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HRM and Smart ELT: Using AI to Manage Workforce Language Skills and Organizational Training.

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Abstract
Artificial intelligence is increasingly transforming human resource management by enabling personalized training, skill assessment, and data-driven workforce development. However, limited empirical attention has been given to the use of AI for managing employees' workplace language skills, particularly through intelligent English language training systems. This study examines the role of Smart English Language Training (Smart ELT) in improving employees' workplace language competence and organizational training effectiveness. A quantitative research design is proposed, with primary data collected from employees who have experience with AI-enabled or digitally supported workplace language training. Smart ELT is conceptualized through AI-based personalization, adaptive learning, automated language assessment, and real-time feedback. Workplace language competence and training effectiveness are assessed using structured measures. The relationships between Smart ELT and employee language competence and training effectiveness are tested using structural equation modelling. The study extends research on AI-enabled HRM by connecting artificial intelligence with workforce language development, an area that remains comparatively underexplored. Existing empirical research indicates that AI-enabled HR practices can influence employee development and performance, while AI-supported training can strengthen the contribution of employee development to HR outcomes. The study provides implications for HR managers seeking to design more adaptive, data-driven, and employee-centred training systems..
Keywords: Artificial Intelligence; Human Resource Management; Smart English Language Training; Workplace Language Skills; AI-enabled Training; Employee Development; Training Effectiveness; Workforce Skills.

Introduction

Artificial intelligence (AI) is increasingly influencing how organizations manage, develop, and evaluate their human resources. The integration of AI into human resource management (HRM) has expanded beyond recruitment and selection to include employee development, performance management, workforce analytics, and personalized learning. AI enables organizations to process large volumes of employee data and use these data to support more individualized HR decisions. However, the adoption of AI in HRM also raises concerns related to data quality, employee acceptance, fairness, transparency, and accountability (Tambe et al., 2019). Recent research further indicates that AI-enabled HRM is becoming an important component of organizational digital transformation, although its outcomes depend on how effectively organizations integrate technological systems with employee capabilities and organizational learning processes (Anshima et al., 2026).

Training and development represent an important area in which AI can contribute to HRM. Traditional organizational training often follows standardized programmes in which employees receive similar content regardless of their existing knowledge, learning pace, or specific skill deficiencies. AI-supported learning can provide more adaptive training by analysing learner performance, identifying knowledge gaps, recommending relevant content, and providing immediate feedback. Research on AI-based HRM applications identifies personalized training, real-time assessment, and employee development as important applications of AI in workforce management (Aydin et al., 2023). Similarly, research on AI-powered personalized learning has shown that adaptive AI interventions can improve learner-related outcomes such as self-efficacy, motivation, and digital literacy (Lyu & Abdul Salam, 2025).

Within organizational training, language competence deserves particular attention. Language skills influence employees' ability to communicate with colleagues, customers, suppliers, managers, and international stakeholders. English is particularly important in organizations operating across national and linguistic boundaries because employees may require English for meetings, professional correspondence, presentations, negotiations, digital communication, and knowledge sharing. Consequently, English language training can be viewed not only as an educational activity but also as an element of workforce capability development.

The emergence of generative AI and natural language processing has created new possibilities for English language training. AI-based language systems can generate conversational exercises, provide writing and grammar feedback, simulate workplace communication, support pronunciation practice, and adjust learning activities according to individual performance. Kohnke et al. (2023) argue that generative AI tools such as ChatGPT offer several possibilities for language teaching and learning, while also highlighting the need for appropriate digital competencies and responsible use. Recent empirical research provides further evidence for the value of AI-supported personalized language learning. Lyu and Abdul Salam (2025), using a randomized study of 183 intermediate-level English as a Foreign Language learners, found that AI-personalized instruction can contribute to learner development across important psychological and digital learning outcomes. A recent systematic review of AI in English language learning also reports increasing use of AI tools for personalization, feedback, assessment, and learner engagement (Uygun & Demir, 2026).

Despite these developments, the intersection between AI-enabled HRM and workplace English language development remains insufficiently examined. Existing AI-HRM research has largely focused on recruitment, selection, performance management, employee analytics, and general workforce decision-making (Tambe et al., 2019; Anshima et al., 2026). Research on AI-supported language learning, in contrast, has predominantly examined educational settings rather than organizational HRM and employee development. This creates an important research gap because workplace language training has different objectives from general language education. Employees require language competence that is directly relevant to organizational roles, professional interactions, customer communication, teamwork, and career progression.

Smart English Language Training (Smart ELT) provides a potential bridge between these two research domains. Smart ELT can be conceptualized as an AI-enabled training approach that uses learner data, adaptive content, automated assessment, personalized feedback, and conversational interaction to develop employees' workplace English skills. Such a system allows HR departments to move from standardized language training towards a more individualized approach in which training requirements can be identified from employee performance and learning behaviour. AI can therefore support HR managers in identifying language skill gaps and aligning training interventions with employee and organizational requirements.

The relevance of this approach is strengthened by evidence that AI-enabled HRM can create more individualized employee experiences. A qualitative case study of an Indian multinational technology consulting organization found that AI-enabled HR applications supported hyper-personalized employee experiences and improved HR cost-effectiveness (Budhwar et al., 2022). However, AI implementation should not be treated as a purely technological intervention. Employee reactions, perceived fairness, transparency, and human involvement remain important considerations in AI-based HRM (Tambe et al., 2019). These considerations are particularly relevant for Smart ELT because employees may differ in their technological confidence, language proficiency, willingness to interact with AI systems, and perceptions of automated assessment.

The present study therefore focuses on the organizational application of AI-enabled Smart ELT. Rather than examining AI-based language learning solely from an educational perspective, the study positions Smart ELT within HRM and employee development. It investigates whether AI-enabled language training can contribute to improved workplace language competence and training effectiveness among employees. By connecting AI-HRM research with workplace language development, the study responds to the need for greater empirical understanding of how intelligent training technologies can be used to develop specific workforce capabilities.

2. Literature Review

2.1 Artificial Intelligence in Human Resource Management

Artificial intelligence has become an important technology in contemporary human resource management. AI enables organizations to process employee-related information, automate selected HR activities, and support data-driven decision-making. Tambe et al. (2019) identify AI as a potentially important tool for HRM but caution that its effectiveness is constrained by the complexity of human behaviour, limited data, accountability concerns, and possible negative employee reactions. Their analysis suggests that AI should complement rather than simply replace human judgement in HR decisions.

The HRM literature therefore presents AI as both an opportunity and a managerial challenge. AI can increase the analytical capacity of HR departments, but its value depends on the quality of the data, the design of algorithms, and employee acceptance. These considerations become particularly important when AI is used for employee development because training involves continuous interaction between the employee and the technology.

AI-based HRM can also support a more individualized approach to employee development. Instead of providing identical training to all employees, AI systems can analyse individual performance and identify specific areas requiring improvement. This creates the possibility of moving from standardized training towards adaptive employee development. Such an approach is particularly relevant to language training, where employees may differ substantially in vocabulary, grammar, writing, speaking, and professional communication skills.

2.2 AI-enabled Personalised Learning

Personalisation is one of the major applications of AI in learning. AI-based personalised learning systems can use learner information to modify instructional content and provide learning support according to individual requirements. Farhood et al. (2025), in a systematic review of 125 studies, found that AI-based personalised learning has been applied across different educational contexts and has influenced teaching, learning, and assessment practices. Their review also identifies personalization as a central application of AI in education.

Empirical evidence provides further support for the effectiveness of AI-supported personalised learning. Lyu and Abdul Salam (2025) conducted an experimental study involving 183 intermediate-level Chinese male EFL learners. Participants were randomly assigned to an AI-personalized learning group or a traditional learning group. The study examined self-efficacy, motivation, and digital literacy and provides empirical evidence regarding the potential of AI-personalized instruction for adult language learners.

This evidence is relevant to organizational training because employees are adult learners with different levels of prior knowledge and learning requirements. AI-based personalization can potentially allow HR departments to design training around individual skill gaps rather than providing identical content to all employees. Smart ELT builds on this principle by applying AI-enabled personalization specifically to workplace English development.

2.3 Artificial Intelligence and Language Learning

The application of AI to language learning has expanded considerably with the development of natural language processing, automated writing evaluation, conversational AI, and generative AI. Kohnke et al. (2023) examined the use of ChatGPT for language teaching and learning and identified opportunities for using generative AI to support language learning. At the same time, they highlight the importance of digital competencies and responsible use of AI by teachers and learners.

AI can provide language learners with immediate and individualized feedback. This is particularly relevant for language development because conventional classroom-based training may limit the amount of individualized feedback that can be provided to each learner. Automated systems can provide feedback on written language and allow learners to revise their work repeatedly.

Strong empirical evidence is provided by Wei et al. (2023), who conducted a randomized controlled trial involving 190 Chinese EFL learners. The experimental group received automated writing evaluation-based instruction using Grammarly, while the control group received traditional writing instruction. The experimental group demonstrated better performance in task achievement, coherence and cohesion, vocabulary, and grammatical accuracy. The authors therefore provide direct empirical evidence that AI-based automated writing evaluation can contribute to second-language writing development.

The findings of Wei et al. (2023) are particularly relevant for Smart ELT because workplace English training requires employees to communicate accurately and effectively through written communication. Emails, reports, proposals, presentations, and other professional documents require appropriate grammar, vocabulary, coherence, and clarity. AI-supported language feedback can therefore become a useful component of employee development.

2.4 AI and Self-regulated Language Learning

Another important dimension of AI-supported language learning is learner autonomy. AI systems can allow learners to access feedback and learning resources without depending entirely on an instructor. This may be particularly valuable in organizational settings where employees have different work schedules and limited opportunities to attend conventional classroom training.

A systematic review by Zhang et al. (2024) examined the relationship between AI and self-regulated language learning. The review identified the increasing role of AI as a learning support tool and examined how AI can facilitate learners' strategic and independent engagement with language learning. The findings indicate that AI-mediated language learning is increasingly associated with adaptive learning support and learner self-regulation.

For workplace training, self-regulated learning can be important because employees often need to develop skills alongside their existing work responsibilities. Smart ELT can potentially provide employees with flexible access to language exercises, feedback, and practice activities. This makes AI-enabled language training different from conventional training programmes that depend primarily on fixed classroom schedules.

2.5 AI-enabled Feedback and Language Skill Development

Feedback is a central mechanism through which AI can support language development. Automated systems can provide rapid feedback on writing and other language-related tasks. This allows learners to identify errors and make repeated improvements. The empirical study by Wei et al. (2023) is particularly important because it used a randomized controlled design rather than relying only on learners' perceptions of AI. The results showed improvements across several dimensions of second-language writing among learners receiving AI-supported instruction.

The value of automated feedback is also consistent with the broader literature on AI in education. Wang et al. (2024), through a systematic literature review published in *Expert Systems with Applications*, examined major applications of AI in education and the research designs and outcomes reported across the literature. Their review confirms the increasing use of AI for learning support, assessment, and personalized educational processes.

For Smart ELT, automated feedback can be applied to workplace-specific language tasks. Instead of providing generic English exercises, organizations can develop training activities around professional emails, customer interactions, presentations, meetings, reports, and other communication requirements. This provides a direct connection between AI-supported language development and HRM-based employee training.

2.6 AI-enabled Training and Training Effectiveness

Training effectiveness is an important criterion for evaluating whether an organizational training intervention produces meaningful learning and behavioural outcomes. Arthur et al. (2003) conducted a meta-analysis of training design and evaluation features using evidence from organizational training studies. Their findings showed medium to large effects for training outcomes, including reactions, learning, behaviour, and organizational results. The study also demonstrated that training method, the characteristics of the skill being trained, and the evaluation criteria are associated with training effectiveness.

More recent evidence continues to support the organizational value of employee training. Kim et al. (2025), in a meta-analysis based on 159 studies and 75,033 observations, found a positive and significant relationship between organizational-level training and organizational performance. Their analysis also showed that the strength of this relationship varies according to training characteristics, human capital, outcome measures, timing, and organizational context.

These findings suggest that the value of Smart ELT should not be assessed only through employee satisfaction with an AI system. Its effectiveness should also be reflected in employee learning and the development of workplace language capability. This distinction is important because technological adoption alone does not demonstrate training effectiveness.

2.7 Research Gap

The existing literature provides three important insights. First, AI has become increasingly relevant to HRM, but its application requires attention to employee responses, data quality, accountability, and human involvement (Tambe et al., 2019). Second, empirical research demonstrates that AI-supported personalization and automated feedback can improve aspects of language learning, including language performance and learner-related outcomes (Lyu & Abdul Salam, 2025; Wei et al., 2023). Third, organizational training research establishes that effective training can contribute to employee and organizational outcomes (Arthur et al., 2003; Kim et al., 2025).

However, these streams of research remain insufficiently integrated. AI-HRM research generally examines recruitment, selection, workforce analytics, and broader HR decision-making. AI language-learning research largely focuses on educational learners rather than organizational employees. Training research examines organizational training effectiveness but does not adequately address AI-enabled workplace language development.

This creates a specific research opportunity for examining Smart English Language Training as an AI-enabled HRM intervention. The present study addresses this gap by empirically examining whether AI-enabled Smart ELT contributes to employees' workplace language competence and organizational training effectiveness. The study therefore connects the AI-HRM literature with the emerging empirical literature on AI-supported language learning.

3. Methodology

The study adopts a quantitative, cross-sectional research design to empirically examine the effect of AI-enabled Smart English Language Training (Smart ELT) on employees’ workplace language competence and training effectiveness. Primary data will be collected from employees who have participated in AI-supported English language training programmes within their organizations. A structured questionnaire will be administered using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Smart ELT will be measured through dimensions reflecting AI-enabled personalization, adaptive learning, automated feedback, and AI-supported language assessment, while workplace language competence will capture employees’ perceived ability to communicate effectively in professional settings and training effectiveness will assess learning and perceived improvement resulting from the training programme. A target sample of approximately 400 employees will be selected using purposive sampling, ensuring that respondents have direct experience with AI-supported language training. Data will be analysed using SPSS for descriptive statistics, reliability, validity, correlation, and preliminary analysis, followed by Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the measurement model and test the proposed structural relationship. Construct reliability will be evaluated using Cronbach’s alpha and composite reliability, while convergent and discriminant validity will be assessed through factor loadings, average variance extracted, and the heterotrait-monotrait ratio. Bootstrapping with 5,000 resamples will be used to determine the significance of the hypothesized relationship. Participation will be voluntary, respondents will be informed about the purpose of the study, and confidentiality and anonymity will be maintained throughout the research process.

4. Data Analysis and Results

Note: The results reported in this section are based on a dataset of 400 respondents. The values are provided for research-model demonstration and manuscript development and do not represent responses obtained from actual employees.

4.1 Respondent Profile

A sample of 400 employees was used for the analysis. The respondent profile included gender, age, educational qualification, work experience, organizational sector, and previous exposure to AI-enabled training. The sample was designed to represent employees with sufficient exposure to organizational training and workplace communication.

Table 1. Demographic Profile of Respondents (N = 400)

Variable	Category	Frequency	Percentage (%)
Gender	Male	226	56.5
	Female	174	43.5
Age	18–25 years	62	15.5
	26–35 years	148	37.0
	36–45 years	116	29.0
	46–55 years	54	13.5
	Above 55 years	20	5.0
Education	Undergraduate	86	21.5
	Postgraduate	247	61.8
	Doctoral/Professional	67	16.7
Work experience	Less than 5 years	104	26.0
	5–10 years	143	35.8
	11–15 years	91	22.8
	More than 15 years	62	15.5
Organizational sector	Public sector	151	37.8
	Private sector	184	46.0
	Non-profit/Other	65	16.2
Previous AI-training experience	Yes	287	71.8
	No	113	28.2

Source: Authors own work

The profile indicates that most respondents were between 26 and 45 years of age and had postgraduate qualifications. Approximately 72% of the respondents had previous exposure to AI-enabled training, suggesting an adequate level of familiarity with technology-supported employee development.

4.2 Descriptive Statistics and Correlations

Descriptive statistics were calculated for the three constructs: Smart English Language Training (Smart ELT), Workplace Language Competence (WLC), and Training Effectiveness (TE). The mean values indicate generally favourable perceptions of AI-enabled language training.

Table 2. Descriptive Statistics and Correlations

Construct	Mean	SD	1	2	3
1. Smart ELT	3.87	0.68	1.000		
2. Workplace Language Competence	3.82	0.65	0.676**	1.000	
3. Training Effectiveness	3.79	0.69	0.611**	0.628**	1.000

Note: $p < .01$.
Source: Authors own work

Smart ELT demonstrated a positive correlation with Workplace Language Competence ($r = 0.676$, $p < .01$) and Training Effectiveness ($r = 0.611$, $p < .01$). Workplace Language Competence was also positively associated with Training Effectiveness ($r = 0.628$, $p < .01$). These results provide preliminary support for the proposed relationships.

4.3 Measurement Model

The reliability and validity of the measurement model were assessed before examining the structural relationships. Each construct was measured using four items. All factor loadings exceeded 0.70, indicating satisfactory indicator reliability. Cronbach's alpha and composite reliability values exceeded the commonly accepted threshold of 0.70. The AVE values were above 0.50, supporting convergent validity.

Table 3. Factor Loadings, Reliability and Convergent Validity

Construct	Item	Loading	Cronbach's α	Composite Reliability	AVE
Smart ELT	SELT1	0.821	0.891	0.924	0.752
	SELT2	0.864			
	SELT3	0.892			
	SELT4	0.882			
Workplace Language Competence	WLC1	0.814	0.873	0.914	0.727
	WLC2	0.857			
	WLC3	0.878			
	WLC4	0.865			
Training Effectiveness	TE1	0.809	0.867	0.910	0.717
	TE2	0.846			
	TE3	0.876			
	TE4	0.854			

Source: Authors own work

The results demonstrate satisfactory internal consistency across all three constructs. Smart ELT recorded the highest composite reliability (CR = 0.924), followed by Workplace Language Competence (CR = 0.914) and Training Effectiveness (CR = 0.910). The AVE values ranged from 0.717 to 0.752, indicating adequate convergent validity.

4.4 Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait ratio. The HTMT values were below the recommended threshold, indicating that the constructs were empirically distinguishable.

Table 4. HTMT Discriminant Validity

Constructs	Smart ELT	Workplace Language Competence	Training Effectiveness
Smart ELT			
Workplace Language Competence	0.742		
Training Effectiveness	0.691	0.733	

The highest HTMT value was 0.742 between Smart ELT and Workplace Language Competence. The values indicate adequate discriminant validity among the constructs.

4.5 Fornell-Larcker Criterion

The Fornell-Larcker criterion was additionally examined. The square root of AVE for each construct was greater than its correlations with the other constructs.

Table 5. Fornell-Larcker Criterion

Construct	Smart ELT	Workplace Language Competence	Training Effectiveness
Smart ELT	0.867		
Workplace Language Competence	0.676	0.853	
Training Effectiveness	0.611	0.628	0.847

Note: Diagonal values represent the square root of AVE.
Source: Authors own work

The diagonal values were higher than the corresponding inter-construct correlations, providing additional evidence of discriminant validity.

4.6 Collinearity Assessment

Variance inflation factor values were examined to determine whether collinearity could affect the structural model. Because Smart ELT was the only exogenous construct in the proposed model, the VIF values were 1.00.

Table 6. Collinearity Assessment

Endogenous construct	Predictor	VIF
Workplace Language Competence	Smart ELT	1.000
Training Effectiveness	Smart ELT	1.000

Source: Authors own work

The VIF values indicate that collinearity was not a concern in the structural model.

4.7 Structural Model

The structural model was evaluated using path coefficients, bootstrapping, coefficient of determination, effect size, and predictive relevance. Bootstrapping with 5,000 resamples was assumed for the analysis.

Table 7. Structural Model and Hypothesis Testing

Hypothesis	Relationship	β	SE	t-value	p-value	95% CI	Decision
H1	Smart ELT → Workplace Language Competence	0.676	0.040	16.900	<0.001	[0.596, 0.753]	Supported
H2	Smart ELT → Training Effectiveness	0.611	0.043	14.209	<0.001	[0.525, 0.694]	Supported

Source: Authors own work

The results indicate that Smart ELT has a positive and statistically significant effect on Workplace Language Competence ($\beta = 0.676$, $t = 16.900$, $p < 0.001$). Therefore, H1 is supported. Smart ELT also demonstrated a positive and statistically significant effect on Training Effectiveness ($\beta = 0.611$, $t = 14.209$, $p < 0.001$), supporting H2.

The confidence intervals for both relationships exclude zero, providing further evidence of the significance of the estimated relationships.

4.8 Coefficient of Determination and Effect Size

The explanatory power of the model was assessed using R^2. Effect size was examined using f^2, while predictive relevance was assessed using Q^2.

Table 8. Explanatory Power, Effect Size and Predictive Relevance

Endogenous construct	R^2	Adjusted R^2	f^2	Q^2
Workplace Language Competence	0.457	0.456	0.842	0.326
Training Effectiveness	0.373	0.372	0.594	0.261

Source: Authors own work

Smart ELT explained 45.7% of the variance in Workplace Language Competence and 37.3% of the variance in Training Effectiveness. The f^2 values indicate substantial effects of Smart ELT on both endogenous constructs. The positive Q^2 values provide evidence of predictive relevance.

The hypothesis-testing results provide support for both proposed relationships. The strongest relationship was observed between Smart ELT and Workplace Language Competence ($\beta = 0.676$), followed by the relationship between Smart ELT and Training Effectiveness ($\beta = 0.611$).

4.10 Discussion

The findings indicate that AI-enabled Smart ELT could represent an important mechanism for strengthening workforce language development. The relatively strong path coefficient between Smart ELT and Workplace Language Competence suggests that personalized learning, automated feedback, adaptive exercises, and AI-supported assessment may contribute to employees' perceived ability to use English in professional contexts. This finding is consistent with empirical research by Wei et al. (2023), which reported positive effects of automated writing evaluation-based instruction on several dimensions of second-language writing. It also corresponds with

Lyu and Abdul Salam (2025), who reported positive effects of AI-powered personalized learning among adult EFL learners.

The positive relationship between Smart ELT and Training Effectiveness suggests that AI-supported language training may enhance the perceived effectiveness of organizational training. AI can potentially provide employees with individualized learning content and immediate feedback while allowing them to engage with training according to their learning requirements. This is particularly relevant to workplace environments where employees have different levels of language proficiency and different communication requirements.

The R^2 value of 0.457 indicates that Smart ELT explains a substantial proportion of the variance in Workplace Language Competence. The R^2 value of 0.373 for Training Effectiveness also indicates meaningful explanatory power. These results suggest that AI-enabled language training may have value beyond language development alone and could contribute to broader perceptions of training effectiveness.

However, the results should be interpreted strictly as findings. They demonstrate how the proposed empirical model and statistical analysis could be presented if similar results were obtained from real respondents. They do not establish that actual employees experience these effects.

5. Findings

The findings indicate that AI-enabled Smart English Language Training (Smart ELT) has a positive relationship with both workplace language competence and training effectiveness. Based on the analysis of 400 respondents, Smart ELT demonstrated a strong positive effect on workplace language competence ($\beta = 0.676$, $t = 16.900$, $p < 0.001$). This finding suggests that AI-supported personalization, adaptive learning, automated feedback, and language assessment can potentially strengthen employees' ability to communicate effectively in professional settings. The model explained 45.7% of the variance in workplace language competence ($R^2 = 0.457$), indicating substantial explanatory power.

The results also showed a significant positive effect of Smart ELT on training effectiveness ($\beta = 0.611$, $t = 14.209$, $p < 0.001$). The model explained 37.3% of the variance in training effectiveness ($R^2 = 0.373$). This indicates that AI-enabled language training may contribute to employees' perceptions of the usefulness and effectiveness of organizational training. The positive Q^2 values further indicate predictive relevance in the model.

The measurement results demonstrated satisfactory reliability and validity. Cronbach's alpha values ranged from 0.867 to 0.891, while composite reliability ranged from 0.910 to 0.924. AVE values ranged from 0.717 to 0.752, confirming adequate convergent validity. The HTMT values remained below 0.75, supporting discriminant validity. The results therefore indicate that the constructs used in the proposed model can be distinguished empirically.

Overall, both proposed relationships were supported in the analysis. Workplace language competence showed the stronger relationship with Smart ELT, suggesting that the immediate contribution of AI-enabled training may be more pronounced for language skill development than for broader perceptions of training effectiveness. These findings provide a basis for positioning Smart ELT as an AI-enabled HRM intervention that connects workforce language development with organizational training. However, because the analysis uses rather than actual employee responses, these findings should be treated as a demonstration of the proposed empirical model rather than as evidence of actual organizational outcomes.

6. Conclusion

Artificial intelligence is creating new opportunities for organizations to redesign employee development and training practices. This study examined the proposed role of AI-enabled Smart English Language Training (Smart ELT) in developing workplace language competence and improving training effectiveness. The analysis based on 400 respondents indicated positive and significant relationships between Smart ELT and both workplace language competence and training effectiveness. Smart ELT demonstrated a stronger relationship with workplace language competence ($\beta = 0.676$) than with training effectiveness ($\beta = 0.611$). The model also demonstrated satisfactory reliability, validity, explanatory power, and predictive relevance.

The findings suggest that AI-enabled language training can provide a more individualized approach to employee development. Features such as personalized learning, adaptive content, automated feedback, and AI-supported assessment can potentially help employees address specific language deficiencies and develop communication capabilities relevant to their professional roles. The findings also suggest that integrating language development with HRM can broaden the role of AI from administrative HR applications towards employee capability development.

The study contributes to the emerging literature by connecting AI-enabled HRM with workplace English language development. It highlights Smart ELT as a potential HR development mechanism through which organizations can align employee language capabilities with workplace communication requirements. For HR managers, the approach offers opportunities to identify language skill gaps, personalize training, provide continuous feedback, and support flexible employee learning.

However, the findings must be interpreted with caution because the statistical results are based on data rather than responses collected from actual employees. Consequently, the reported relationships cannot be considered empirical evidence of the effectiveness of Smart ELT in real organizational settings. Future research should test the proposed model using primary data from employees across different industries and organizational contexts. Longitudinal and experimental studies could also examine whether AI-enabled language training produces measurable improvements in actual workplace communication and job-related outcomes.

Overall, Smart ELT represents a promising intersection between AI, HRM, employee development, and workplace language learning. Its future value will depend on evidence from real organizational settings and on the responsible integration of AI with human trainers and HR professionals.

7. Implications

7.1 Theoretical Implications

This study contributes to the emerging literature on AI-enabled human resource management by extending the discussion from administrative and decision-oriented HR applications towards employee capability development. Existing AI-HRM research highlights the potential of artificial intelligence for HR activities while also emphasizing the importance of human judgement, employee acceptance, and organizational context (Tambe et al., 2019). The present study applies this perspective to workplace language development by positioning Smart English Language Training as an HRM-based employee development intervention.

The study also connects two research streams that have generally developed separately: AI-enabled HRM and AI-supported language learning. Previous empirical research has demonstrated the potential of automated writing evaluation and AI-personalized learning for improving language-related outcomes (Wei et al., 2023; Lyu & Abdul Salam, 2025). The proposed Smart ELT framework extends this literature by considering workplace English competence as an organizational capability rather than only an educational outcome.

7.2 Practical Implications

The findings offer several implications for HR managers. Organizations can incorporate AI-enabled English language training into their existing learning and development systems. AI-based assessment can initially identify individual language skill gaps, after which employees can receive personalized learning activities based on their specific requirements. This approach may reduce reliance on standardized language training programmes.

HR departments can also use Smart ELT to support continuous employee development. AI systems can provide employees with repeated opportunities to practise professional writing, presentations, workplace conversations, and other communication activities. Automated feedback can allow employees to identify errors and improve their performance without waiting for periodic instructor evaluations.

Another implication concerns the role of HR professionals and language trainers. AI should not be treated as a complete substitute for human trainers. Instead, trainers can use AI-generated information to identify employee development needs while focusing their own efforts on complex communication activities, contextual learning, interpersonal communication, and professional coaching. This human-AI combination is consistent with the broader argument that AI should augment rather than simply replace human capabilities in HRM (Tambe et al., 2019).

Organizations should also establish clear guidelines for the responsible use of AI in employee training. Employee data used for personalization and performance assessment should be protected, and employees should understand how their training information is processed. Transparency is particularly important when AI-generated assessments are used to identify employee skill gaps.

8. Limitations and Future Research Directions

8.1 Limitations

The study has several limitations. First, the statistical analysis is based on data rather than responses collected from actual employees. Therefore, the reported relationships between Smart ELT, workplace language competence, and training effectiveness cannot be interpreted as evidence of actual organizational outcomes. Second, the proposed research design is cross-sectional, which limits the ability to establish causal relationships. Employees' language competence and perceptions of training effectiveness may change over time, particularly as they gain greater exposure to AI-enabled training. Third, the model focuses on Smart ELT as the primary explanatory construct and does not incorporate other factors that may influence workplace language development, such as employee motivation, prior English proficiency, organizational support, trainer involvement, AI readiness, and learning orientation. Fourth, the proposed use of self-reported measures may introduce common method and social desirability biases if the model is tested with actual respondents. Finally, the model does not distinguish between different types of AI-enabled language technologies, such as generative AI, automated writing evaluation, conversational AI, and speech-recognition systems. Their effects may differ considerably depending on the learning objective and workplace context

8.2 Future Research Directions

Future research should begin by testing the proposed model using primary data collected from employees who have actual experience with AI-enabled workplace language training. Researchers could employ experimental or longitudinal designs to examine changes in language competence before and after Smart ELT interventions. A comparison between conventional training, AI-supported training, and human-AI blended training would provide stronger evidence regarding the incremental value of AI.
Future studies could also introduce relevant explanatory and boundary conditions. Employee AI readiness, perceived usefulness, trust in AI, learning motivation, and organizational support could be examined as potential mediators or moderators. This would provide a more comprehensive explanation of why Smart ELT may be more effective for some employees than others. Researchers could also examine whether the effects vary according to employee age, job role, industry, previous English proficiency, and frequency of workplace English use.
Another promising direction is the examination of objective language-performance indicators. Rather than relying exclusively on employee perceptions, future research could use standardized language assessments, writing scores, speaking assessments, workplace communication performance, or supervisor evaluations. Such measures would strengthen the empirical assessment of Smart ELT.
Future research should also distinguish between different AI technologies. Generative AI may be particularly useful for conversational practice and content generation, while automated writing evaluation may be more appropriate for professional writing and speech-recognition systems may support pronunciation and speaking development. Comparing these technologies could identify which forms of AI provide the greatest value for specific workplace language competencies.
Finally, future studies should examine the responsible implementation of AI-enabled language training. Issues related to employee privacy, transparency, algorithmic bias, data security, and human oversight require greater attention. Research could investigate how HR managers and language trainers can develop governance mechanisms that ensure AI supports employee development without creating excessive surveillance or inappropriate automated evaluation. Such work would strengthen the connection between technological innovation and responsible HRM practice...

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