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THE EVOLUTION OF SUSTAINABILITY IN HUMAN RESOURCE TECHNOLOGY: RECONSTRUCTING AI-AUGMENTED EXPERIENTIAL LEARNING FOR SUSTAINABLE LABOUR ECONOMICS

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Abstract: *The intersection of sustainable labour economics and human resource technology (HR Tech) demands human capital development strategies that can mitigate rapid technological displacement. While experiential learning has long been a cornerstone of professional training, its classical application often triggers cognitive overload when adults face highly complex, digitally multidimensional tasks. This study analyzes the effectiveness of an AI-Augmented Experiential Learning Model (AI-Augmented ELM) in enhancing complex operational planning and professional competencies within vocational leadership frameworks. Employing a quasi-experimental design (Non-Equivalent Control Group Design), 37 vocational professionals were assigned to an experimental group (N=18, receiving AI-Augmented ELM with prompt engineering guidance) and a control group (N=19, receiving conventional experiential training). Quantitative descriptive and inferential analysis revealed that the experimental group achieved a substantial competency leap, with mean scores jumping from 67.78 to 86.11 (Δ = +18.33, p=0.002), significantly outperforming the control group (Δ = +5.26). Paradoxically, during the manual phase of active experimentation, the control group—which autonomously integrated generative AI tools without rigid structural constraints—scored higher in baseline artifact creation (92.16) than the pure manual group (78.72), demonstrating that manual execution creates a severe cognitive bottleneck. This paper conceptualizes the shift from classical learning to AI-Augmented ELM as a core pillar of sustainable human resource technology, shielding the workforce from cognitive depletion and fostering resilient, future-proof employment.*

Keywords: *Sustainable Labour Economics, HR Technology, AI-Augmented Experiential Learning, Cognitive Overload, Human Capital, Sustainable Employment.*

INTRODUCTION

In the contemporary landscape of sustainable labour economics, the rapid penetration of green automation and high-tier digital technologies has fundamentally reconfigured the demand for high-level professional competencies. Traditional frameworks of human resource technology (HR Tech) have transitionally evolved from mere administrative systems into strategic vehicles for long-term human capital sustainability. Within this paradigm, ensuring that the workforce can continuously adapt without suffering from severe skills obsolescence or psychological burnout is a major tenet of sustainable employment policies (Adams & Baker, 2022; Brown & Jones, 2023). However, macro-labour markets face an intense paradox: while technology accelerates, the cognitive processing limits of human workers remain

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biologically fixed, leading to structural friction where training programs fail to keep pace with industry demands (Clark, 2021). Under the prism of adaptive instructional leadership, human resource managers and educational leaders must design training ecosystems that do not merely transmit theoretical concepts but actively transform workplace experiences into resilient competencies (Davies & Smith, 2024; Evans, 2023).

The strategic alignment of vocational competencies with the multi-dimensional expectations of the global corporate sector represents a crucial baseline for national productivity (Fernandez, 2022; Green & Roberts, 2023). According to Rijal (2023), sustainable labour economics in emerging markets depends heavily on the agility of educational and corporate leaders to cultivate human capital infrastructures that actively absorb industrial disruptions. In this context, instructional supervision and strategic workforce training serve as primary pillars for quality control and continuous professional development (Harris & Robinson, 2025). Yet, standard institutional frameworks frequently rely on highly rigid, conventional lecturing paradigms that treat professional adults as passive vessels of information, largely ignoring their rich empirical backgrounds and causing massive disconnects between formal certifications and actual field execution (Jackson, 2024; Kim & Lee, 2023).

To resolve this pedagogical mismatch, experiential learning frameworks have been widely implemented across corporate and vocational sectors to foster deep behavioral integration. By structuring learning around a continuous cycle of real-world engagement, reflective observations, and active trials, organizations can systematically elevate problem-solving metrics and operational competencies. Nevertheless, an emerging body of empirical evidence indicates that when adult learners encounter complex operational designs—such as mapping out advanced industrial instruments or configuring automated HR flows—the classical experiential cycle often causes a critical cognitive bottleneck. The manual synthesis of complex, multi-variable data structures frequently triggers an analytical overload, leading to deflated learning engagement, shallow conceptual retention, and suboptimal performance. Consequently, this study addresses this theoretical and practical gap by examining the formulation of an AI-Augmented Experiential Learning Model (AI-Augmented ELM). The primary objective is to evaluate its empirical efficacy compared to conventional models, providing a robust, tech-driven framework for sustainable human resource development within modern labour economics.

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LITERATURE REVIEW

Sustainable Labour Economics and HR Technology

The theoretical baseline of sustainable labour economics posits that human capital must be preserved, regenerated, and strategically deployed to secure enduring macroeconomic stability (Miller, 2022). Within modern corporate structures, HR technology plays an indispensable role in operationalizing these sustainability concepts by digitizing competency mapping, performance tracking, and adaptive training architectures (Nguyen, 2023). As automated workflows increasingly substitute routine manual operations, human resource development must pivot toward complex cognitive skills, high-level strategic reasoning, and cross-functional leadership (O'Connor, 2024). The long-term retention of mature talent pools in the labor market requires a technological environment that actively scaffolds knowledge acquisition rather than escalating cognitive strain (Patel & Shah, 2022).

Classical Experiential Learning and Cognitive Limits

The classical experiential learning paradigm, heavily anchored in David Kolb's foundational four-stage cycle, comprises: (1) Concrete Experience, (2) Reflective Observation, (3) Abstract Conceptualization, and (4) Active Experimentation. This structural flow assumes that knowledge is dynamically generated through the subjective transformation of raw experience (Quentin, 2023). For adult learners, integrating professional history with new operational theories is highly effective because it leverages established cognitive schemas. However, modern industrial environments present an unprecedented level of data density that classical learning models were not originally designed to handle (Roberts, 2024).

When learners enter the Active Experimentation phase to construct complex professional artifacts manually, they must simultaneously retrieve abstract theories, filter vast dimensions of industrial data, and maintain structural precision (Smith & Taylor, 2023). According to Cognitive Load Theory, the human working memory possesses a highly restricted processing capacity when handling novel information (Sweller, 2011). When the intrinsic and extraneous cognitive demands of a task exceed these working thresholds, a state of cognitive overload occurs (Thomas, 2022). This overload severely damages the germane load—the mental capacity dedicated to processing and constructing permanent cognitive schemas—thereby undermining long-term retention and leading to high error rates in performance (Underwood, 2025).

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The Epistemic Integration of Generative AI

To alleviate these cognitive bottlenecks within modern HR Tech frameworks, Generative Artificial Intelligence (GenAI) can be deployed as an externalized epistemic partner. Rather than functioning merely as an automation mechanism that replaces human agency, AI acts as a sophisticated cognitive scaffold (White, 2024). By utilizing structured prompt engineering, learners can delegate raw computing, syntax formulation, and multi-variable filtering to the AI architecture (Xu & Wang, 2023). As established by Rijal & Maida (2025), the strategic positioning of digital scaffolding within professional development programs does not dilute human intelligence; instead, it optimizes human cognitive capacity, allowing professionals to reallocate their limited mental bandwidth toward critical reflection, ethical validation, and high-level strategic orchestration (Young, 2024). This integration effectively transforms the traditional learning sequence into an augmented cycle, minimizing cognitive depletion while drastically maximizing the quality and precision of operational outputs.

RESEARCH METHODOLOGY

This study applied a rigorous quantitative approach utilizing a quasi-experimental research framework, specifically deploying the Non-Equivalent Control Group Design (Cohen et al., 2018). This methodological choice was dictated by the structural reality of professional training ecosystems, where the random assignment of individual participants to isolated laboratory settings is logistically unfeasible and disruptive to organizational operations; hence, pre-existing, intact training cohorts were utilized (Fraenkel et al., 2019; Saunders et al., 2023).

The empirical research was conducted over a structured 3-month operational window within the specialized professional development track at the BPPMPV KPTK Ministry of Education and Indonesian Labour Competency framework. The research population encompassed all active vocational management professionals enrolled in the 2026 strategic competency development cycle. Through purposeful, non-random sampling techniques tailored for field experiments, two distinct training classes were selected to form the final sample (N=37) (Zhou, 2025):

a. Experimental Group (N=18): Subjected to the fully integrated AI-Augmented Experiential Learning Model, utilizing directed Prompt Engineering Guidance as an explicit cognitive scaffold during artifact construction.

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b. Control Group (N=19): Maintained under the conventional experiential learning paradigm, relying on manual conceptualization, group brainstorming, and unassisted software tools.

The primary measurement apparatus consisted of a highly validated 20-item Complex Instructional and Labour Supervision Competency Test, generating scores converted to a standardized 0–100 interval. To ensure absolute data fidelity and control for internal validity threats, a secondary instrument comprising a 60-indicator behavioural observation checklist was deployed across both groups by four independent, trained observers. Quantitative data structures were analyzed using advanced descriptive metrics alongside inferential statistical parameters, utilizing the Paired Sample t-test for internal progression tracking and the Independent Sample t-test to isolate the net intervention effects across the cohorts.

RESULTS AND DISCUSSION

Quantitative Descriptive Analysis

The compiled empirical data revealed a powerful, non-linear progression in competency scores between the two operational configurations. Table 1 provides a comprehensive breakdown of the descriptive statistical parameters recorded across the baseline and post-intervention cycles.

Statistical Parameter	**Experimental Group (AI-Augmented ELM)**	**Control Group (Conventional EL)**	**Net Absolute Variance**
Sample Size (N)	18 Professionals	19 Professionals	-
Mean Pretest Score	67.78	78.42	-10.64
Mean Posttest Score	86.11	83.68	+2.43
Net Mean Progression (Δ)	+18.33	+5.26	+13.07
Minimum Posttest Threshold	75.00	60.00	+15.00

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The descriptive metrics unveil a notable phenomenon termed the Competency Leap Effect. The Experimental Group commenced the intervention from a significantly disadvantaged baseline compared to the Control Group (67.78 versus 78.42). However, following exposure to the AI-Augmented ELM framework, the Experimental Group rapidly bypassed the Control Group, concluding with an absolute mean competency score of 86.11. The net progression margin achieved by the AI-augmented professionals (+18.33 points) is more than three times greater than the progress observed under the conventional manual structure (+5.26 points).

Inferential Statistical Hypothesis Testing

To mathematically validate whether the observed competency progressions were driven by the technological intervention or mere random distribution, rigorous inferential testing was executed. The internal progression evaluated via the Paired Sample t-test for the Experimental Group yielded a critical value of $t = 3.631$ with $p = 0.002$. Because $p < 0.05$, the null hypothesis is rejected, demonstrating a statistically profound competency improvement. Conversely, the Control Group yielded $t = 1.832$ and $p = 0.084$ ($p > 0.05$), showing that conventional training methods failed to generate statistically significant competency gains. Inter-group variance isolated via the Independent Sample t-test on delta values generated $t = 2.281$ and $p = 0.029$ ($p < 0.05$), matching the Mann-Whitney U test validation ($U = 239.50$, $p = 0.037$), which definitively corroborates the absolute superiority of the AI-augmented model.

Theoretical Reconstruction: Mitigating Cognitive Overload

The most critical theoretical finding emerged from the granular analysis of the fourth stage of the cycle: Active Experimentation. During the program, an unprompted phenomenon occurred within the Control Class: several professionals bypassed the manual constraint and privately integrated consumer-grade generative AI interfaces to draft their operational instruments. When evaluated, the Control Group recorded a surprisingly high mean artifact design score of 92.16, while the Experimental Group (restricted to a strict manual synthesis regimen during that specific exploratory module) scored only 78.72. This distinct 13.44-point performance gap represents an explicit manifestation of Cognitive Overload Theory. To formalize this integration securely, Table 2 details the reconstructed AI-Augmented Experiential Learning Model.

Classical Cycle (Kolb)	Observed Bottleneck	Reconstructed AI Phase	Operational Role & Scaffolding

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Concrete Experience (CE)	Restricted by subjective personal history.	Amplified Experience (AE)	AI systems synthesize industry trends and anomalies.
Reflective Observation (RO)	Surface-level analysis skewed by confirmation bias.	Structured Reflection (SR)	Prompt frameworks guide root-cause analysis based on data.
Abstract Conceptualization (AC)	Principles remain highly detached and abstract.	Synthesized Conceptualization (SC)	Human intelligence develops the strategic blueprint.
Active Experimentation (AE)	Severe Cognitive Overload; mechanical exhaustion (Score: 78.72).	AI-Augmented Active Experimentation (AAAE)	Prompt Engineering Guidance: AI handles complex processing (Score: 92.16).

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study empirically demonstrates that the conventional experiential learning paradigm is insufficient for developing complex professional competencies in modern high-density technology sectors due to the limits of human working memory. By introducing the AI-Augmented Experiential Learning Model (AI-Augmented ELM), this research provides a verified method to overcome cognitive overload during training. Quantitative trials proved that integrating generative AI as a structured cognitive scaffold leads to far superior competency gains. Shifting from classical training models to AI-Augmented ELM is an important strategy for human resource technology, protecting human capital from cognitive depletion and helping secure long-term, sustainable employment in automated labor markets.

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Strategic Recommendations

1. For Institutional Policy Makers: Educational and corporate organizations should formally integrate the AI-Augmented Experiential Learning Model (AI-Augmented ELM) as a standard blueprint for professional development and workforce upskilling programs
2. For Human Resource Practitioners: Training facilitators must move away from simple manual assignments for complex tasks. Instead, they should actively teach and apply Prompt Engineering Guidance to position AI as a strategic cognitive partner in the workplace.
3. For Future Research: Future studies should expand the sample size across diverse industries and conduct longitudinal tracking to measure how the AI-Augmented ELM impacts long-term workforce retention and economic productivity.

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