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RESEARCH ARTICLE

The Nexus of Human and Machine: Exploring Perception as a Spur in AI-Powered Employee Training

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Abstract: More phased than before, organizations are relying on artificial intelligence (AI) in an increasing capacity to develop and/or train workers. However, we still do not know what leads to the successful performance of AI-based training platforms. This study examines the following dynamics: content quality, personalization, usability, skill development, employee motivation, and organizational support, which are likely to influence perceived platform effectiveness, with employee perception acting as a moderating variable. Data were collected from 300 participants across multiple companies and analyzed using Partial Least Squares Structural Equation Modeling. The results indicate that employees' perceptions related to the value of training provided via an AI-enabled training platform are positively influenced by relevant information, engaging learning opportunities, perceived development of skills, and motivational factors. The perceived organizational support has a direct, large effect on platform impact, while perceived usability has a small effect on perceived platform impact. More specifically, the data indicate that employee perceptions associated with the platform influence the platform's features and the effectiveness of the training. Overall, this study has implications for better design toward impactful AI-enabled training systems and contributes to the developing field of AI and organizational learning. It underlines the significance of user-centered approaches and organizational readiness for maximizing training effectiveness.

Keywords: artificial intelligence (AI), AI-powered training, employee perception, learning effectiveness, organizational support

1. Introduction

AI has transformed all areas of business, including marketing, operations, and human resources. Workforce training and development (T&D) is considered to be one of the most significant applications of artificial intelligence (AI), and this is where AI-based systems have turned the conventional learning systems upside down. AI-based applications are superior to conventional learning management systems because they offer AI-driven learning pathways tailored to individuals with real-time feedback, predictive analytics, and scalable proficiency advancement in a variety of sectors [1–3]. This competency is particularly important in the context of the seemingly dynamic knowledge economy of the present time, as only by continuously updating and reskilling its staff can an organization retain its top status.

Nevertheless, the implementation of AI-based platforms depends on user acceptance, use, and IT support, despite the obvious technological potential of the new service. Not only would the narrow-mindedness of AI-based training systems grow with technological progress, but it would also rely on the extent to which employees become inspired and motivated by those systems and find them helpful. Consequently, researchers and practitioners

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are interested in determining the factors that define the Effectiveness of AI Training Platforms. This study is motivated by the necessity to offer organizations more tangible advice than generic technology acceptance models can provide and by the knowledge of real determinants of the success of learning in AI-empowered environments. The observation is pertinent since AI-based training systems will be an investment priority of organizations in the future. In an organization that lacks a clear picture of what factors are in play to ensure successful deployment, poor user adoption, wasted spending, and inability to achieve the learning and development goals are to be expected when deploying the known technology.

On the other hand, although there is an increased adoption of AI-based learning systems in organizations, there is no empirical study on the success factors of such systems. Much of the current literature has concentrated either on the technical aspect of AI systems or the satisfaction of users in the general e-learning setting without adequately considering the behavioral, technological, and organizational perspectives in a holistic model [1, 4]. The popular Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) provide broad information on the behavior of system acceptance.

Nevertheless, all of these models focus on how easy and useful it is in general terms and not on the evaluation of advanced AI-based adaptive training settings. The conventional acceptance models do not put enough consideration on factors like Quality and Relevance of Training, Interactivity and Personalization, Perceived Effectiveness in Skill, and Employee Motivation to Use Platforms.

Further, the topic of Employee Perception as a cognitive and affective mediator between training system properties and learning performance, and the Effectiveness of AI Training Platforms has received little research. Trust, the sense of fairness, and transparency are essential elements of acceptability in AI-enabled systems, where automation and personalization are typical, but not researched as extensively in the existing literature.

Moreover, the aspects of Organizational Support as a factor of managerial support, ethical use of AI, and resource distribution have proven to be important in general technology adoption research but have not yet been examined in employee training based on AI applications. Nonetheless, the impact of organizational factors on the perceived success of such platforms is not well understood.

As a result, a research gap exists on the joint technological, cognitive, and organizational factors that can lead to the effectiveness of AI-based T&D platforms. This paper sets out to fill this gap by building and analyzing an integrative research framework that fills these neglected relations. It is against this background of the stated limitations that the study will attempt to reveal the key success aspects of AI-enabled T&D platforms in a holistic, multidimensional view.

In particular, the given research will establish the role of technology attributes (usability, Interactivity and Personalization, and Quality and Relevance of Training), employee attributes (Employee Motivation to Use Platforms and Perceived Effectiveness in Skill), and organizational attributes (Organizational Support) in employee attitudes toward AI-based training platforms. It also looks at the mediating role of Employee Perception on platform attributes and training effectiveness and the Effectiveness of AI Training Platforms. Moreover, this paper aims to extend the TAM with other dimensions that include Interactivity and Personalization, Perceived Effectiveness in Skill, Employee Motivation to Use Platforms, and Organizational Support. Lastly, it contains not only theoretical but also functional suggestions on how companies can maximize their investment returns on AI-based learning programs.

2. Theory, Related Literature, and Hypothesis Development

The conceptual framework of the study was made by using the TAM of the research as a partial theoretical basis [5]. Two elements of TAM were modified—design quality and content—which are indirectly reflected in the concept of perceived usefulness, and the ease of following progress is used to map the perceived ease of use. The rest of the categories—Interactivity and Personalization, Perceived Effectiveness in Skill, Employee Motivation to Use Platforms, and Organizational Support—are not directly grounded on the TAM, UTAUT, or Technology-Organization-Environment (TOE) frameworks, as they were designed to be flexible to emerging factors of AI-driven training platforms. Additionally, the Employee Perception was justified as a mediating variable to bring classical TAM to the cognitive and emotional response in AI learning conditions. An extended paradigm allows for a broader measure of technological and organizational antecedents of training effectiveness and Effectiveness of AI Training Platforms.

2.1. Relevance of AI-powered training platforms in organizational learning

Over the past years, organizations have experienced rising pressures to have employee training systems that are not only quick but also scalable, which has led to a move toward digital-learning systems. AI is one of them and has become a revolutionary change in the transformation of T&D programs in different sectors. The AI-driven platforms are more effective than the traditional LMS to provide personalized, adaptive, real-time learning experiences to customers with predictive analytics, enhance learner retention, lower costs in total, and enable just-in-time upskilling/reskilling across industries [1, 2, 6, 7].

It puts the learning process as learner-centered, which evolves as employees grow, and positions, in this case, are dynamic. The same results include AI in LMS tools involved in business and higher education research and studies that give priority to successful uses of AI in learning retention and student satisfaction [2], pointing to the possibility of the revolutionization of professional development in this area.

Such platforms can support lifelong learning and acquisition of skills on a just-in-time basis, which is essential as we fit into the world of work. Studies have suggested that AI-based e-learning helps in workplace performance and application of the knowledge, and therefore, such services are particularly useful in a sphere where the adaptability and the capacity to learn new information on a case-by-case basis are paramount [1]. AI solutions reduce repetitions of training exercises by personalizing the delivery of the content and making it more effective, thus minimizing the expenses [7].

Besides, AI solutions can offer uniform, quality training across nations with minimal interaction and make use of predictive analytics during the design of learning directions, development practices, and performance estimations [8].

Therefore, the AI-enhanced training systems have now become more than merely experimental devices and are key to strategic human capital development. The effectiveness they have is their ability to be personalized, scalable, and measurable in terms of performance and aligned to organizational goals, qualities that make them critical to the workforce of the future.

Table 1
Summary of research work on AI-powered training and development platforms

Author(s)	Year	Focus of study	Methodology	Key findings
Maity, S.	2019	Opportunities for AI in training and development practices	Conceptual analysis	Identified personalization and adaptive delivery as major enhancements to traditional T&D methods.
Thuan, T., De, N., and Toai, N.	2024	Development of AI-based adaptive learning platforms	Platform development	Adaptive systems personalize content, improving learner engagement and retention.
Ahn, H.	2024	AI-powered e-learning's impact on performance and knowledge application	Empirical study (survey)	Real-time feedback improves learning outcomes and lifelong learning capabilities.
Chatterjee, S.	2023	Effects of AI-powered training on skill development and career growth	Mixed methods	AI enhances upskilling and increases productivity.
Alotaibi, N.	2024	Impact of AI-LMS integration on higher education transformation	Literature review	AI-LMS integration leads to higher learner satisfaction and learning performance.
Luo, Q.	2023	Adaptive AI platforms in classroom education	Quasi-experimental study	Personalization leads to significant improvements in student performance.
Liu, S. et al.	2024	Emerging technologies in sports training	Empirical analysis	Organizational support is critical to effective technology use in training.
Lamb, N.	2025	AI use in Medical Science Liaison (MSL) training	Case-based narrative	Integration into workflows enhances training utility and daily task efficiency.
Sharma, R.	2024	Teacher training through AI	Descriptive study	Emphasizes the importance of institutional support for continuous AI-based training.
Chen, Z.	2024	Responsible AI use in organizational training	Theoretical and applied review	Trust, transparency, and privacy practices enhance user engagement and platform effectiveness.
Ejjami, R.	2024	AI's role in vocational training and employability	Literature synthesis	Employee perception affects AI platform adoption and long-term learning outcomes.
Dixit et al.	2024	Evolving needs of learners and role of artificial intelligence, Professional Development	Theoretical and applied review	AI helps address learner needs through innovative approaches.

Table 1 summarizes previous studies that have been conducted on the effectiveness of AI-powered training and development platforms.

2.2. The role of quality and relevance of AI-curated training content in shaping employee perception

The most critical factors that contribute to how employees perceive AI-enabled learning platforms are the quality, relevance, and timeliness of the training content created by AI. Proper content creation leads to coordinating with the job requirements, the needs of a particular learner, and other aspects of present-day industry requirements that grossly affect the learner's involvement, self-confidence, and the overall value that arises out of training. The content in AI-based learning systems is constantly improved using machine learning, which adjusts to the interaction patterns and engagement measures of employees [9].

Employees will consider the platform credible and with the support of their professional development when they think that the training resources are practical, job-relevant, and well-organized. Such perception creates long-term involvement and better results of learning. It was stressed by Chatterjee [7] that the content of training can greatly influence perceived effectiveness, especially when the training content handles personal skill deficiencies, as well as role-specific goals. Personalization as the natural feature of AI helps to increase the satisfaction of learners, as the contents will be customized according to the reported needs in terms of developmental progress [10].

Perception is also a factor of design quality. The interactive capabilities (modular content management, built-in multimedia features, and real-time feedback loops) help in establishing and supporting the validity and functionality of the system. On the other hand, underdeveloped interfaces or generic content decrease trust and engagement and cause a lack of trust in AI-generated suggestions. Luo and Hsiao-Chin [11] proved that user perceptions tend to change in the first interaction with the system, and it is crucial to align the outputs of the platform with the expectations of the learners.

This way, the quality of content and design excellence determines the success of the platform indirectly, namely, through the perceptions of the employees. With the learners' liking and having confidence in AI-selected materials, they would be more engaged, memorize information, and make better use of skills.

Based on this, the hypotheses include the following:

H1a: The quality and relevance of AI-curated training content positively influence employees' perceptions of training platforms.

H1b: Employee perceptions mediate the relationship between content quality and platform effectiveness.

2.3. Influence of interactivity and personalization on perceived effectiveness

Combined with the high level of personalization and interactivity, AI-based training platforms can stand out from the crowd with their ability to influence employee perception and engagement in learning in a profoundly personalized way. In comparison to the old-fashioned inactive e-learning, AI-enabled environments provide dynamic interaction in terms of responsive simulations, intelligent chatbots, and gamified modules, as well as systems that can produce responses in real time, depending on user actions [10].

Even the process of learning can be more significant through individualized learning paths, which are based on the activity of an individual, his or her interests, and his or her progress. These adaptive processes are useful in keeping motivation and autonomy to achieve effective adult learning. According to Luo and Hsiao-Chin [11], adaptive learning can be used to improve satisfaction and cognitive retention because it provides flexibility and control. Equally, as Maity [9] points out, personalization minimizes the cognitive load, as it helps to guide learners to high-relevance job-specific content.

These interactive and adaptive design features are also important to enhance engagement and affect how employees rate the overall effectiveness of the platform. The systems, which can be said to be responsive and learner-centric, are likely to create trust and stimulate continuous use as well as positive evaluations of the training results. Employee perception, therefore, is a strong mediator among the interactive features and platform success.

On these understandings, the following hypotheses are formulated:

H2a: Interactivity and Personalization have a positive and significant effect on employees' perceptions.

H2b: Interactivity is mediated by employee perception of the relationship with platform effectiveness.

2.4. The impact of ease of tracking progress on training effectiveness

Another important feature of AI-based learning systems is usability, especially the way the system can be navigated, interact with the training materials, and the way to monitor the progress. The common features of high-performing systems are user-friendly dashboards, automatic feedback, and self-managed learning features where employees will be able to track their progress and control the learning channels effectively [1].

Radio frequency indicators of progress and areas of improvement make AI-based progress tracking more transparent and enhance motivation as they are displayed in real time. Liu et al. [1] established that individual feedback increases the level of engagement as learners get to know their competencies and areas of need. On the same note, [12] established that tracking technologies enhance learner satisfaction by facilitating goal-oriented training, especially in skill-intensive areas.

Furthermore, new technology like VR, motion sensors, and smart simulations gives the capabilities of the progress-tracking systems an extra dimension that is not digital. These simulated tools are a simulation of real-world environments, making them experiential learning tools. According to Ejjami [13], AI-upgraded VR and sensor-related systems can greatly enhance vocational skills learning and hands-on preparation, particularly in the technical and healthcare industries.

The success of these technologies, however, lies in the access and ease of use of the technology. Excessively complicated systems can deter interaction and have undesirable outcomes on user perception, but properly constructed interfaces, which are user-friendly, contribute to steady adoption.

On this basis, the hypotheses are as follows:

H3a: Tracking progress positively influences employee perception.

H3b: Employee perception mediates the relationship between progress tracking and effectiveness.

2.5. The role of perceived effectiveness in skill development in platform evaluation

Perceived learning outcomes are outcomes of self-reported increase of knowledge, skills, and competencies attained using AI-based training systems. The perceptions play a crucial role in measuring the success of the platform since they will dictate short-term user satisfaction and long-term loyalty. Employees would be willing to persist in using a platform when they think that it is an effective tool for developing their skills, and they would refer a colleague and use the skills gained in their work behaviors that support organizational learning performance.

According to Ahn [1] and Chatterjee [7], the positive impressions of the learning outcomes have a powerful impact on motivation and the chances of the new behaviors' adoption. The ability to track and measure their progress by automated feedback, skill-testing modules, and performance analytics makes use of AI systems contribute to the maintenance of the impression of actual progress in learners.

The obvious indication of skill improvement improves platform authority and boosts the confidence of the employees toward AI-based learning tools. Thuan et al. [10] held that these perceptions create trust in the system to accommodate professional development and suit general organizational goals.

Most importantly, the influence of perceived learning outcomes on the effectiveness of platforms is mediated by employee perception. The value of training as perceived is not on the basis of the actual performance gains but rather on the interpretation of the employees of the performance gains. Measurable progress that is reflected and platforms that combine learning and career development paths enhance positive perceptions and lead to continued engagement.

Thus, the hypothesis is as follows:

H4a: Perceived effectiveness of skill development positively influences employee perceptions.

H4b: Employee perception mediates the relationship between skill development and platform effectiveness.

2.6. The influence of employee motivation and organizational support on employee perception

Motivation of employees is important in influencing the perception of the technology-supported learning by the individuals. These intrinsic motivators (mastery, curiosity, and personal development) and extrinsic motivators (recognition, promotion opportunities, or rewards) encourage learners to engage with AI-based training systems [1]. Based on Self-Determination Theory (SDT), intrinsically motivated learners can thrive when they are granted autonomy, competence, and relatedness. These psychological needs can be maximized using AI-based platforms, which provide adaptive content difficulty, on-the-fly individualized feedback, and collaborative learning functionalities that facilitate social connectedness [7]. Under these motivational conditions, employees will form more positive attitudes toward AI-based training, demonstrate higher confidence in the platform, and be more willing to continue their process of learning process.

Organizational support also enhances this relationship through the establishment of a conducive environment for effective learning. The supportive organizational culture, which includes providing time to train and implement AI in daily work and setting clear policies related to data privacy and governance, is an indicator that the organization is interested in its employees and is willing to develop them [4]. These practices improve the sense of fairness, utility, and practice, thus promoting continued platform use. Notably, studies have shown that organizational support has an indirect effect: it increases confidence and the motivation of users toward accepting the technology instead of having a direct positive impact on performance [2]. Through this, organizational support can be viewed as a contextual scaffold that enhances positive employee perceptions.

On the grounds of these arguments, the following hypotheses are put forward:

H5a: Employee motivation positively influences employees' perceptions of AI-powered training platforms.

H5b: Employee perception mediates the relationship between employee motivation and platform effectiveness.

2.7. Employee perception as a driver of platform effectiveness and the moderating role of organizational support

The existing evidence on digital and AI-enhanced learning reveals that user perceptions, in particular in terms of relevance, ease of use, and trust in algorithmic suggestions, are potent predictors of the success of the training [9, 11]. Correct perceptions enhance the level of thinking, completion, and long-term participation. Employees who feel that AI systems are precise, impartial, and focused on their development tend to accept new knowledge and implement the skills gained in their workplace more readily.

Yet, it is the degree of organizational support that defines the strength of the correlation between the perception of the employees and their perceived platform effectiveness. The presence of high levels of organizational support, such as managerial encouragement, availability of technical support, and openness in management of the AI mechanisms, diminishes some residual skepticism and the ability to use the platform regularly [14]. In this scenario, the positive perceptions become easier to transform into the quantifiable improvement of performance. On the other hand, even positive perceptions cannot produce any meaningful results in an environment that has little support because employees do not have the time, the institutional approval, or the psychological trust to utilize what they have learned. To achieve the transformational potential of AI-based training, proper coordination of AI technologies with human-focused organizational systems is thus crucial.

Based on these insights, the last hypothesis pair is suggested:

H6: Employee perceptions positively influence the effectiveness of AI-powered training platforms.

H7: Organizational support moderates the relationship between employee perception and platform effectiveness, such that the relationship is stronger when organizational support is high.

These relationships need to be empirically studied in future research by implementing mixed methods of research. Quantitative surveys can be used to evaluate the employee perceptions, motivation, and reported outcomes, whereas qualitative interviews can be used to shed light on the organizational processes, ethics, and contextual factors that influence the implementation of AI in the learning process within the workplace.

Figure 1 depicts the conceptual framework of this study.

3. Materials and Methods

3.1. Data collection and sample

This paper used the TAM by Davis [5] as the basis of formulating the measurement model. The content and design quality constructs were also modified to effectively measure the Quality and Relevance of Training indirectly, and the Ease of Progress Tracking was directly converted to perceived ease of use. To help the traditional TAM frameworks satisfy the requirements of the unique characteristics of AI-based learning settings, additional constructs, including Interactivity and Personalization, Perceived Learning Outcomes, Employee Motivation to Use Platforms, and Organizational Support, were included in them. As an intervening variable, Employee Perception was added to the TAM, which was broadened to incorporate the cognitive and affective judgment of AI systems.

This strategy has ensured that the research design considers not only the well-known technology acceptance variables but also the emergent variables that can affect the AI-based training platforms. It involved a quantitative research approach where the success of Effectiveness of AI Training Platforms in organizations has been investigated by the use of a structured questionnaire. The data were gathered among the employees working in various fields where AI-based learning systems were applied. The valid responses were 300 in number, hence offering a strong sample to check the findings and generalize the results.

The respondents were selected through purposive and convenience sampling and represented different sectors and levels of organizations. The survey was distributed through internet sites, email, and internal HR distribution networks in partner organizations. Informed consent was obtained from all the volunteers to be involved, and both confidentiality and anonymity were observed as per ethical requirements in conducting research.

The demographic profile of the sample is presented by a large range of ages and genders and industry distribution, which is indicated in Table 2. The 25–35 age group was the most

Figure 1
Conceptual framework

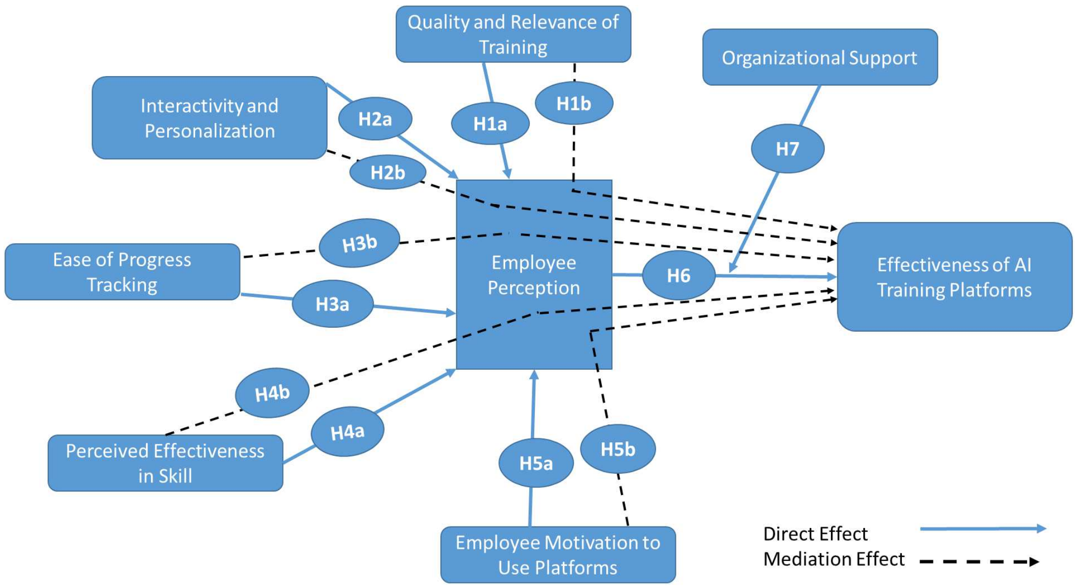


Table 2
Respondents' demographic information

		Frequency	Percent (%)
Age	25–35	166	55.3
	36–45	64	21.3
	46–55	54	18.0
	56–63	16	5.3
Note: Within the 25–35 age group (55.3%): ages 25–28 (born 1997–2000) = 27.7% → Generation Z, ages 29–35 (born 1990–1996) = 28.0% → Millennials.			
Gender	Male	207	69.0
	Female	93	31.0
Industry sector of yourorganization	Technology/IT	75	25.0
	Healthcare	60	20.0
	Finance/banking	37	12.3
	Education	50	16.7
	Manufacturing	50	16.7
	Government	28	9.3
Rank categories	Entry level	132	44.0
	Mid-level	108	36.0
	Senior level	60	20.0
Generation	Generation X	70	23.3
	Millennials	147	49.0
	Generation Z	83	27.7
Education level	Higher secondary	45	15.0
	Bachelor's degree	135	45.0
	Master's degree	90	30.0
	Professional certification	30	10.0

represented (55.3%), followed by 36–45 (21.3%), 46–55 (18%), and 56–63 (5.3%). The age demographic shows that young and middle-career workers make up the overwhelming majority of the users of the training platforms dedicated to AI, which is not an exception to the overall trends in the use of digital learning.

The respondents comprised 69.0% male and 31% female, a gender diversity to examine any potential difference in perception based on gender. The range of industries represented by respondents was large, as they comprised technology/IT (25.0%), healthcare (20.0%), finance/banking (12.3%), education (16.7%), manufacturing (16.7%), and government (9.3%) industries. With this mixture, it is possible to thoroughly examine the success of AI training within the private and governmental sectors and knowledge-intensive and operational companies.

In order to gain a more descriptive model of the workforce using AI-related training portals, the given research gathered information concerning the positions of participants in their jobs, generational stratification, and the level of their education, where basic demographics, including age, sex, and economic activity sector, were used. The 300 respondents consisted of 20% of higher rank, 36% of intermediate rank, and 44% of fresher as an entry-level rank. This categorization will provide a balanced picture of the organizational hierarchy. Regarding generational stratification, most of the participants are young professionals who are digitally savvy by default: 27.7% of the participants were of Generation Z, 49.0% of Millennials, and 23.3% of Generation X. Regarding literacy level, 45% of them were bachelors, 30% were masters, 15% were higher secondary students, and 10% were professionals. The categorization above represents the diversified workforce with different types of middle-level education and implies that the results can be distributed over different professions and levels of education. Most importantly, these were effects to ensure the demographic profile is strong but not expected to play a major or moderate role in the direct impact on the structural model.

The demographic variety of the sample helps to test the research model in a multidimensional way and has valuable results concerning the practical application of the Effectiveness of AI Training platforms in different organizational structures.

3.2. Measurement of the constructs

The research constructs adopted in this case were modified on technological acceptability, organizational learning, and AI in training studies. Multiple-item Likert scales (between 1, strongly disagree, and 5, strongly agree) were used to operationalize all the constructs.

Independent variable Quality and Relevance of Training Content indicators have been adjusted from Dixit et al. [15] and Ejjami [13]; Interactivity and Personalization from Alotaibi [2], Maity [9], and Thuan et al. [10]; Ease of Progress Tracking from Thuan et al. [10]; Perceived Effectiveness in Skill Development from Sharma [14]; Employee Motivation to Use Platforms from Ahn [1] and Chatterjee [7], Alotaibi [2], and Chen [4] Employee Perception; Lamb [8] and Liu et al. [12] Organizational Support; and the indicators of the dependent variable, Effectiveness of AI Training Platforms, are taken from Maity [9].

The quality of the content and design was measured with the help of the items that analyzed the relevance, clarity, structure, and job alignment of AI-curated training material (e.g., “The AI training platform content is relevant to my job needs”). The measures were adjusted based on the existing validated models of learning effectiveness [9, 7].

Interactivity and Personalization included claims of the AI platform as an adaptive and interactive system, for example, modifying learning paths or immediate feedback (e.g., “The platform modulates the content depending on my learning progress”). This design conveys the interactive nature of the user experience of AI training systems [11, 10].

It was determined how easy it is to ensure that the platform is easy to navigate, track progress, and use learning materials on the platform; this was termed technological usability (e.g., “It is easy to track my learning progress using the platform”). They were items that were founded on usability scales used in the past in AI and e-learning environments [1]. These items are processed as Ease of Progress Tracking since they coincide with Ease of Progress Tracking.

The items used to measure Perceived Effectiveness in Skill reflected the alterations in skills, confidence, and job performance (e.g., “This platform has helped me acquire new job-related skills”), which were informed by models on the skill development and training effects literature [7].

Job motivation is the intrinsic motivation (e.g., learning to grow as an individual) and extrinsic motivation (e.g., rewards/compliments) that determine training attendance. Since these items fit in Employee Motivation to Use Platforms, they were adapted to the generic motivation inventories applied to technology learning situations [1].

Organizational Support used the level of perceived organizational support to help employees use AI-enhanced training (e.g., “My organization encourages the use of AI tools to train and develop employees”), based on the literature on HR support and technology adoption [4, 14]. The moderating effect was automatically calculated in SmartPLS 4 in an interaction term (Employee Perception × Organizational Support).

As in a responsible AI-centered research, Employee Perception was operationalized as a mediating construct of trust, fairness, and belief in the usefulness of the platform (e.g., “I think the AI training platform provides fair learning recommendations”), which was the focus of the research [2, 4].

Typical training evaluation metrics [7, 12] were used to evaluate the Effectiveness of AI Training Platforms, dependent variable (e.g., overall satisfaction, learning utility, and post-training performance improvement, e.g., “The training platform enhances my job performance”).

All the scales were rigorously tested before full implementation in terms of clarity and internal consistency. In data analysis, factor analysis and reliability testing (e.g., Cronbach’s alpha) were conducted to determine construct validity and reliability.

3.3. Analytical approach

To test the hypothetical relationships and confirm the given conceptual framework, a two-step analysis process was conducted with the help of SPSS 25 as the preliminary data processing tool and SmartPLS 4 as the main statistical software. Data from the surveys were coded, screened, and descriptively analyzed in SPSS, and measurement models were assessed, and structural models were tested in SmartPLS 4 with the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

The measurement model was tested in step one and assessed on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The reliability of indicators was tested through the review of the outer loads with 0.70 or above as acceptable. Composite reliability (CR) and Cronbach’s alpha were examined as the internal consistency reliability techniques, with a 0.70 or more being considered satisfactory. The convergent validity was also supported at the point where the average variance extracted (AVE) per concept was over 0.50. Discriminant validity was confirmed using the Fornell–Larcker criterion and comparison of cross-loadings, with the square root of the AVE of each construct exceeding the correlation of the construct with others.

The second step was the evaluation of the structural model to find out whether the proposed relationships among the constructs were supported. Direct effects were measured in inner model paths (H1a–H6). The theorized moderating effect in H7 was tested by creating an interaction construct (Employee Perception × Organizational Support) and testing the pathway to Effectiveness of AI Training Platforms using the product-indicator method in SmartPLS 4. The significant test was done with a 5000-sample bootstrap. The predictive relevance of the model (Q^2 values) was tested by blindfolding. Q^2 values above one show when there is adequate predictive power. The explanatory strength of the endogenous constructs was tested with the values of the coefficient of determination (R^2).

Employee Perception also had a theorization as a moderator between the features of AI training platforms and the performance of the platform. The mediation effects were tested by means of bootstrapping the indirect path significance. Without moderation analysis, Organizational Support was subject to a test to establish its direct impact on the Effectiveness of AI Training Platforms.

The use of PLS-SEM in SmartPLS 4 allowed conducting the assessment of the empirical and adaptable measurement and structural framework with a precise understanding of the associations between the significant variables that affect the performance of the Effectiveness of AI Training Platforms.

4. Analysis and Results

4.1. Assessing PLS-SEM measurement model

A thorough evaluation of the measurement model was done to determine the strength of the proposed research model with the help of PLS-SEM. The analysis started by assessing the reliability of the indicators, internal consistency reliability, convergent validity, and multicollinearity based on factor loadings, Cronbach's alpha, CR, AVE, and variance inflation factor (VIF) as summarized in Table 3.

Strong indicator reliability was obtained in all constructs, with factor loadings more than the recommended level of 0.70. In particular, loadings of all items on the constructs,

Table 3
Factor loadings, reliability, convergent validity, and VIF analysis

	Factor loadings	Cronbach alpha	Composite reliability	AVE	VIF
DV 1		0.924	0.926	0.768	
DV1.1	0.879				2.877
DV1.2	0.849				2.608
DV1.3	0.877				2.781
DV1.4	0.887				3.302
DV1.5	0.889				3.337
IV 1		0.898	0.900	0.712	
IV1.1	0.877				2.901
IV1.2	0.774				1.766
IV1.3	0.880				2.982
IV1.4	0.838				2.206
IV1.5	0.844				2.371
IV 2		0.894	0.894	0.702	
IV2.1	0.847				2.435
IV2.2	0.846				2.432
IV2.3	0.870				2.821
IV2.4	0.814				1.975
IV2.5	0.811				1.975
IV 3		0.901	0.901	0.716	
IV3.1	0.853				2.468
IV3.2	0.824				2.160
IV3.3	0.843				2.327
IV3.4	0.835				2.244
IV3.5	0.875				2.742
IV 4		0.901	0.901	0.716	
IV4.1	0.825				2.155
IV4.2	0.843				2.260
IV4.3	0.836				2.223
IV4.4	0.846				2.334
IV4.5	0.861				2.483

(*Continued*)

Table 3
(*Continued*)

IV 5		0.896	0.897	0.706	
IV5.1	0.813				2.072
IV5.2	0.871				2.663
IV5.3	0.843				2.262
IV5.4	0.829				2.184
IV5.5	0.844				2.270
MRV		0.902	0.902	0.719	
MRV1.1	0.864				2.617
MRV1.2	0.850				2.455
MRV1.3	0.842				2.267
MRV1.4	0.853				2.400
MRV1.5	0.830				2.134
MV		0.907	0.908	0.730	
MV1.1	0.812				2.111
MV1.2	0.873				2.742
MV1.3	0.882				2.863
MV1.4	0.857				2.500
MV1.5	0.847				2.414
MRV x MV	1.00				1.00

Table 4
Discriminant validity analysis (Fornell and Larcker criteria)

	DV1.	IV1.	IV2.	IV3.	IV4.	IV5.	MRV1.	MV1.
DV1.	0.876							
IV1.	0.853	0.874						
IV2.	0.851	0.869	0.867					
IV3.	0.859	0.839	0.863	0.846				
IV4.	0.830	0.847	0.861	0.875	0.842			
IV5.	0.819	0.844	0.820	0.823	0.865	0.879		
MRV1.	0.851	0.844	0.865	0.881	0.845	0.853	0.848	
MV1.	0.839	0.844	0.838	0.851	0.897	0.840	0.842	0.854

including Quality And Relevance of Training (IV1), Interactivity and Personalization (IV2), Ease Of Progress Tracking (IV3), Perceived Effectiveness in Skill (IV4), Employee Motivation to Use Platforms (IV5), Organizational Support (MRV1), Employee Perception (MV1), and Effectiveness of AI Training Platforms (DV1) were between 0.774 and 0.889, indicating that all items represented their own constructs appropriately.

Internal consistency reliability was established, and Cronbach's values of alpha were more than 0.89 on all constructs, representing high internal consistency. Construct consistency was supported by the CR values of 0.894–0.926, all of which were well above the 0.70 expected level. Moreover, the AVE of all constructs is above 0.70, above the value of 0.50, which proves convergent validity.

More so, there was no fear of multicollinearity as all values of VIF were between 1.766 and 3.337, which is much lower than the critical value of 5. This shows that the indicators of every construct are independent enough, and this meets the requirements of multivariate analysis.

The Fornell and Larcker criterion was used to determine the discriminant validity of the constructs (Table 4). The square roots of the AVE (which are indicated on the diagonal) were higher than the off-diagonal inter-construct correlations, indicating adequate discriminant validity of all the constructs.

To conclude, the measurement model proved to have a good indicator reliability, internal consistency, convergent, and discriminant validity. This proves that the constructs in this study are smart and valid in measuring the relationships hypothesized in the conceptual framework of the study.

4.2. Model validation

The Q^2 statistic calculated with the aid of the blindfolding process of the PLS-SEM was used to measure the predictive relevance of the research model. Table 5 shows that the Q^2 of the observed items in both the dependent (DV1.1–DV1.5) and mediating (MV1.1–MV1.5) variables are significantly greater than zero, and the range of the values is 0.503–0.682.

These Q^2 values point out that the model is highly predictive in terms of direct and mediating outcomes. In particular, the large Q^2 values of Effectiveness of AI Training Platforms items (DV1) indicate that the independent and mediating variables (Quality and Relevance of Training, Interactivity and Personalization, Ease of Progress Tracking, Perceived Effectiveness in

Table 5
Determining the predictive power of the model (Q square)

	DV1.1	DV1.2	DV1.3	DV1.4	DV1.5	MV1.1	MV1.2	MV1.3	MV1.4	MV1.5
Q^2predict	0.619	0.503	0.649	0.577	0.654	0.559	0.638	0.682	0.625	0.65

Skill, Employee Motivation to Use Platforms, Employee Perception, and Organizational Support) are effective in explaining the variability in user-reported training effectiveness.

In the same way, Q^2 values of items of Employee Perception (MV1) indicated that the independent variables could predict the mediating construct significantly, and it preferred a mediating role in the overall model. According to Sarstedt et al. [16], the Q^2 value of above 0.35 means that the model is predictively relevant, which is the same in this instance.

The findings of testing the model depict that the structural model testing fit of the real data is valid, and all the given indices are at the required level. These findings confirm that the proposed framework is valid and create an argumentation of the interrelationships within this framework.

4.3. Assessing the structural model

A structural model was estimated to test the relationships between the constructs in the proposed conceptual framework. Path coefficients, t-values, and p-values were tested with SmartPLS 4 with 5000 subsamples and a bootstrapping method. Table 6 gives direct relationships between the independent, mediating, and dependent variables.

The H1a was supported by the strong and positive correlation existing between Employee Perception and Quality and Relevance of Training ($\beta = 0.205$, $t = 4.177$, $p < 0.000$). Similarly, H2a was substantiated by the positive effects of Interactivity and Personalization on Employee Perception ($\beta = 0.161$, $t = 2.927$, $p = 0.003$). The support of H3a is not provided, though, since the correlation between Employee Perception and Ease of Progress Tracking was not significant ($\beta = 0.049$, $t = 0.917$, $p = 0.359$).

The strong impact of Perceived Effectiveness in Skill on Employee Perception ($\beta = 0.315$, $t = 4.656$, $p < 0.001$) supported H4a. On the same note, H5a was substantiated by how Employee Motivation to Use Platforms had a significant positive influence on Employee Perception ($\beta = 0.261$, $t = 5.314$, $p = 0.001$).

The test result of the association of Effectiveness of AI Training Platforms and Employee Perception provided support for H6 because the result showed a significant and strong effect ($\beta = 0.302$, $t = 5.556$, $p < 0.001$) of the two variables. The interaction term also showed that Organizational Support moderated the effect of Employee Perception on Effectiveness of AI Training Platforms significantly ($\beta = 0.136$, $t = 5.876$, $p < 0.001$), which supported H7.

The entire report of the direct and moderating effect path coefficients is provided in Table 6. The model of PLS-SEM path and the model containing outer loadings and inner path coefficients are demonstrated in Figures 2 and 3, respectively.

4.4. Mediation analysis

The mediation analysis applied to determine the mediating role of Employee Perception (MV1) in the relations between the five independent variables and the Platform Effectiveness (DV1) was done through bootstrapping with 5000 resamples in PLS-SEM. With the help of this method, it is possible to estimate the indirect effects and determine the importance of individual effects, according to the recommendations of Sarstedt et al. [16]. The objective of the analysis was to identify whether Employee Perception is a cognitive-emotional process, in which the characteristics of AI-based training platforms interact with the assessment of the training effectiveness by the employees.

The results of the mediation analysis are given in Table 7. The results have revealed that four of the five independent variables have significant indirect effects on Platform Effectiveness via Employee Perception and therefore substantiate most of the hypotheses of mediation relations.

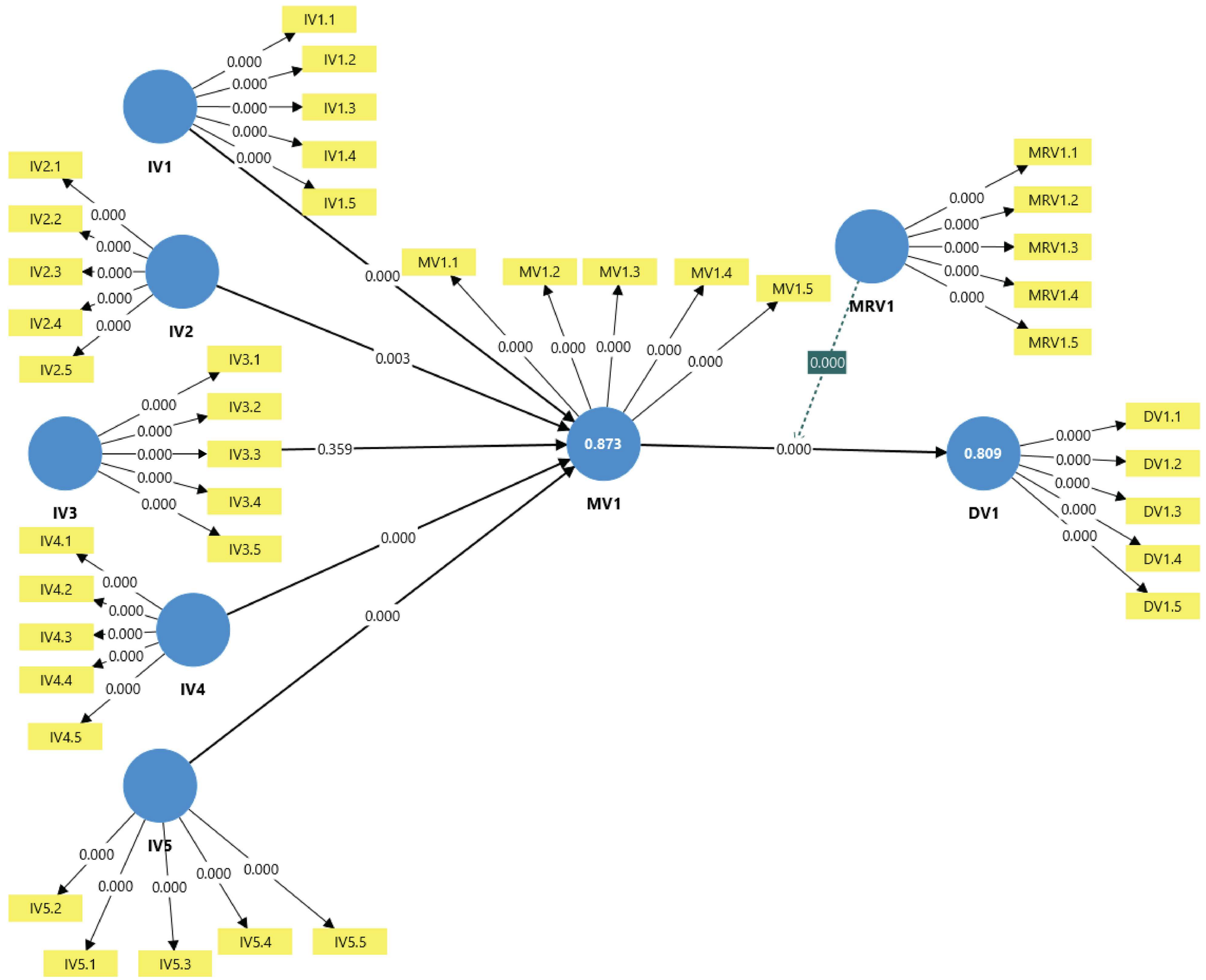
First, one of the important indirect impacts on Platform Effectiveness through Employee Perception was found between Content and Design Quality (IV1) and Platform Effectiveness ($\beta = 0.086$, $t = 3.727$, $p < 0.001$), which supported H1b. This means that quality AI-generated training material boosts the perceived platform effectiveness, especially when the employees perceive the material as pertinent, authoritative, and well-organized.

The significant indirect impact was also demonstrated between Interactivity and Personalization (IV2) ($\beta = 0.067$, $t = 2.521$, $p < 0.01$), which corresponds to H2b. Though the

Table 6
Hypothesis testing

	Original sample (O)	T statistics (|O/STDEV|)	p-values	Status
H1a. IV1. → MV1.	0.205	4.177	0.000	Accepted
H2a. IV2. → MV1.	0.161	2.927	0.003	Accepted
H3a. IV3. → MV1.	0.049	0.917	0.359	Rejected
H4a. IV4. → MV1.	0.315	4.656	0.000	Accepted
H5a. IV5. → MV1.	0.261	5.314	0.000	Accepted
H6. MV1. → DV1.	0.302	5.556	0.000	Accepted
H7. MRV1. × MV1 → DV1.	–0.252	5.876	0.000	Accepted

Figure 2
Final output model (bootstrapping)



interaction feature enhances the interactive level, the effects of such features on perceived platform success are achieved mainly via the positive assessment of employees of the roles that such interactive features play in their learning process.

On the contrary, Technological Usability (IV3) had no significant indirect impact via Employee Perception (β = 0.021, t = 0.825, p > 0.05), which rejected H3b. This implies that usability can facilitate participation but not have a great influence on the perceptions of platform effectiveness unless they are supplemented by their greater motivational or learning-based advantages.

Perceived Learning Outcomes (IV4) gave a significant and strong indirect effect (β = 0.132, t = 4.178, p < 0.001) to support H4b. It means that in case employees think the training improves their knowledge and skills, their positive attitude to the platform will be one of the main channels that affect their evaluation of its overall efficiency. H7 (mediation and moderation) hypotheses were tested individually.

Likewise, the indirect impact of Employee Motivation (IV5) on Platform Effectiveness through perception was significant (β = 0.108, t = 4.047, p < 0.001) in favor of H5b. This observation indicates that motivated employees will have more positive attitudes toward AI training tools, and these attitudes will, in turn, reinforce their judgment of the usefulness and effectiveness of the platform.

In general, the mediation analysis substantiates the idea that Employee Perception is at the center of mediation in the role of determining the effect of content quality, interactivity, learning outcomes, and motivation on the perceived training effectiveness. The results point to perception as one of the key processes that allow AI-based training environments to benefit from learning evaluation and results.

5. Discussion

The results point to the conclusive impact of Quality and Relevance of Training on the Employee Perception of the employees toward AI-based training platforms. It is aligned with the earlier testimony of the relevance of content to training, comprehension, and employment launch ability as the leading predictors of digital training success [9, 7]. The direct effect (H1a), as well as the indirect effect via Employee Perception (H1b), was significant and confirmed that the Quality and Relevance of Training should be appropriate to the professional context of a learner. Good organization was observed to raise user confidence and trust toward

Figure 3
Final output model (PLS-SEM)

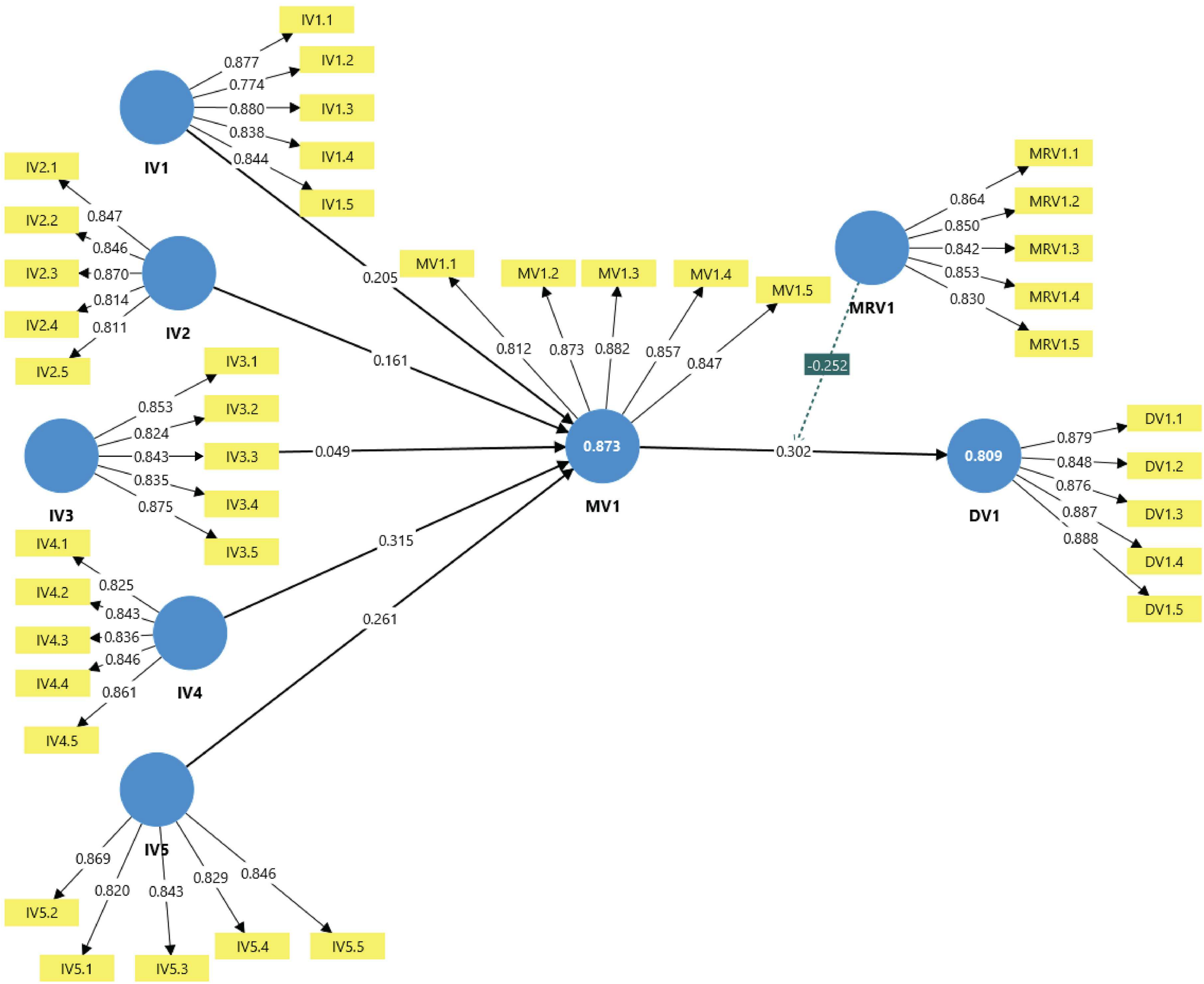


Table 7
Mediation analysis

	Original sample (O)	T statistics (|O/STDEV|)	*p*-values	Status
H1b. IV1. → MV1. → DV1.	0.086	3.474	0.001	Accepted
H2b. IV2. → MV1. → DV1.	0.067	2.605	0.009	Accepted
H3b. IV3. → MV1. → DV1.	0.020	0.877	0.381	Rejected
H4b. IV4. → MV1. → DV1.	0.132	4.084	0.000	Accepted
H5b. IV5. → MV1. → DV1.	0.108	5.735	0.000	Accepted

the platform, which supports the idea that Quality and Relevance of Training is a top priority in the Effectiveness of AI Training Platforms [17].

Effectiveness of AI Training Platforms also showed a significant connection with Interactivity and Personalization via Employee Perception (H2a) and Effectiveness of AI Training Platforms Via Employee Perception (H2b) [18]. Such results are correlated with the studies that provide evidence that personalized learning trajectory, instant feedback, and interactive resources can make learners more engaged [10, 11]. Interactivity and Personalization facilitate more in-depth learning because of the relevance of content and interactive learning [19]. The mediation also shows that Interactivity and Personalization can only be effective when the learners interpret and appreciate these features positively. This highlights the importance of AI systems to justify and put into context the idea of personalization to enhance Employee Perception.

The Ease of Progress Tracking hypotheses (H3a and H3b) were not proved. Although Ease of Progress Tracking was presumed to help boost perception and effectiveness, findings obtained lent no support to significant direct or mediated effects. One of the methodological reasons is that survey questions reflected simple navigational clarity, which does not necessarily differ in digitally mature and younger groups represented by 55.7% of the respondents aged 25–35 years. Ease of Progress Tracking can be a hygiene factor: it must exist to allow access but is not sufficient to influence Employee Perception or Effectiveness of AI Training Platforms at a level beyond a certain standard [20]. In mature digital settings, such as AI systems used by skilled experts, accessibility acts like a hygiene aspect: it allows access but does not create a motivation to go deeper. Usability can be weighed down in favor of usefulness, engagement, and relevance in the case of advanced digital environments [21]. This is in opposition to previous research that gave importance to usability in e-learning [1], implying that with more advanced AI, Ease of Progress Tracking ceases to be a major factor of performance.

Perceived Effectiveness in Skill is also crucial, as it has been reinforced by the study and has a considerable impact on Employee Perception (H4a) and Effectiveness of AI Training Platforms via Employee Perception (H4b). Once the employees find out that a platform improves their abilities, they rate it higher and consider it more efficient. This is in line with the argument that learning outcomes entail actual gains as well as confidence in the gains [22]. Learning improvement is clearly communicated with the use of analytics, simulations, assessments, and AI platforms, which contribute to the improvement of Perceived Effectiveness in Skill [23, 24]. The excellent value of the effect makes Perceived Effectiveness in Skill a fundamental contributor to Effectiveness of AI Training Platforms [25].

In addition, the research proves that Employee Motivation to Use Platforms is a significant contributor to Employee Perception (H5a) and Effectiveness of AI Training Platforms via Employee Perception (H5b). This is in line with the motivational theory, indicating that motivated learners embrace more of the training systems [1, 7]. Gamification, goal setting, and career-aligned learning structures can be used to support Employee Motivation to Use Platforms in AI environments, and it is important to consider integrating motivational design principles [12].

A significant conclusion is that there is a high moderating impact of Organizational Support on the connection between Employee Perception and Effectiveness of AI Training Platforms (H7). The success of the platform requires a favorable organizational atmosphere, regardless of the level of technology. The employees will be more inclined to use AI systems successfully when they have the feeling that they are valued, supported, and ethically governed. Such qualitative aspects of Organizational Support as equitable AI regulation and definite training purpose are vital [4, 14].

The impact of Employee Perception, perhaps, is the most integrative theoretical contribution that showed that there is a significant relationship between several antecedents, Quality and Relevance of Training, Interactivity and Personalization, Employee Motivation to Use Platforms, Perceived Effectiveness in Skill, and Effectiveness of AI Training Platforms. This is an extension of TAM in the sense that Employee Perception is the primary mental filter linking the technology and organizational conditions to the results. The Effectiveness of AI Training Platforms improves when the platforms are seen to be transparent, fair, and relevant [26]. Employee Perception, therefore, comes out as the psychological interface between system design and organizational climate, and training performance.

Combined, these results have a number of practical implications. To maintain digital learning success, organizations need to make sure they have Quality and Relevance of Training, integrate Interactivity and Personalization, make Ease of Progress Tracking a basis and not a differentiator, improve Perceived Effectiveness in Skill through a feedback mechanism, entrench Employee Motivation to Use Platforms, and reinforce Organizational Support.

In conceptual terms, the study contributes to the digital transformation research in HRD by suggesting a model, which incorporates Quality and Relevance of Training, Interactivity and Personalization, Ease of Progress Tracking, Employee Motivation to Use Platforms, Employee Perception, Perceived Effectiveness in Skill, and Organizational Support. The results are contrary to the naive usability-centric models and focus on how workers perceive, believe, and emotionally connect with AI systems.

Overall, this research demonstrates that the workability of AI-based training systems is affected both by the technological functionality and the perception and supporting aspects in the organizational environment. These insights will be important as organizations proceed with the digitalization of the learning systems to inform AI tools design and implementation strategies.

6. Conclusions and Implications

6.1. Conclusions

The results indicate that stimulating and high-quality material and adaptive learning experiences, as they are represented by Quality and Relevance of Training and Interactivity and Personalization, influence Employee Perception that, in turn, dictates the overall Effectiveness of AI Training Platforms. Quality and Relevance of Training and Interactivity and Personalization were found to be the main sources of engagement and perceived value, whereas Perceived Effectiveness in Skill and Employee Motivation to Use Platforms were the main predictors of positive impressions and successful training results.

Interestingly, technological usability, namely, Ease of Progress Tracking, did not have a strong impact on Employee Perception, which is why such features can be arguably critical, but not enough to positively influence the Effectiveness of AI Training Platforms alone. Conversely, Organizational Support, especially leadership support and responsible AI behaviors, had a direct positive effect on Effectiveness of AI Training Platforms, which highlights that technological tools can produce the most significant outcomes when incorporated into a favorable organizational environment.

One of the main findings of this research is the mediating effect of Employee Perception, which acts as a cognitive and emotional filter where the features of the platform are transformed into learning outcomes. The implication of this finding is the necessity of the functional soundness of AI training systems, where trust, transparency, and relevance are the defining features of the user experience.

The study supplements the body of academic research because it endorses a comprehensive model, which relates design-level factors (Quality and Relevance of Training, Interactivity and Personalization), psychological processes (Employee Motivation to Use Platforms, Employee Perception), and organizational facilitators (Organizational Support) to training results. The findings can provide practical recommendations on how practitioners can design, implement, and manage successful, equitable, and scalable AI-based training systems.

6.2. Theoretical implications

The present research contributes greatly to the body of literature on the effectiveness of AI-based T&D systems. This research connects various fields: digital learning, human resource development (HRD), and responsible implementation of AI in training at the workplace by building and legitimizing a research model that encompasses technical, behavioral, and organizational facets.

The introduction of Employee Perception as a mediating variable can be seen as one of the greatest contributions to the field of theoretical thought since it provides a more comprehensive perspective of cognitive and emotional reactions of users to AI training features. Empirically, the study confirms that only technical attributes such as Quality and Relevance of Training, Interactivity and Personalization, or Ease of Progress Tracking cannot be used to determine the Effectiveness of AI Training Platforms without being filtered through the perceptions of users. This result substantiates and broadens user-oriented models by adding a more subtle aspect of perceptions to AI settings.

Also, the results highlight the situational relevance of Organizational Support in the determination of digital training outcomes. Although the literature has focused on design and functionality of systems to a large extent, the given study contributes to the theoretical framework by illustrating that external enablers, like management commitment and ethical practices in AI, can have a profound effect on both perceived and actual training outcomes. It extends sociotechnical systems such as organizational learning and HRD ecosystems by placing AI adoption into institutional structures.

Perceived Effectiveness in Skill and Employee Motivation to Use Platforms being confirmed as antecedents of effectiveness adds to the motivational theory in online learning, including SDT. The paper emphasizes that perceived competence, personal relevance, and autonomy should be incorporated in AI learning systems to be successful.

6.3. Managerial implications

Along with theoretical knowledge, the study has practical implications for managers, HR professionals, and organizational leaders who may be interested in the introduction or further development of AI-based training systems.

First, the results emphasize the importance of investing in high-quality and job-relevant Quality and Relevance of Training. The content generated or edited by AI should be more specific to the tasks of particular employees and the obstacles they encounter in their professions. The managers are advised to work with AI developers and instructional designers to guarantee that training material can be both technical and culturally acceptable. User value and Effectiveness of AI Training Platforms are maximized by the content that matches authentic learning requirements.

Second, companies should pay attention to the enhancement of Interactivity and Personalization. The firms need to focus on adaptive learning trajectories, gamification, and real-time feedback systems when choosing or personalizing AI systems. The features help to improve the interaction and a feeling of responsiveness, which will lead to a higher level of loyalty to the system.

Third, as Ease of Progress Tracking was not a major factor in this research, it is still a fundamental supporting factor. Accessibility is also important for ease of navigation and clarity of the system, especially among those employees with low levels of digital literacy. Managers should make sure that systems can reach a minimum of usability levels and that they have technical support.

Fourth, the analysis reveals that Perceived Effectiveness in Skill and Employee Motivation to Use Platforms are significant in the formation of Employee Perception and, finally, the Effectiveness of AI Training Platforms. The HR departments are to formulate AI training in the form of clear learning objectives, measurable outcomes, and alignment with career pathways. Badges, certificates, or promotions can enhance extrinsic motivation.

Fifth, Organizational Support rose to become the most potent predictor of the Effectiveness of AI Training Platforms. Companies have to show their interest in digital learning by investing resources, gaining leadership support, and ensuring an open communication channel. Platform strategy: The strategy of responsible AI (data transparency, ethical content governance, and inclusive design) should be implemented to create trust and long-term engagement.

Lastly, the leadership should consider AI-driven learning as a change management program and not a purely technological one. These efforts must be coordinated between HR, IT, compliance, and operations in order to be successful in deployment. The AI policies, practices, and the feedback loop on learners should be ruled by cross-functional teams.

6.4. Implication for policymakers

With AI-driven training systems at the very heart of national upskilling policies, policymakers need to develop regulatory and support systems that would strike a balance between technological development and humanistic principles of learning.

First, policymakers would want to set standards that would make AI-based training systems focus on the relevancy of content, personalization, and active learning. This could be accompanied by a national AI Training Quality Seal or some other certification where platforms must demonstrate the following capabilities: adaptive content delivery, real-time analysis of skill gaps, and a system of constant feedback to the user. These standards could be supported by minimum requirements on the usability, transparency, and effectiveness in developing a skill. Audits of algorithmic personalization and transparency of progress in accordance with ISO would make the further enhancement of accountability and guarantee to stakeholders the integrity of the system. Moreover, the industry-specific standards would be useful in aligning AI training tools with the changing labor market requirements.

Second, the ethical AI practices should be placed as one of the central requirements in the training context. Policymakers must come up with unambiguous policies that deal with data security, transparency in algorithms, and equity in learning systems based on AI. To boost user trust and increase adoption, the introduction of the requirements of explainable AI, including the ability of platforms to explain how learning paths are created, how progress is tracked, and how learner data are utilized in plain language, would assist in attracting users.

Third, the digital infrastructure and workforce reskilling must be put on the national agenda. The policymakers need to understand that introducing AI in the training process should be accompanied by not only technological preparedness but also cultural and behavioral changes. Companies whose employees efficaciously complete accredited AI training modules should receive incentives. Moreover, grants aimed at improving digital readiness can be used to boost faster adoption within organizations. Likewise, motivation and participation can be further stimulated by public campaigns that will increase the awareness of the value and possibilities of the AI-enabled training.

Lastly, enhanced cooperation between government bodies, industry players, and higher education is the key to ongoing innovation and the development of evidence-based policies. Government, technology firms, and higher education institutions could also form tripartite AI Training Innovation Hubs, which could be co-funded by government, tech firms, and universities to prototype, test, and develop advanced training solutions at scale. Long-term implications of the proactive use of AI-based learning tools create two additional aspects of longitudinal studies that would aid in the refinement of the regulations and national skill set policies by policymakers.

7. Limitations and Future Research Directions

7.1. Limitations

Despite the fact that this paper delivers valuable insights into the facilitators and obstacles that affect the success of AI-based learning and development platforms, multiple limitations should be mentioned.

First, a cross-sectional survey does not provide the opportunity to make conclusions based on causation. Due to the fact that data was gathered at one point in time, one cannot define how the perception of employees or the effectiveness of the platforms changes. Such changes would require longitudinal designs to follow through the long durations.

Second, self-reporting of all data was done. As much as they are reasonable in studying subjective perceptions, self-report measures are prone to biases, including social desirability and common method variance [27]. The research can be improved in future research by adding more data sources with objective system analytics, supervisor ratings, or objective behavioral performance measures.

Third, its sample did not stratify based on sector or organization size, even though the participants had worked in various industries. The trends in AI usage, the education and training required, and the legal limitations tend to differ considerably, also depending on the area of use, that is, healthcare, finance, or manufacturing, which may constrain the external validity of the results.

Finally, the research was conducted to look into the variables that were developed based on the available literature and professional recommendations. Even though these constructs are valuable, they do not provide a complete understanding of the dynamic and complex nature of AI-mediated learning. Further studies ought to extend the model to cover other predictors like digital literacy, AI trust, technostress, and perceived fairness so as to have a broader picture of user experiences in AI-enhanced training settings.

7.2. Future research directions

Based on the limitations, this research offers some avenues for future research. First, longitudinal research designs should be embraced in future studies in order to enhance causality and variable changes of user acceptance with time. Researchers could use a three-wave design, which involves data collection before the rollout of the platform, several months later, and a long-term follow-up to monitor the changes in perception, motivation, and effectiveness of the AI-enabled training systems as the employees get to be more familiar with them.

Second, it should conduct comparative research in different industries. It may be that high-skill, high-stakes environments like healthcare, finance, aviation, or government have different adoption patterns and challenges and levels of success than other industries. This knowledge of these sectoral differences may aid in more specific and applicable policy and practice.

Third, as employee perception was the main mediator in this model, future studies should implement more psychological constructs such as trust in AI, digital self-efficacy, perceived autonomy, and technostress to better illustrate user experiences and behavioral outcomes in AI-driven learning settings.

Fourth, this research determined the effectiveness of the platform from the perspective of the learner. Future studies need to combine other outcome measures, like supervisor ratings, performance-based measures, productivity measures, and organizational return on investment measures, to give a multidimensional interpretation of training effects.

Finally, with the continued development of generative AI technologies, future research should look at how these instruments change the ways people engage, their motivation, personalization, and skill-building.

Ethical Statement

All subjects provided informed consent for inclusion before participating in the study. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Departmental Ethics Committee for Research Involving Human Subjects at the University of Dhaka, Bangladesh (Reference Number: IBDUREC-2025-08).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.18435557.

Author Contribution Statement

Chanchal Molla: Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Khaled Islam:** Conceptualization, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Md. Razib Hossain:** Conceptualization, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Pronoy Kumar Paul:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Md. Najibul Kabir:** Conceptualization, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Abu Naser Mohammad Saif:** Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Rehnuma Mostafa:** Methodology, Validation, Resources, Writing – review & editing.

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Appendix

Constructs	Items	Ref.
Quality and Relevance of Training Content	IV1.1. The training info is correct and helpful. IV1.2. The content fits my job well. IV1.3. The platform teaches me new, useful things. IV1.4. The lessons match what I need at work. IV1.5. The training helps me with my job problems.	[13, 15]
Interactivity and Personalization	IV2.1. The platform changes to fit how I learn. IV2.2. Fun activities like games keep me interested. IV2.3. The AI knows what I'm good or bad at. IV2.4. The training feels exciting because of the rewards. IV2.5. I like how the platform makes learning fun.	[2, 9, 10]
Ease of Progress Tracking	IV3.1. I can see how far I've come easily. IV3.2. The progress screen is simple to understand. IV3.3. The platform tells me when I finish steps. IV3.4. It's easy to check my improvement. IV3.5. Seeing my progress makes me want to keep going.	[10]
Perceived Effectiveness in Skill Development	IV4.1. The training helped me improve job-related skills. IV4.2. I can apply what I learned in my daily work. IV4.3. The platform made me feel more competent at my job. IV4.4. This training supported my career development goals. IV4.5. The skills I learned will benefit my future performance.	[14]
Employee Motivation to Use Platforms	IV5.1. I use the platform to grow in my job. IV5.2. I like getting rewards for finishing training. IV5.3. The platform makes me happy to learn. IV5.4. It's easy to use, so I want to try it. IV5.5. The training helps me get ahead at work.	[1, 7]
Employee Perception	MV1.1. I trust the platform to help me. MV1.2. The platform is easy to figure out. MV1.3. The AI treats everyone the same. MV1.4. I feel good about using this platform. MV1.5. The system works well for my training.	[2, 4]
Organizational Support	MRV1.1. My job makes it easy to use the platform. MRV1.2. My boss tells me to try the training. MRV1.3. I feel okay because it's clear and open. MRV1.4. My info is safe when I use it. MRV1.5. The platform feels fair to everyone.	[8, 12]
Effectiveness of AI Training Platforms	DV1.1. The platform helps me get better at my job. DV1.2. I do my work faster after using the platform. DV1.3. I like using this platform for training. DV1.4. The platform makes me good at my tasks. DV1.5. My work is better because of this training.	[9]