41]. On the right-hand side, Fig. 5 visualizes the model structure indicated by the HC algorithm that optimizes the model's goodness of fit to the data with a penalty for the number of parameters in the structural model (using Bayesian Information Criterion - BIC). A bootstrapping procedure was applied to the sample data, involving the generation of five hundred structures of network and constructing the average Directed Acyclic Graph (DAG) by applying a threshold range between 0 and 1. This threshold determined the minimum proportion of occurrences required for a relationship to be included in the final network. An optimal threshold of 0.50 was identified, indicating that only relationships appearing in at least 50 % of the bootstrapping iterations were retained in the final model [57].

Optimized for the BIC, the HC algorithm demonstrated slightly better performance in terms of BIC score compared to the GS algorithm, though the difference in their scores was minimal. Despite this slight variation, the graphical structures produced by both algorithms were largely consistent. In terms of predictive accuracy, the evaluation of cross-validated Root Mean Square Error (cv-RMSE) revealed that both GS and HC algorithms performed comparably in predicting the outcome variables of attitude and intention. Notably, both algorithms identified additional links to the outcome variables attitude and intention, beyond those in the original conceptual model. These findings suggest that both models provide compelling alternative structures, warranting further theoretical consideration [41].

4.4. Evaluation of the theoretical feasibility of the models and the discovered connections

A wide array of research has produced multiple adaptations and expansions of the Technology Acceptance Model (TAM), each drawing from distinct theoretical frameworks [56,59]. In their meta-analysis, Marikyan et al. (2023) synthesized the literature, underscoring perceived usefulness and perceived ease of use as consistent predictors of the intention to adopt various technologies. Similarly, research by Alnemer (2022) and Liu et al. (2022) have reported comparable findings. This alignment with the results from both the GS and HC algorithms further validates their significance. Fazal-e-Hasan et al. (2021) offered theoretical justification for the positive association between perceived novelty and the intention to utilize smart retail technologies, a finding that was also supported by both GS and HC algorithms.



Grow-Shrink (GS)	cv-RMSE	BIC*
Overall		-2317.264
Intention (I)	.536	
Attitude (A)	.570	

Hill-Climbing (HC)	cv-RMSE	BIC*
Overall		-2276.839
Intention (I)	.536	
Attitude (A)	.564	

Note: * = The calculation of the Bayesian Information Criterion (BIC) in the *bnlearn* package indicates that higher values denote superior model fit.

Fig. 5. Network structures identified using the Grow-Shrink (GS) algorithm (left) and the Hill-Climbing (HC) algorithm (right).

Additionally, Shibly et al. (2022) provided empirical support for the critical role of top management support and corporate culture in shaping attitudes toward adopting Enterprise Resource Planning (ERP) technology, reinforcing the importance of these variables in the broader context of technology acceptance.

Furthermore, while theoretical support exists for the relationships between perceived usefulness, perceived ease of use, and perceived novelty with intention, as well as for the connections between top management support and corporate culture with attitude, no established theories were found to substantiate certain new associations identified by the HC algorithm, particularly the link between perceived novelty and corporate culture. Consequently, the theoretical soundness of the model generated by the GS algorithm is more robustly supported and, therefore, considered more appropriate in comparison to the model produced by the HC algorithm.

4.5. Model comparisons

In this analysis, the new models identified by BN algorithms were transferred into PLS-SEM to facilitate a detailed comparison with the original conceptual model. The objective of this integration was to evaluate the predictive performance of the BN algorithm models relative to the established conceptual framework [41]. The PLSpredict outcomes for the GS algorithm model (Appendix D) demonstrated predictive accuracy consistent with that of the conceptual model, suggesting both models exhibit similarly strong predictive capabilities. Conversely, the HC algorithm (Appendix E) displayed only moderate predictive ability, as most, though not all, indicators within the PLS-SEM analysis produced smaller prediction errors when compared to the baseline Linear Regression Model (LM). This performance was notably inferior to that of both the conceptual model and the GS algorithm.

To ensure a thorough evaluation and to capture the nuances in performance between the models, a variety of key metrics were applied. These included Q^2 predict, R^2, and the BIC, which are widely recognized indicators for evaluating model fit and explanatory power. Beyond these traditional metrics, more sophisticated procedures such as the Cross-Validity Predictive Ability Test (CVPAT) and the Akaike Weight assessment were also employed. These methods allowed for a detailed comparison of the models (Table 3), focusing on their predictive strength and each model's relative likelihood of being the optimal solution given the observed data [41,62].

The results of these assessments strongly favored the GS algorithm model, which demonstrated superior performance compared to the original conceptual model and the HC algorithm model. The GS algorithm model consistently outperformed the conceptual framework and the HC algorithm model in key areas of evaluation, particularly in terms of predictive relevance and model fit. The newly identified relationships, through the application of the GS algorithms, were especially significant in reinforcing the structure and theoretical coherence. These relationships (Table 4 or Fig. 6), which had not been considered in the conceptual model, provided critical insights into the underlying dynamics of AIPMR technology acceptance in the mining industry, with their structure aligning well with previously established theories.

5. Discussion

While substantial research has examined technology adoption across various sectors, a notable gap persists in understanding this process within the mining industry, particularly in developing nations [11]. Therefore, this research seeks to explore the factors that facilitate the acceptance of AIPMR technology in the Indonesian mining sector. The empirical findings indicate that five critical factors, perceived usefulness, perceived ease of use, perceived novelty, top management support, and corporate culture, significantly influence mining employees' attitudes toward adopting AIPMR technology, which subsequently fosters their intention to embrace this innovation.

The empirical findings highlight a significant association between perceived usefulness and both attitude ($\beta = .324$, $p < .001$) and intention ($\beta = .204$, $p < .01$). While prior research has yielded mixed outcomes regarding this relationship [25,26], the present findings build upon and extend existing research on immersive technologies [10,23,63], with particular emphasis on the mining industry. The results reveal that a heightened perception of the usefulness of AIPMR technology among mining industry employees directly contributes to a more favorable attitude, thereby increasing the likelihood of adopting this technological innovation. Furthermore, the positive impact of perceived usefulness on

Table 3
Model comparison along with predictive accuracy and relative likelihood consideration.

Model	Path	Q^2 Predict	RMSE	R^2	BIC	PLS – IA Loss	PLS – LM Loss	Akaike
Conceptual Model								
Overall	5					-.836***	-.032*	
I	2	.688	.561	.680	-324.623	-1.035***	-.035	.001
A	3	.676	.574	.685	-329.201	-.637***	-.029*	.017
Grow-Shrink (GS) Algorithm-Enhanced Model								
Overall	11					-.850***	-.046***	
I	6	.688	.553	.726	-354.861	-1.049***	-.050***	.513
A	5	.690	.561	.703	-335.940	-.651***	-.043***	.500
Hill-Climbing (HC) Algorithm-Enhanced Model								
Overall	16					-.485***	-.012***	
I	6	.565	.663	.726	-354.755	-.848***	-.017**	.486
A	5	.581	.652	.703	-335.865	-.547***	-.013***	.483
PU	1	.599	.638	.602	-269.928	-.552***	-.008	NC
PN	1	.467	.735	.470	-182.851	-.435***	-.012*	NC
TMS	2	.473	.731	.615	-273.996	-.468***	-.007	NC
CC	1	.200	.902	.349	-120.104	-.133***	-.015*	NC

Note: IA = Indicator Average; LM = Linear Regression Model; Akaike = Akaike Weights (Relative Model Likelihood); *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NC = Non-Comparable.

Table 4
Statistical significance and relevance of the path coefficients from Grow-Shrink (GS) algorithm-enhanced model.

Path					Path Coefficient	P-Value	Result
PU	⇒	A			.324	***	Supported
PEOU	⇒	A			.265	***	Supported
PN	⇒	A			.134	**	Supported
TMS	⇒	A			.155	*	Supported
CC	⇒	A			.106	**	Supported
PU	⇒	I			.204	*	Supported
PEOU	⇒	I			.159	*	Supported
PN	⇒	I			.130	*	Supported
TMS	⇒	I			.181	***	Supported
CC	⇒	I			.128	**	Supported
A	⇒	I			.213	***	Supported
PU	⇒	A	⇒	I	.069	*	Complementary (Partial Mediation)
PEOU	⇒	A	⇒	I	.056	*	Complementary (Partial Mediation)
PN	⇒	A	⇒	I	.029	NS	Direct-Only
TMS	⇒	A	⇒	I	.033	NS	Direct-Only
CC	⇒	A	⇒	I	.023	NS	Direct-Only

Note: I = Intention; A = Attitude; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; TMS = Top Management Support; CC = Corporate Culture; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = Non-Significance.

intention is partially mediated by attitude (β = .069, $p < .05$), meaning that while perceived usefulness has a direct effect on intention, it also indirectly influences intention by fostering a favorable attitude, which further strengthens the likelihood of adoption [10,26].

The statistical results further confirm a significant positive relationship between perceived ease of use and both attitude (β = .265, $p < .001$) and intention (β = .159, $p < .05$). These findings align with prior empirical studies across diverse technological domains [25,26,32], including augmented and virtual technology [10,23], notwithstanding some mixed results reported in the literature [20,22,24]. These results imply that mining industry employees pay critical attention to the degree of ease or difficulty in using AIPMR technology innovations. In other words, the perception that the AIPMR technology is easy to use directly fosters a positive attitude and increases employees' intention in the mining industry to adopt it. While perceived ease of use also directly enhances the intention to adopt, this effect is partially mediated by attitude (β = .056, $p < .05$), meaning that employees who view the AIPMR technology ease or effortless develop a positive attitude, which further amplifies their acceptance of the innovative technology. This complementary mediation indicates that both direct and indirect effects are at play, with attitude acting as a reinforcing factor between perceived ease of use and the ultimate intention to adopt the technology [10,26].

Furthermore, perceived novelty was found to have a positive impact on both the attitude (β = .134, $p < .01$) towards and the intention (β = .130, $p < .05$) to adopt AIPMR among mining industry employees. Notably, attitude functions as a direct-only effect in this relationship, meaning there is no mediation between perceived novelty and AIPMR acceptance. These findings align with previous research [8,9,33], reinforcing the idea that the newness or uniqueness of AIPMR technology significantly enhances employees' favorable attitudes, which in turn directly influences their intention to adopt the innovation [60]. In this context, attitude serves as a crucial direct pathway, rather than acting as an intermediary mechanism, in shaping the relationship between perceived novelty and adoption intention.

In addition, top management support emerged as a critical determinant, influencing both employees' attitudes (β = .155, $p < .01$) toward and their intention (β = .181, $p < .05$) to adopt AIPMR technology in the mining industry. The positive significant relationships are consistent with the results obtained by previous research in different industries and diverse context of technologies [17,34–36]. Interestingly, attitude functions as a direct-only factor in this relationship, without mediating the effect of top management support on intention. This suggests that the encouragement and support provided by top management in mining industry directly foster positive attitudes toward AIPMR technological innovation among mining industry employees, which subsequently strengthens their intention to adopt these innovations. In this case, attitude does not serve as an intermediary variable mediating the relationship between top management support and the intention to adopt AIPMR technology but rather operates as a direct and significant influence.

This research also revealed that corporate culture plays a significant role in shaping both employees' attitudes (β = .106, $p < .01$) toward and their intention (β = .128, $p < .01$) to adopt AIPMR technology innovations in the mining industry. Similar to the findings for perceived novelty and top management support, attitude functions as a direct-only factor, without mediating the relationship between corporate culture and intention. These findings are consistent with previous studies across various industries and technologies [35,37,38]. They underscore that a supportive, competitive, and innovative-friendly corporate culture directly fosters positive attitudes toward technological advancements, which in turn directly enhances employees' intention to adopt such innovations. In this context, attitude does not mediate the effect of corporate culture on the acceptance of AIPMR but rather acts as a direct

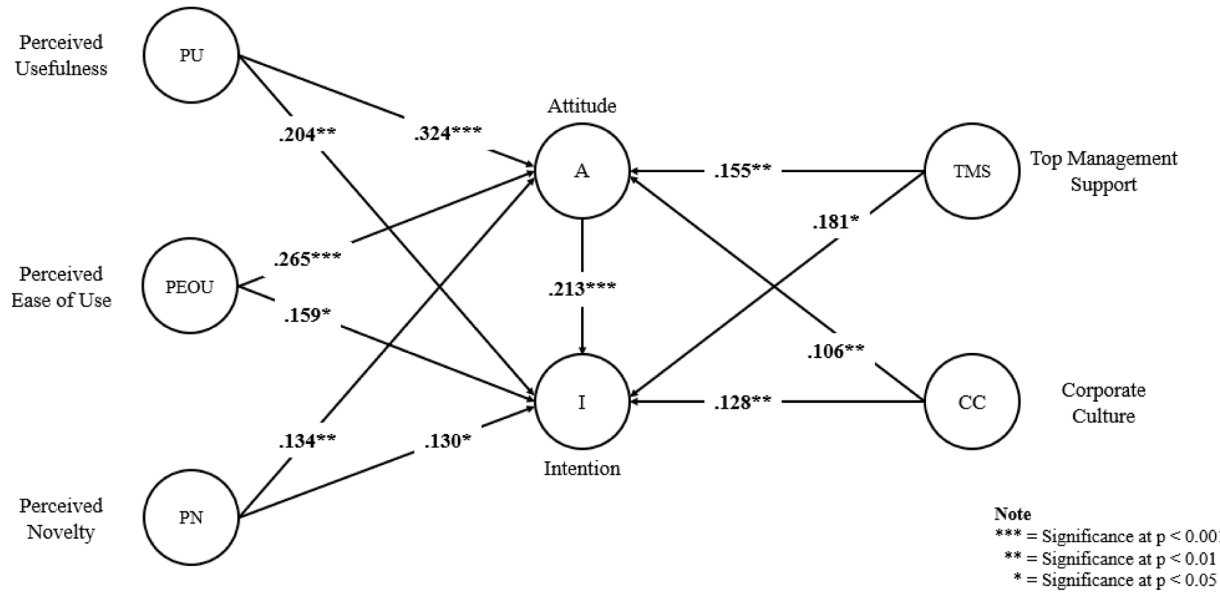


Fig. 6. Grow-Shrink (GS) algorithm-enhanced model.

pathway.

Further, the findings indicate that, among all the factors examined, attitude ($\beta = .213, p < .001$) emerges as the transcendent determinant in the acceptance of AIPMR among employees in the mining industry. This result is consistent with the broader body of literature on technology acceptance [10,20,23–25,28,29,32,61]. Not only does attitude stand out as the transcendent determinant in driving the adoption of AIPMR among employees, but it also behaves as a critical mediator for other factors such as perceived usefulness and perceived ease of use [10,26]. These findings suggest that employees in the mining industry are highly motivated to adopt AIPMR technology when they possess a positive attitude toward this innovation, highlighting the pivotal role of fostering favorable attitudes in promoting the acceptance of technological advancements within the sector. Develop integrated strategies that simultaneously address perceived usefulness and attitudes. For example, combining informative sessions about the technology's benefits with activities that build positive attitudes can lead to higher adoption rates.

5.1. Theoretical implications

From a theoretical perspective, the empirical results of this research significantly extend the established Technology Acceptance Model (TAM) and its expanded versions by focusing on the mining industry, a sector that lacks substantial guidance in technology adoption, particularly in the developing countries of Southeast Asia. The original TAM [30,31], which was developed based on Western cultural contexts in advanced economies, differs considerably from the socio-cultural and economic conditions present in Indonesia, a developing nation. While extensions of TAM have provided empirical insights not only in developed countries [10,58,60] but also in developing regions such as Pakistan [25] and Fiji [17], this research represents the first attempt to enhance the theoretical framework within the specific context of the mining industry. This previously unexplored sector adds significantly to the understanding of the factors affecting the intention to adopt AIPMR.

Moreover, this research is the first empirical research to emphasize the integrated concept of Artificial Intelligence (AI) and Mixed Reality (MR) technology within a practical industrial context. With the rapid advancement of AI technologies, this research not only builds upon previous research on chatbot AI [17], generative AI [25], and CRM-AI [64] but also extends the body of knowledge related to immersive technologies such as augmented and virtual reality [10]. This research offers novel insights into how the convergence of AI and MR technologies influences employee attitudes and adoption intentions, thereby contributing both to the theoretical literature on TAM and to the broader understanding of AI-enhanced immersive technology adoption in industrial settings.

5.2. Practical implications

Based on empirical evidence on this research, mining companies in Indonesia can derive practical insights to advance digital transformation and sustainable management initiatives. Prioritizing the practical advantages of AIPMR technology, particularly its usefulness, can enhance employee attitudes and drive adoption intentions. This can be effectively supported through targeted communication strategies, live demonstrations, and structured training sessions that clearly convey the benefits of technology. Establishing a supportive environment that proactively addresses employee concerns and encourages positive engagement with AIPMR technology is crucial for fostering lasting favorable attitudes. Moreover, ensuring the user-friendliness of AIPMR technology is essential. Emphasis on intuitive interface design, comprehensive training, and robust support services can positively influence employee perceptions, fostering a more favorable view of adoption. Implementing a continuous feedback mechanism to address usability concerns will help to sustain a positive perception of ease of use, which significantly impacts employee attitudes and intentions to integrate this technology into their work.

In addition, highlighting the innovative and novel aspects of AIPMR technology is a strategic priority. Marketing and communication efforts should emphasize the technology's uniqueness and groundbreaking features to generate interest and acceptance. Evidence-based demonstrations of its benefits, backed by clear communication, can foster positive attitudes and increase adoption rates. Building a culture that encourages exploration and experimentation, supported by adequate resources, will further reinforce positive attitudes toward AIPMR technology. The role of top management in endorsing and actively supporting technological innovation cannot be understated. Direct communication from leadership regarding the strategic importance of AIPMR technology, aligned with resource allocation and training programs, will significantly influence employee attitudes. The establishment of recognition and incentive schemes for employees who can be a role model in optimizing AIPMR technology will further amplify the impact of top management's support on adoption intentions. Additionally, fostering an organizational culture that values and supports innovation is imperative. Clear and consistent messaging from all levels of the organization, employee engagement in technology's development and implementation, and alignment of policies with innovative objectives will strengthen employees' positive attitudes and their intentions to adopt AIPMR technology. Leaders should exemplify the innovative culture they aim to promote, as their actions and attitudes play a critical role in shaping the broader organizational culture.

By strategically addressing these perceptions, attitudinal dimensions, and organizational aspects, mining companies can more effectively manage the transition toward advanced innovations (i.e., AIPMR), as illustrated in Appendix F. This innovation have the potential to play a pivotal role in driving sustainable digital transformation within the mining industry by integrating intelligent systems into daily operations [1]. It enables more adaptive, data-driven, and collaborative work environments that enhance both productivity and safety [4]. The adoption of AIPMR fosters smart mining solutions through the deployment of real-time decision support systems, empowering mining workforces to make informed operational decisions under complex and hazardous conditions. Furthermore, it redefines human-machine interaction by facilitating intuitive, immersive, and context-aware interfaces that bridge the gap between digital intelligence and on-site human expertise.

6. Conclusions

This research demonstrates that mineral industry employees' intention to adopt AIPMR technology is primarily influenced by attitude, perceived usefulness, perceived ease of use, top management support, and, to a lesser degree, corporate culture. By investigating the perceptions, attitudinal dimensions, and organizational aspects of mining industry employees, this research aims to offer valuable contributions to the broader discourse on technology acceptance, human-machine interaction, and the realization of sustainable digital transformation within industrial sectors. While valuable, the research's findings may be limited by certain factors. The relatively modest sample size ($n = 304$) drawn from Indonesian mining employees may constrain the generalizability of the results to the broader mining workforce. Future research should aim to increase sample sizes for more robust national insights or even consider conducting integrated research with developed countries or Western contexts to further enrich insights into the adoption of innovative technologies within the mining industry. In addition, future research would benefit from employing machine learning on larger datasets to create more advanced and precise models for predicting technology acceptance.

Furthermore, the HC algorithm uncovered new associations, notably between perceived usefulness and top management support, which warrant deeper investigation. Future research might also explore additional factors like trust, privacy, and security that could impact AIPMR adoption. Examining the influence of gender and cultural differences on AIPMR acceptance would also be valuable. A longitudinal approach would further capture changes in employee acceptance over time, providing richer insights into the long-term dynamics of technology adoption. Finally, future research should explore how AIPMR technology can be integrated with existing operations and infrastructure, utilizing qualitative or mixed methods to offer a more nicety knowledge of innovative technology acceptance within the mining industry.

CRediT authorship contribution statement

Wecka Imam Yudhistyra: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chalita Srinuan:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.100874.

Appendices

Appendix A
Reliability and validity of the research instrument.

	Loading values			α	ρA	Composite Reliability	Average Variance Extracted
I				.92	.92	.94	.81
	I1	=	.916				
	I2	=	.904				
	I3	=	.896				
	I4	=	.903				
A				.90	.90	.93	.77
	A1	=	.897				
	A2	=	.872				
	A3	=	.881				
	A4	=	.868				
PU				.91	.91	.93	.78
	PU1	=	.894				
	PU2	=	.886				
	PU3	=	.893				
	PU4	=	.880				

(*continued on next page*)

Appendix A (*continued*)

	Loading values			α	ρA	Composite Reliability	Average Variance Extracted
PEOU				.92	.92	.94	.76
	PEOU1	=	.874				
	PEOU2	=	.859				
	PEOU3	=	.874				
	PEOU4	=	.872				
	PEOU5	=	.882				
PN				.90	.90	.93	.83
	PN1	=	.919				
	PN2	=	.912				
	PN3	=	.909				
TMS				.91	.91	.93	.79
	TMS1	=	.896				
	TMS2	=	.886				
	TMS3	=	.889				
	TMS4	=	.888				
CC				.92	.92	.94	.76
	CC1	=	.872				
	CC2	=	.879				
	CC3	=	.861				
	CC4	=	.862				
	CC5	=	.885				

Note: I = Intention; A = Attitude; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; TMS = Top Management Support; CC = Corporate Culture; α = Cronbach's Alpha; ρA = Rho A.

Appendix B
HeteroTrait-MonoTrait discriminant validity results.

	I	A	PU	PEOU	PN	TMS	CC
I							
A	.84						
PU	.82	.84					
PEOU	.81	.83	.84				
PN	.74	.72	.65	.75			
TMS	.78	.77	.84	.75	.61		
CC	.58	.54	.42	.49	.64	.45	

Note: I = Intention; A = Attitude; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; TMS = Top Management Support; CC = Corporate Culture.

Appendix C
PLSpredict result of the conceptual model.

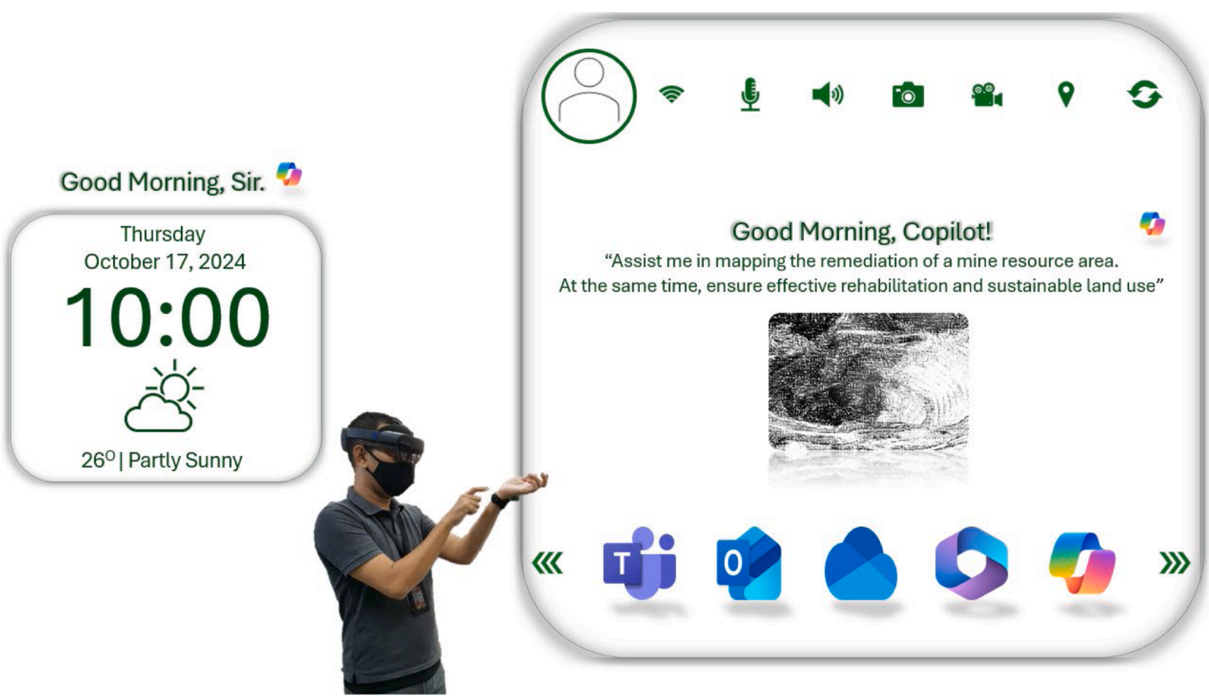
	Q^2 Predict > 0	PLS RSME	LM RSME	PLS – LM RMSE < 0
Intention (I)				
I1	.604	.934	.941	Yes
I2	.559	.887	.912	Yes
I3	.540	.891	.907	Yes
I4	.546	.851	.879	Yes
Attitude (A)				
A1	.568	.806	.807	Yes
A2	.510	.754	.781	Yes
A3	.517	.759	.787	Yes
A4	.478	.723	.747	Yes

Appendix D
PLSpredict result of the Grow-Shrink (GS) algorithm-enhanced model.

	Q^2 Predict > 0	PLS RSME	LM RSME	PLS – LM RMSE < 0
Intention (I)				
I1	.615	.921	.939	Yes
I2	.566	.881	.907	Yes
I3	.550	.882	.908	Yes
I4	.549	.848	.882	Yes
Attitude (A)				
A1	.585	.791	.808	Yes
A2	.517	.749	.786	Yes
A3	.518	.759	.791	Yes
A4	.489	.716	.750	Yes

Appendix E
PLSpredict result of the Hill-Climbing (HC) algorithm-enhanced model.

	Q^2 Predict > 0	PLS RSME	LM RSME	PLS – LM RMSE < 0
Intention (I)				
I1	.495	1.056	1.064	Yes
I2	.440	1.001	1.008	Yes
I3	.449	.975	.985	Yes
I4	.465	.923	.929	Yes
Attitude (A)				
A1	.484	.880	.883	Yes
A2	.455	.796	.801	Yes
A3	.437	.820	.832	Yes
A4	.437	.767	.778	Yes
Perceived Usefulness (PU)				
PU1	.486	.872	.869	No
PU2	.468	.757	.760	Yes
PU3	.497	.765	.775	Yes
PU4	.430	.728	.738	Yes
Perceived Novelty (PN)				
PN1	.395	.880	.885	Yes
PN2	.398	.825	.835	Yes
PN3	.375	.764	.771	Yes
Top Management Support (TMS)				
TMS1	.384	.953	.956	Yes
TMS2	.355	.908	.914	Yes
TMS3	.397	.857	.857	No
TMS4	.350	.821	.820	No
Corporate Culture (CC)				
CC1	.152	.917	.925	Yes
CC2	.160	.861	.869	Yes
CC3	.143	.856	.866	Yes
CC4	.158	.808	.816	Yes
CC5	.153	.867	.871	No



Appendix F. An Illustration of AIPMR for the mining industry demonstrates a Copilot AI assisting in mapping the remediation of a mine resource area, utilizing voice-controlled commands integrated with MR technology.

Data availability

The authors do not have permission to share data.

References

[1] F. Sánchez, P. Hartlieb, Innovation in the mining industry: technological trends and a case study of the challenges of disruptive Innovation, Mining, Metall. Explor. 37 (2020) 1385–1399, https://doi.org/10.1007/s42461-020-00262-1.
[2] A. Ediriweera, A. Wiewiora, Barriers and enablers of technology adoption in the mining industry, Resour. Policy 73 (2021) 102188, https://doi.org/10.1016/j.resourpol.2021.102188.

[3] W. Wang, C. Zhang, Evaluation of relative technological innovation capability: model and case study for China's coal mine, Resour. Policy 58 (2018) 144–149, https://doi.org/10.1016/j.resourpol.2018.04.008.
[4] A. Rahmani, R. Aboojafari, A. Bonyadi Naeini, J. Mashayekh, Adoption of digital innovation for resource efficiency and sustainability in the metal industry, Resour. Policy 90 (2024) 104719, https://doi.org/10.1016/j.resourpol.2024.104719.
[5] C. Colther, JP. Doussoulin, Artificial intelligence: driving force in the evolution of human knowledge, J. Innov. Knowl. 9 (2024) 100625, https://doi.org/10.1016/j.jik.2024.100625.
[6] A. Wu, Improving realty management ability based on big data and artificial intelligence decision-making, PLoS One 19 (2024) e0307043, https://doi.org/10.1371/journal.pone.0307043.
[7] S. Liu, J. Xie, X. Wang, H. Meng, Mixed reality collaboration environment improves the efficiency of human-centered industrial system: a case study in the mining industry, Comput. Ind. Eng. 180 (2023) 109257, https://doi.org/10.1016/j.cie.2023.109257.
[8] W.I. Yudhistyra, C. Srinuan, Exploring the acceptance of mixed reality technology innovation among mining industry workers, Acta. Psychol. (Amst) 251 (2024) 104580, https://doi.org/10.1016/j.actpsy.2024.104580.
[9] J. Sun, Y. Wang, W. Miao, W. Wei, C. Yang, J. Chen, et al., A study on how to improve users' perceived playfulness in and continuance intention with VR technology to paint in virtual natural landscapes, Heliyon 9 (2023) e16201, https://doi.org/10.1016/j.heliyon.2023.e16201.
[10] J. Jang, Y. Ko, W.S. Shin, I. Han, Augmented reality and virtual reality for learning: an examination using an extended technology acceptance model, IEEE Access 9 (2021) 6798–6809, https://doi.org/10.1109/ACCESS.2020.3048708.
[11] J.H. Gruenhagen, R. Parker, Factors driving or impeding the diffusion and adoption of innovation in mining: a systematic review of the literature, Resour. Policy 65 (2020) 101540, https://doi.org/10.1016/j.resourpol.2019.101540.
[12] PF. Drucker, HBR's 10 Must Reads on Innovation, Featuring "The Discipline of Innovation, Harvard Business School Publishing Corporation, 2013.
[13] V. Lath, G. Peacocke, How digital innovation will transform Indonesia's mining industry, McKinsey Co (2020).
[14] A. Daly, D. Humphresys, J.D. Raffo, G. Valacchi, Global Challenges for Innovation in Mining Industries, 87, Cambridge University Press, 2022, https://doi.org/10.1017/9781108904209.
[15] I. Arbulu, V. Lath, M. Mancini, A. Patel, O. Tonby, Reinvigorating ASEAN manufacturing for the future, McKinsey Co (2018) 26.
[16] Drucker PF. Management: Tasks, Responsibilities, Practices. Transaction Publishers; 2007.
[17] S. Sharma, G. Singh, N. Islam, A. Dhir, Why do SMEs adopt artificial intelligence-based chatbots? IEEE Trans. Eng. Manag. 71 (2024) 1773–1786, https://doi.org/10.1109/TEM.2022.3203469.
[18] ÖF. Ursavaş, Conducting Technology Acceptance Research in Education, Springer International Publishing, Cham, 2022, https://doi.org/10.1007/978-3-031-10846-4.
[19] L. Kent, C. Snider, J. Gopsill, B. Hicks, Mixed reality in design prototyping: a systematic review, Des. Stud. 77 (2021) 101046, https://doi.org/10.1016/j.destud.2021.101046.
[20] E. Holdack, K. Lurie-Stoyanov, HF. Fromme, The role of perceived enjoyment and perceived informativeness in assessing the acceptance of AR wearables, J. Retail. Consum. Serv. 65 (2022) 102259, https://doi.org/10.1016/j.jretconser.2020.102259.
[21] F. Schuster, B. Engelmann, U. Sponholz, J. Schmitt, Human acceptance evaluation of AR-assisted assembly scenarios, J. Manuf. Syst. 61 (2021) 660–672, https://doi.org/10.1016/j.jmsy.2020.12.012.
[22] S. Shen, K. Xu, M. Sotiriadis, Y. Wang, Exploring the factors influencing the adoption and usage of Augmented Reality and Virtual reality applications in tourism education within the context of COVID-19 pandemic, J. Hosp. Leis. Sport. Tour. Educ. 30 (2022) 100373, https://doi.org/10.1016/j.jhlste.2022.100373.
[23] Y.C. Huang, L.N. Li, H.Y. Lee, MHEM Browning, CP. Yu, Surfing in virtual reality: an application of extended technology acceptance model with flow theory, Comput. Hum. Behav. Reports 9 (2023) 100252, https://doi.org/10.1016/j.chbr.2022.100252.
[24] G. Koutromanos, A.T. Mikropoulos, D. Mavridis, C. Christogiannis, The mobile augmented reality acceptance model for teachers and future teachers, Edu. Inf. Technol. 29 (2024) 7855–7893, https://doi.org/10.1007/s10639-023-12116-6.
[25] N. Saif, S.U. Khan, I. Shaheen, A. ALotaibi, M.M. Alnfiai, M. Arif, Chat-GPT; validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism, Comput. Human. Behav. 154 (2024) 108097, https://doi.org/10.1016/j.chb.2023.108097.
[26] S. Chatterjee, R. Chaudhuri, D. Vrontis, A. Thrassou, SK. Ghosh, Adoption of artificial intelligence-integrated CRM systems in agile organizations in India, Technol. Forecast. Soc. Change 168 (2021) 120783, https://doi.org/10.1016/j.techfore.2021.120783.
[27] S. Chatterjee, N.P. Rana, Y.K. Dwivedi, AM. Baabdullah, Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model, Technol. Forecast Soc. Change 170 (2021) 120880, https://doi.org/10.1016/j.techfore.2021.120880.
[28] AM. Baabdullah, The precursors of AI adoption in business: towards an efficient decision-making and functional performance, Int. J. Inf. Manage. 75 (2024) 102745, https://doi.org/10.1016/j.ijinfomgt.2023.102745.
[29] S.H. Hadi, A.E. Permanasari, R. Hartanto, I.S. Sakkinah, M. Sholihin, R.C. Sari, et al., Developing augmented reality-based learning media and users' intention to use it for teaching accounting ethics, Edu. Inf. Technol. 27 (2022) 643–670, https://doi.org/10.1007/s10639-021-10531-1.
[30] FD. Davis, User acceptance of information technology: system characteristics, user perceptions and behavioral impacts, Int. J. Man Mach. Stud. 38 (1993) 475–487, https://doi.org/10.1006/imms.1993.1022.
[31] FD. Davis, Perceived usefulness, Perceived ease of use, and user acceptance of information technology, MIS Q 13 (1989) 319, https://doi.org/10.2307/249008.
[32] R.C. Chanda, A. Vafaei-Zadeh, H. Hanifah, D.M. Ashrafi, T. Ahmed, Achieving a sustainable future by analyzing electric vehicle adoption in developing nations through an extended technology acceptance model, Sustain. Futur. 8 (2024) 100386, https://doi.org/10.1016/j.sftr.2024.100386.
[33] J.D. Wells, D.E. Campbell, J.S. Valacich, M. Featherman, The effect of perceived novelty on the adoption of information technology innovations: A risk/reward perspective, Decis. Sci. 41 (2010) 813–843, https://doi.org/10.1111/j.1540-5915.2010.00292.x.
[34] W.I. Yudhistyra, C. Srinuan, Exploring the acceptance of technological innovation among employees in the mining industry: A study on generative artificial intelligence, IEEE Access 12 (2024) 165797–165809, https://doi.org/10.1109/ACCESS.2024.3493242.
[35] F. Qutaishat, A. Abushakra, L. Anaya, M. Al-Omari, Investigating the factors affecting the intention to adopt cloud-based ERP systems during the COVID-19 era: evidence from Jordan, Bus. Process Manag. J. 29 (2023) 653–670, https://doi.org/10.1108/BPMJ-09-2022-0462.
[36] S. Sun, D.J. Hall, CG. Cegielski, Organizational intention to adopt big data in the B2B context: an integrated view, Ind. Mark. Manag. 86 (2020) 109–121, https://doi.org/10.1016/j.indmarman.2019.09.003.
[37] B. Ahn, H. Ahn, Factors affecting intention to adopt cloud-based ERP from a comprehensive approach, Sustainability 12 (2020) 6426, https://doi.org/10.3390/su12166426.
[38] A. Behl, M. Chavan, K. Jain, I. Sharma, V.E. Pereira, JZ. Zhang, The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations, Int. J. Manpow. 43 (2022) 569–586, https://doi.org/10.1108/IJM-03-2021-0178.
[39] J.W. Creswell, JD. Creswell, Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, 6th ed., SAGE Publications, Inc., Thousand Oaks, California, 2023.
[40] NK. Malhotra, Marketing Research: An Applied Orientation, 7th ed., Pearson, Singapore, 2020.
[41] N.F. Richter, AA. Tudoran, Elevating theoretical insight and predictive accuracy in business research: combining PLS-SEM and selected machine learning algorithms, J. Bus. Res. 173 (2024) 114453, https://doi.org/10.1016/j.jbusres.2023.114453.
[42] J.F. Hair, J.J. Risher, M. Sarstedt, CM. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (2019) 2–24, https://doi.org/10.1108/EBR-11-2018-0203.
[43] J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE Publications, Inc., Los Angeles, 2022.
[44] D. Chung, P. Jeong, D. Kwon, H. Han, Technology acceptance prediction of robo-advisors by machine learning, Intell. Syst. Appl. 18 (2023) 200197, https://doi.org/10.1016/j.iswa.2023.200197.
[45] D. Margaritis, Learning Bayesian Network Model Structure from Data, Carnegie Mellon University, 2003.
[46] A. Kuznetsov, E. Frontoni, L. Romeo, N. Poluyanenko, S. Kandiy, K. Kuznetsova, et al., Optimizing hill climbing algorithm for S-boxes generation, Electronics 12 (2023) 2338, https://doi.org/10.3390/electronics12102338.
[47] A.J. Bush, JF. Hair, An assessment of the mall intercept as a data collection method, J. Mark Res. 22 (1985) 158, https://doi.org/10.2307/3151361.
[48] T.K. Dijkstra, J. Henseler, Consistent partial least squares path modeling, MIS Q 39 (2015) 297–316, https://doi.org/10.25300/MISQ/2015/39.2.02.
[49] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. Acad. Mark Sci. 43 (2015) 115–135, https://doi.org/10.1007/s11747-014-0403-8.
[50] J.F. Hair, J.J. Risher, M. Sarstedt, CM. Ringle, The results of PLS-SEM, Eur. Bus. Rev. 31 (2019) 2–24.
[51] N. Kock, GS. Lynn, Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations, J. Assoc. Inf. Syst. 13 (2012) 546–580, https://doi.org/10.17705/1jais.00302.
[52] M. Stone, Cross-validatory choice and assessment of statistical predictions, J. R. Stat. Soc. Ser. B Stat. Methodol. 36 (1974) 111–133, https://doi.org/10.1111/j.2517-6161.1974.tb00994.x.
[53] S. Geisser, The predictive sample reuse method with applications, J Am Stat Assoc 70 (1975) 320, https://doi.org/10.2307/2285815.
[54] J. Henseler, C.M. Ringle, RR. Sinkovics, The use of partial least squares path modeling in international marketing, in: R.R. Sinkovics, P.N. Ghauri (Eds.), New Challenges to Int. Mark, New Challenges to Int. Mark, 20, Emerald Group Publishing Limited, 2009, pp. 277–319, https://doi.org/10.1108/S1474-7979(2009)0000020014.
[55] WW. Chin, Handbook of Partial Least Squares, 206, Springer Berlin Heidelberg, Berlin, Heidelberg, 2010, https://doi.org/10.1007/978-3-540-32827-8.
[56] D. Marikyan, S. Papagiannidis, G. Stewart, Technology acceptance research: meta-analysis, J. Inf. Sci. (2023), https://doi.org/10.1177/01655515231191177.
[57] M. Scutari, R. Nagarajan, Identifying significant edges in graphical models of molecular networks, Artif. Intell. Med. 57 (2013) 207–217, https://doi.org/10.1016/j.artmed.2012.12.006.
[58] HA. Alnemer, Determinants of digital banking adoption in the Kingdom of Saudi Arabia: A technology acceptance model approach, Digit. Bus. 2 (2022) 100037, https://doi.org/10.1016/j.digbus.2022.100037.

[59] Y.Y.Y. Liu, J. Henseler, YYY. Liu, What makes tourists adopt smart hospitality? An inquiry beyond the technology acceptance model, Digit Bus 2 (2022) 100042, https://doi.org/10.1016/j.digbus.2022.100042.

[60] S.M. Fazal-e-Hasan, A. Amrollahi, G. Mortimer, S. Adapa, MS. Balaji, A multi-method approach to examining consumer intentions to use smart retail technology, Comput. Human. Behav. 117 (2021) 106622, https://doi.org/10.1016/j.chb.2020.106622.

[61] Shibly HR, Abdullah ABM, Murad MW. ERP adoption in organizations: the factors in technology acceptance among employees. 2022. https://doi.org/10.1007/978-3-031-11934-7.

[62] P.N. Sharma, B.D. Liengaard, J.F. Hair, M. Sarstedt, CM. Ringle, Predictive model assessment and selection in composite-based modeling using PLS-SEM: extensions and guidelines for using CVPAT, Eur. J. Mark. 57 (2023) 1662–1677, https://doi.org/10.1108/EJM-08-2020-0636.

[63] K. George, M.T. Anastasios, M. Dimitrios, C. Christos, The mobile augmented reality acceptance model for teachers and future teachers, Edu. Inf. Technol. (2023), https://doi.org/10.1007/s10639-023-12116-6.

[64] S. Chatterjee, N.P. Rana, S. Khorana, P. Mikalef, A. Sharma, Assessing organizational users' Intentions and behavior to AI integrated CRM systems: a meta-UTAUT approach, Inf. Syst. Front. 25 (2023) 1299–1313, https://doi.org/10.1007/s10796-021-10181-1.