CHAPTER 5

Adoption of AI Tools in Corporate Learning Pedagogy

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ABSTRACT

Artificial Intelligence has developed extremely fast during the recent years and has already begun transforming the manner in which learning and training processes and programs take place within organizations. Previous methods of corporate learning were largely executed in form of classroom learning and predetermined training programs which are no longer individual. Nonetheless, most organizations are gradually implementing AI-based applications to make the learning process more efficient, time saving, and effective to meet needs of individual employees (Holmes et al., 2019). This paper is an attempt to determine how firms are introducing AI tools into their learning systems, through such frameworks as technology Acceptance Model (TAM) (Davis, 1989) and Unified Theory of Acceptance and Use of technology (UTAUT2) (Venkatesh, Thong, & Xu, 2012). The study was modified to be a mixed research approach. A structured questionnaire was used to gather quantitative data and they were analysed using Relative Importance Index (RII). Simultaneously, semi-structured interviews with corporate trainers were used as the means of collecting qualitative data by employing snowball sampling method. As findings of the study demonstrate, anticipated performance enhancement, perceived utility of AI tools, and presence of organizational support are relevant when it comes to the adoption of AI. Majority of trainers believe that AI assists in personalizing learning process and saving time as well as advancing skills. Nevertheless, there are still concerns that pertain to data privacy, ethical concerns, and general organizational barrier (Holmes et al., 2019). The analysis concludes that not only technology is important to successful and long-term implementation of AI in corporate learning. Leadership support, coherent moral codes, and frequent training of trainers are also crucial. Such study contributes to existing body of research in the area of technology adoption, as the researcher implements TAM and UTAUT2 (Venkatesh et al., 2012) in the process of corporate learning and provides valuable insights to organizations that consider the use of AI in a responsible way.

Keywords: Artificial Intelligence, Corporate Learning, Technology Adoption, Organizational Readiness, Training Innovation.

1.0 Introduction

The modern business world has become fast-changing with technology, globalizing, digitally

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disruptive, and with rapid skill obsolescence. Companies in all sectors are being placed under continuous pressure to not only increase the ability of the working group, but also to increase productivity, innovativeness, cost efficiency. Consequently, the corporate learning and development (L&D) operations have become avoidance functions that add value as strategic facilitators of organizational competitiveness and long-term viability.

The classical corporate forms of learning that largely depend on classroom learning, frozen e-learning sessions, and standardized training courses are increasingly being ineffective to meet the dynamic business demands. These models usually do not consider the different profiles of learners, different levels of skills as well as demands of role that change rapidly. Organizations are therefore in search of technology-based solutions that would enable provision of scalable, adaptive, and outcome-based learning experiences.

Artificial Intelligence has become a disruptive technology that can radically change corporate learning pedagogy. Artificial intelligence can be used to develop intelligent tutoring systems, adaptive learning platforms, conversational agents, automated assessment engines and learning analytics dashboards to help organizations transition to a data-driven approach to learning rather than a reactive training strategy. Through these tools, it is possible to monitor the engagement and performance of learners in real-time, anticipate the existence of skills gaps, as well as continuously optimize learning interventions (Holmes et al., 2019).

Along with these benefits, AI tools usage in corporate learning setting is not even. As technologically mature organizations have started exploring the use of AI in their training environments, other organizations continue to experience challenges associated with the lack of digital infrastructure, trainer preparedness, change resistance and ethical issues. Concerns about data privacy, algorithmic bias, transparency and compliance with regulations also make the process of adoption more complicated, especially in organizations that deal with sensitive employee and business data (Holmes et al., 2019).

Corporate trainers are at the centre of this change. Trainers who are change agents, instructional designers and facilitators have ability to guide the perception, implementation, and use of AI tools in learning. Their affirmation of AI technologies can largely influence the attitude of learners and condition the presence of a deep application of AI or its shallow performance (Holmes et al., 2019).

It is thus important to know the determinants of AI in corporate learning pedagogy. Technology adoption theories offer theoretical models used to analyze user acceptance and usage. Technology Acceptance Model (TAM) (Davis, 1989) focuses on perceived usefulness and ease of use as factors that predict adoption whereas Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh, Thong, & Xu, 2012) expands on this view, introducing new constructs like social influence, facilitating condition and habit as well as price value.

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The research examine how AI tools can be adopted in corporate learning pedagogy by incorporating the TAM and UTAUT2 (Venkatesh, Thong, & Xu, 2012) models. The study concentrates on the views of corporate trainers and will be based on a mixed method design. Taking an analytical approach to study of performance-driven motivations and the contextual constraints, the research set out to equip a detailed and empirically-based explanation of AI adoption dynamics within corporate learners.

2.0 Literature Review

2.1 Artificial intelligence in corporate learning

Artificial Intelligence the computational systems that can execute processes normally performed by the human intelligence are called artificial intelligence, such as learning, reasoning, prediction, and decision-making. AI applications are getting integrated in learning management systems, virtual learning platforms and performance support systems in corporate learning settings. These applications are adaptive learning engines, intelligent tutoring systems, automated assessments systems, chatbots and predictive learning analytics (Holmes et al., 2019).

According to previous studies, AI-based corporate learning styles can also be useful in improving training through personalization, scaling, and real-time feedback. Using AI systems, the behaviour of learners, their level of engagement, assessments and patterns of progression are studied to make suitable content delivery. This kind of adaptability based on data is a solution to shortcomings of single-fit training models, especially in an organization with a wide learner base and functional specialists. The AI-based learning analytics also enable organizations to elevate training impact more closely and focus learning results on strategic business goals (Holmes et al., 2019).

Nevertheless, researchers warn that introduction of Ai in corporate learning is not a technical endeavour. The success of AI-powered learning is subject to organizational culture, ability of trainers, and governance systems. Heavy automation without pedagogical guidance can lead to lack of motivation in learners and shallow learning. Therefore, AI is generally considered as an additive resource, i.e., something that can improve human-based teaching, but not substitute it.

2.2 AI-enabled personalization and learning effectiveness

Among most frequently mentioned advantages of AI use in the corporate pedagogy, personalised learning should be listed. AI applications apply algorithms to examine personal learner traits of previous knowledge, learning rate, work job specifications and past performance. On the basis of this analysis, individualized learning paths, testing and feedback

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systems are produced. Empirical research shows that individualized learning enhances learner engagement, satisfaction and knowledge retention. Personalized increase the relevance and application of training in corporate setups where time is a critical factor and the individual competencies of the job are of utmost importance. Continuous learning process through AI-based personalization helps to recognize the emerging skills gaps and suggest specific interventions. As trainer, it can be observed that personalization made with the help of AI can be performed with more knowledge. Trainers are able to concentrate on instructional tasks that are of higher order like mentoring, coaching and contextual problem solving and AI takes care of repetitive and analytical jobs. This semi-teaching style enhances general pedagogical performance.

2.3 Technology Acceptance Model (TAM)

Technology Acceptance Model hypothesizes that attitude variables, are major predictors of technology adoption. Perceived usefulness is a measure that indicates levels of perception of person using the system that it leads to higher job performance and Perceived ease of use measures amount of effort necessary to use system (Davis, 1989).

TAM (Davis, 1989) has been greatly used in research considering adoption of educational technologies, e-learning platforms and digital tools of collaboration. Results are always consistent showing that perceived usefulness is a more significant factor in influencing behavioural intention than ease of use. This means that we could expect users to go through usability hurdles provided that technology gives them quantified in performance.

Perceived usefulness is manifested in the context of AI-based corporate learning tools as a high quality of learning, efficiency, personalization, and accuracy of evaluation. Perceived ease of use also affects adoption by making it easy to operate especially at early stages of implementation. TAM therefore offers a structural basis on explaining the acceptance of AI tools by trainers (Davis, 1989).

2.4 Unified Theory of Acceptance and Use of Technology (UTAUT2)

UTAUT2 (Venkatesh, Thong, & Xu, 2012) builds on the previous adoption models by adding other constructs that apply to the organizational and consumer settings. These are performance expectancy, social influence, facilitating conditions, habit and price value. UTAUT2 (Venkatesh, Thong, & Xu, 2012) can be especially relevant to the corporate learning scenario in which use of technology is conditioned by institutional policy, leadership decisions, and availability of infrastructure.

Performance expectancy is closely related to perceived usefulness and indicates the level of improvement in training results and efficiency caused by AI tools. Facilitating conditions include the accessibility of technical infrastructure, organizational support, and

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training resources required to be used in the long-run. Social influence is used to indicate the effect of leadership encouragement and peer behaviour on adoption level. The continuation of technology use is described by the habit construct which includes regular assimilation into work practice whereas perceived cost benefits trade-offs is determined by the price value. UTAUT2 (Venkatesh, Thong, & Xu, 2012) thus offers a holistic perspective on the study of both the first and second-order adoption of AI tools in corporate learning pedagogy.

2.5 Organizational change, trainer readiness, and resistance

The literature on organizational change points out that the introduction of technology is commonly followed by technology resistance that emanates due to uncertainties, skills, and perceived threats to professional identity. In the case of corporate learning, the trainers might be unwilling to adopt AI because they fear lack of relevance, decrease in instructional autonomy, or rise in surveillance.

Research has shown that, preparation of capability and readiness of trainers is very important in alleviating resistance. The acceptance is increased with the help of well-organized training programs, participatory implementation strategies, and articulated communication of the augmentative nature of AI. Leadership assistance also justifies the use of AI and removes anxiety surrounding change.

2.6 Ethical, privacy, governance considerations

Ethics have become the core of the argument on AI adoption. Corporate learning environments are usually a subject to delicate employee information, corporate expertise, and confidential communications. Issues regarding data privacy, algorithmic bias, transparency, regulatory compliance affect the adoption.

Moderating variables in technology acceptance are trust and ethical assurance. Crystal governance structures, use of clear data usage policies and adherence to legal requirements are necessary in creation of confidence between trainers and learners. The adoption of AI in a responsible manner hence involves need to harmonize technological innovation with ethical accountability.

3.0 Research Methodology

3.1 Research Design

The proposed research takes the mixed-method research design to investigate quantitative and qualitative aspects of AI implementation in corporate learning pedagogy. Both survey-based analysis and in-depth interviews allow to triple triangulate the findings, as well as to improve the validity and strength of results.

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3.2 Sampling technique

Snowball sampling was used to select corporate trainers who had experience in application of AI tools in training and development. The first participants were identified through professional networks and referrals, and further ones were identified through recommendations of the participants. Such a method was suitable due to the niche character of the target population and exploratory character of the study (Holmes et al., 2019).

3.3 Data collection

A structured questionnaire was used to collect quantitative data that were measured among respondents. The questionnaire employed the five-point likert scale and scales of construct in accordance with TAM (Davis, 1989) and UTAUT2 (Venkatesh, Thong, & Xu, 2012) which were performance expectancy, effort expectancy, facilitating conditions, social influence, habit, price value and ethical concerns. The qualitative data would be collected as a result of semi-structured interviews with the targeted corporate trainers. The interviews addressed AI perception, adoption issues, organizational assistance, and expectations.

3.4 Data analysis techniques

The Relative Importance Index (RII) was used to prioritize the importance of factors of adoption. Transcripts of qualitative interviews were summarised, denoised, and put through thematic analysis and AI-aided transcript mining. The theme analysis was conducted by examining the frequency of words to determine the prevalent themes to use during AI adoption.

4.0 Data Analysis

4.1 Relative Importance Index (RII)

In paper, RII was used to prioritize the variables that affect the adoption of AI tools in corporate learning pedagogy and, thus, allow organized interpretation in accordance with the constructs of TAM (Davis, 1989) and UTAUT2 (Venkatesh, Thong, & Xu, 2012).

4.2 RII Results: Performance expectancy and perceived usefulness

Performance expectancy proved to be the most significant predictor of AI adoption. Variables of learning effectiveness, personalization, and efficiency registered the RII highest values, which means that the respondents agreed the most. The dominance of these variables implies that, above all, corporate trainers' resort to using AI tools in case they can provide quantified changes in the quality of training and training outcomes. Results are a strong confirmation of the construct of Perceived Usefulness of TAM and Performance Expectancy in UTAUT2 (Venkatesh, Thong, & Xu, 2012). The trainers are open to employing AI in pedagogy in case its role in effectiveness and efficiency is obvious.

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Table 1: RII Results

Variable	RII Value	Interpretation
AI enhances learning through personalization	0.81	Strongly perceived as the most critical benefit
AI improves overall training efficiency	0.78	Viewed as a key performance enabler
AI simplifies administrative training tasks	0.78	Reduces trainer workload significantly
AI improves assessment accuracy and feedback	0.78	Enhance instructional precision

Source: Created by authors

4.3 RII results: Effort expectancy and ease of use

The variables of expectancy regarding effort had significantly moderate levels of RII, which reflected overall nature of respondents in that they tend to find AI tools within their control and easy to master. Although the start-up issues were reported, trainers reported issues to be reduced over time (Holmes et al., 2019).

Table 2: RII Results

Variable	RII Value	Interpretation
AI tools are easy to learn and operate	0.75	Low perceived complexity
Initial challenges reduce with experience	0.73	Learning curve stabilizes over time

Source: Created by authors

These findings confirm the TAM hypothesis that perceived ease of use is an indirect facilitator of adoption because it strengthens perceived usefulness. Nevertheless, evidence has also indicated that usability is not enough but effort expectancy should be reinforced with sufficient training and organizational support in order to maintain adoption (Davis, 1989).

4.4 RII Results: Facilitating Conditions and Organizational Readiness

Facilitating conditions became one of the most important determinants of AI adoption, and the importance of organizational infrastructure, technical support, and training mechanisms need to be highlighted.

Table 3: RII Results

Variable	RII Value	Interpretation
Organizational support for AI transition	0.79	Strong requirement for institutional backing
Availability of infrastructure and resources	0.72	Moderate readiness across organizations
Adequate training provided to trainers	0.67	Identified skill and capability gap

Source: Created by authors

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The lower value of RII on adequacy of training process indicates that there is a serious obstacle to successful use of AI. Although organizations can commit resources to AI technologies, they will not use them optimally without paying adequate attention to preparation of trainers and their competencies. These results are high in relation to the construct of UTAUT2 (Venkatesh, Thong, & Xu, 2012) namely Facilitating Conditions, which directly impacts actual usage behaviour (Venkatesh et al., 2012).

4.5 RII Results: Social influence, habit, price value

The value of RII between social influence and those variables associated with habits was moderate and high, which underscores importance of organizational culture and frequent use in ensuring continuations of adoption of AI.

Table 4: RII Results

Variable	RII Value	Interpretation
Leadership encouragement influences adoption	0.74	Managerial support legitimizes AI usage
Peer usage encourages AI adoption	0.75	Social norms reinforce acceptance
AI tools are used routinely in training	0.76	Evidence of habit formation
Benefits justify financial investment	0.77	Positive perception of price value

Source: Created by authors

These results suggest that adoption of AI is not a personal choice, but it is greatly influenced by leadership support and social behaviour. The habit formation implies that AI tools are shifting toward being experimental to embedded pedagogical practice, which confirms that UTAUT2 (Venkatesh, Thong, & Xu, 2012) is based on need to continue using tools after initial intent (Venkatesh et al., 2012).

4.6 RII Results – Ethical concerns and trust

The highest RII value were obtained in case of ethical considerations, which indicated high levels of responsibility in corporate trainers in relation to use of AI.

Table 5: RII Results

Variable	RII Values	Interpretation
Ethical regulation of AI tools is necessary	0.81	Critical condition for acceptance
Concerns regarding bias and fairness	0.69	Moderate apprehension
Data privacy and security concerns	0.71	Conditional trust in AI systems

Source: Created by authors

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The fact that ethical regulation is rated highly means that trainers do not object to use of AI but prudent and discriminating. Trust and ethical governance is thus considered moderating variables that affect perceived usefulness and behavioural intention.

4.7 Qualitative transcript mining analysis

The qualitative data collected by conducting semi-structured interviews underwent process of transcript mining and thematic analysis to complement and put into perspective the quantitative data. All transcripts of the interviews were initially re-collated and purged of filler words, repetitions and interviewer prompts in order to provide clarity in the analysis. The purified textual data were then processed under AI-assisted word frequency and thematic clustering method to give conceptually related NVvivo-based qualitative data analysis.

High-frequency words that were identified during the transcript mining process were AI, training, learning, quality, engagement, personalization, support, leadership, privacy, ethics, and human. The predominance of these words points to dimensions of centrality as a result of which corporate trainers perceive and sense adoption of AI in learning pedagogy.

One of the most powerful themes that have come out of analysis was close relation of AI with the increased training effectiveness. AI tools were always characterized by trainers as factors that enabled enhanced engagement of learners, expedited understanding, and enhanced coherence between training content and needs of the learners. Analytics and feedback mechanisms that were driven by AI were also seen as especially useful when tracking learner progress and determining which areas need instructional interventions. This qualitative observation supports the quantitative results of performance expectancy and perceived usefulness (Holmes et al., 2019).

The other theme that was prominent was AI as an enabler of personalization and skills cultivation. According to the trainers, AI-based learning routes allow focused upskilling and reskilling, as they focus on personal competency holes. Corporate training wise, this ability was considered to be essential in facilitating lifelong learning and labour mobility. The trainers emphasized that because AI-assisted diagnostics enables trainer to concentrate on the strategic facilitation instead of manual evaluation.

One of the important contextual themes that came out was organizational and leadership influence. According to interviewees, leadership support, organizational clarity, and peer acceptance played an important role in their readiness to adopt AI tools. Trainers in organizations where the leadership was actively promoting AI initiatives told them they felt more confident and receptive to experimentation. On other hand, there were no clear guidelines and institutional backing leading to guarded or selective embrace (Holmes et al., 2019). Ethical issues and data privacy was another major thematic cluster. The trainers were more cautious of use of AI tools to capture the sessions, generate transcripts, and assess the

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behaviour of the learners. Misuse of data, breach of confidentiality, bias in algorithms, among others, were all demarcations that raised concerns in adoption particularly in high-stakes or sensitive learning environments. These findings demonstrate that ethics and trust are not peripheral problems but are central determinants that identify behaviour of AI adoption.

Lastly, the motif of human enhancement versus prostitution was repeatedly made. Those who worked as trainers vehemently said that AI ought to act as an aid instead of replacing the role of a human trainer. Emotional intelligence, contextual judgement, mentoring, and facilitation were considered to be quite human abilities that can never be replicated by AI. This is a strengthening aspect of hybrid pedagogy model where AI has increased efficiency and insight and pedagogical control is still held by human trainers.

On the whole, qualitative transcript mining proves the fact that AI implementation in corporate learning pedagogy is viewed as performance sensitive, contextual, and ethically constrained. The qualitative data give RII analysis its richness and complexity and enhance the explanatory strength of constructs of TAM and UTAUT2 (Venkatesh, Thong, & Xu, 2012) in the context of corporate training.

5.0 Findings / Results

5.1 Performance expectancy and perceived usefulness

The RII analysis indicates that performance expectancy and perceived usefulness registered the highest index values, which means that AI-enabled personalization, enhanced training effectiveness, enhanced assessment accuracy, and administrative efficiency are main triggers of adoption. Qualitative transcript mining supports this trend by mentioning terms of effectiveness, quality, personalization, and engagement repeatedly, which can be explained by the attention of trainers to outcome-oriented advantages. These results correspond to previous studies that have stated perceived usefulness as the ultimate predictor of technology acceptance and indicated the beneficial effect of AI-enabled personalization on learning performance (Davis, 1989; Holmes et al., 2019).

5.2 Effort expectancy

The results show that effort expectancy is not a dominating factor but a supportive one in the adoption of AI and the RII values are moderately high which implies that AI tools are not seen as being excessively complicated by trainers. According to results of the interview, the initial usability issues are reduced as the experience and reuse increase, and less effort is perceived over time. This trend can be matched with TAM that suggests influence of perceived ease of use indirectly on adoption by fortifying perceived usefulness (Davis, 1989).

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5.3 Facilitating conditions and organizational readiness

Facilitating conditions proved to be an influential factor in AI adoption, and high RII scores of organizational support and infrastructure imply that adoption heavily relies on the institutional willingness, whereas lower RII scores of training adequacy show that there is gap in capacity. Qualitative analysis reveals that approach of implementing it systematically, providing technical assistance, and supporting the leadership facilitates an easier adoption process, and lack of training and ambiguous policies inhibit the application despite the perceived utility. These findings are in line with UTAUT2 which determines facilitating conditions as direct indicator of technology use in organizational settings (Venkatesh et al., 2012).

5.4 Social influence

RII findings mean that encouragement of leadership and peer usage has moderate effect on adoption of AI, which implies that concept of social context could influence readiness of trainers to use AI tools. Findings of interview indicate that leadership approval removes uncertainty and legitimizes use of AI, which enhances trainer confidence when implementing AI. This trend is similar to UTAUT2 that mentions social influence as reinforcing variable, especially in initial phases of technology adoption (Venkatesh et al., 2012).

5.5 Habit formation and sustained usage

Variables related to habits showed rather high RII, which means that routine use facilitates the continuation of AI adoption, and frequent users demonstrated less effort expectancy and increased reliance on AI when it comes to performing routine training activities. Qualitative results illustrate that with repetitive exposure, AI tools are integrated into training processes, and initial attitudes are not relied upon. This tendency is consistent with UTAUT2 that recognizes habit as factor of further use of technology (Venkatesh et al., 2012).

5.6 Ethical trust

Ethical issues had the highest RII scores especially in rights to privacy of data, transparency, and regulatory procedures, which shows that the role of ethical governance as a precondition of AI adoption is factual. The analysis of transcripts reveals that often, privacy, trust, and accountability are mentioned, and trainers are conditional about AI tools according to understanding in the data treatment and algorithm transparency. The results are in line with the existing literature which places trust and ethical assurance as moderator variables in technology acceptance (Dwivedi et al., 2019).

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6.0 Conclusion and Implications

The paper has discussed the implementation of Artificial Intelligence tools in corporate learning pedagogy through the combined use of the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology (Venkatesh, Thong, and Xu, 2012). The mixed- method research design was applied to study, which involved quantitative analysis along with qualitative input of corporate trainers that made it possible to understand what drivers' adoption more effectively and what are the experiential aspects of AI application within corporate learning settings.

Results show that use of AI in corporate learning is mainly value and performance based. The strongest predictors were perceived usefulness and performance expectancy, which means that the trainers are encouraged to use AI tools in case they contribute to improved learning effectiveness, efficiency, and personalization. Facilitating factors like institutional support, and leadership engagement as well as technical infrastructure proved to also have a huge impact on results of adoption, whereas comparatively low focus on training sufficiency reflects the current gap in the ability to use the technology fully, despite technological presence.

The perceived social influence and addition further stimulated the long-term adoption, where acceptance of leadership and peers made it easy to integrate AI tools into regular pedagogical routines. Results provide empirical evidence of TAM and UTAUT2 applicability to corporate learning setting and further expand these models using ethical assurance and trust as context moderators, which supports the significance of the human-centred and ethically sound approach toward AI integration.

7.0 Recommendations

- AI Governance: have a clear governance structure to handle ethical use, data privacy, transparency, and regulatory compliance a means to establish trust and address the issue of surveillance and prejudice.
- Trainer Capability Development: Introduce unceasing development and learning initiatives regarding AI-related proficiency, integration and data interpretation to improve trainer preparedness and diminish skill-associated opposition.
- Phased Implementation: Have a pilot-based, roll out to assess the effectiveness, overcoming situational issues, and proving value prior to increasing adoption.
- Leadership Endorsement: Proactive leadership support should be ensured by means of resources distribution, communication, and reinforcement of the culture of experimentation and learning.

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- Augmentation Focus: Place AI as augmentative technology that supplements effectiveness of instruction without replacing a key role of human trainers.

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Declaration: I here by declare that the research paper titled "Adoption of AI Tools in Corporate Learning Pedagogy" submitted to the "NLPGRS-2026" is my original work and has not been generated using any artificial intelligence tools or assistance. I confirm that content has been checked for plagiarism and that similarity index of paper is below 10%. I understand that any violation of this declaration may result in rejection of the paper or disciplinary action as per institutional guidelines.

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