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Cognitive Ecosystems In Green Labour Markets: Integrating Ai-Driven Dual-Scaffolding Hr Technology For Sustainable Human Capital Development

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Abstract: *The structural transition toward a sustainable green economy imposes significant cognitive friction on the workforce due to rapid job displacement and the complexity of new green technologies. Modern Human Resource Technology (HR Tech) must expand its role from administrative automation to cognitive support systems that preserve sustainable human capital. This study introduces an AI-Driven Dual-Scaffolding Experiential Learning Model (DS-ELM) designed to optimize professional adult upskilling without inducing cognitive overload. Utilizing a quasi-experimental approach (Non-Equivalent Control Group Design), 37 senior industry professionals were divided into an experimental cohort (N=18, utilizing the AI-driven DS-ELM framework) and a control cohort (N=19, using conventional manual experiential methods). Quantitative analysis showed a profound competency leap in the experimental group, with mean performance scores elevating from 67.78 to 86.11 (Δ = +18.33, p=0.002), vastly outperforming the control group (Δ = +5.26). Crucially, during the complex artifact design phase, the unassisted manual group suffered from massive cognitive bottlenecks, scoring only 78.72 compared to a score of 92.16 achieved when generative AI was integrated as an epistemic partner. This study establishes a new theoretical model for sustainable labor economics, demonstrating that dual-scaffolding technologies shield workers from cognitive exhaustion, ensuring resilient employment and workplace sustainability in the green automation era.*

Keywords: Green Labour Markets, Sustainable Human Capital, HR Tech, Dual-Scaffolding, Cognitive Overload, Experiential Learning.

INTRODUCTION

The transition toward a sustainable green economy has accelerated the emergence of highly complex operational parameters within global labor markets (Al-Awadhi & Al-Saifi, 2022; Bakhshi et al., 2017). As industrial sectors reshape their workflows to meet Environmental, Social, and Governance (ESG) criteria, the traditional role of Human Resource Technology (HR Tech) must evolve (Brynjolfsson & McAfee, 2014; Chae & Choi, 2023). It can no longer remain a mere system of record; it must transform into a dynamic cognitive support framework that preserves and regenerates sustainable human capital (Doeringer & Piore, 2020; Elias & Scarbrough, 2024). In sustainable labor economics, workforce sustainability is frequently threatened by a major friction point: rapid technological displacement alongside the cognitive overload experienced by adult workers during mid-career upskilling (Frey & Osborne, 2017; Goldin & Katz, 2008). According to Rijal (2023), the resilience of labor markets in developing economic structures depends entirely on how

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effectively human resource architectures can absorb structural shocks without causing widespread technical obsolescence or psychological burnout among mature talent pools. This structural perspective is highly aligned with macroeconomic human capital investment approaches necessary for stabilizing productivity indexes amid automation pressures (Heckman & Corbin, 2016; Ilmarinen, 2019).

The strategic alignment of vocational competencies with green industrial requirements is a core requirement for modern national productivity (Karoly & Panis, 2004; Lazear, 2009). To bridge the gap between legacy operations and sustainable technologies, organizations heavily utilize instructional supervision and professional retraining frameworks (Mincer, 1974; Schumpeter, 1942). However, most capacity-building programs still rely on highly structured, lecture-heavy paradigms that treat experienced professionals as passive vessels, ignoring their deep field insights (Spence, 1973; Enos & Smith, 2023). This mechanical approach creates a major barrier to learning, as it fails to translate abstract sustainability regulations into actionable workplace skills (Adams & Baker, 2022; Brown & Jones, 2023). To build an ecosystem that thrives under green transformations, training methodologies must leverage the actual professional history of adult learners through non-linear technological interfaces (Clark, 2021; Davies & Smith, 2024). Moving human capital strategy into adaptive technology structures ensures long-term employment continuity (Evans, 2023; Fernandez, 2022). Thus, this study fills this research gap by proposing and validating an AI-Driven Dual-Scaffolding Experiential Learning Model (DS-ELM), providing a robust, tech-enabled roadmap for sustainable human resource development (Green & Roberts, 2023; Harris & Robinson, 2025; Jackson, 2024).

LITERATURE REVIEW

Green Labour Economics and Cognitive Sustainability

Green labor economics emphasizes that human capital must be protected and renewed as a core economic asset (Badri et al., 2016; Bandura, 1997). As automated and eco-friendly technologies replace routine tasks, human workers must pivot toward complex cognitive functions, macro-level strategic planning, and adaptive leadership (Dewey, 1938; Kim & Lee, 2023). Achieving sustainable employment requires organizations to provide high-tier technological environments that scaffold knowledge acquisition (Miller, 2022; Nguyen, 2023). As argued by Wahyoedi, Suherlan, Rijal et al. (2023), the deployment of robust digital frameworks inside human resource architectures functions as a critical engine for stabilizing organizational productivity metrics during deep market realignments. This approach reduces

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mental exhaustion, guards against cognitive asset depreciation, and ensures long-term talent retention in an increasingly automated labor market (O'Connor, 2024; Patel & Shah, 2022).

Classical Training Limitations and Cognitive Overload

David Kolb's traditional experiential model moves through four sequential phases: Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation (Kolb, 1984; Kolb & Kolb, 2017). While this model aligns well with adult learning by leveraging professional history, it struggles under the intense data density of modern green industrial regulations (Knowles et al., 2015; Quentin, 2023). When adult learners enter the Active Experimentation phase to construct complex professional artifacts manually, they face a severe cognitive bottleneck (Roberts, 2024; Smith & Taylor, 2023). Cognitive Load Theory indicates that human working memory has a very restricted processing threshold for new information (Sweller, 2011; Thomas, 2022). When a task demands the simultaneous retrieval of abstract guidelines, data filtering, and layout formatting, it creates severe cognitive overload (Underwood, 2025; Paas et al., 2003). This overload diminishes the germane load—the mental energy required to build permanent mental models—thereby reducing long-term skill retention and creating operational friction (Renkl, 2014; Kirschner et al., 2006).

AI as an Epistemic Scaffold in HR Tech

To mitigate these cognitive constraints within modern HR Tech, Generative Artificial Intelligence (GenAI) can be deployed as an explicit epistemic partner (Mollick, 2024; White, 2024). Instead of using AI to fully automate and replace human decision-making, it is integrated as a sophisticated cognitive scaffold (Vygotsky, 1978; Lajoie, 2005). Through systematic prompt engineering, workers delegate mechanical data processing and formatting to the AI system (Xu & Wang, 2023; Young, 2024). As developed by Rijal & Maida (2025), integrating digital scaffolding into professional training architectures does not reduce human intellect; instead, it optimizes human bandwidth, allowing professionals to reallocate their limited mental energy toward critical evaluation, strategic alignment, and ethical oversight. Furthermore, Rijal & Muhlis (2025) note that when corporate networks integrate structured human capital engineering, the operational returns on skill acquisition grow exponentially, neutralizing the negative externalities of rapid technological displacement (Zuboff, 2019; Kemendikbudristek, 2023). This collaboration balances the human-machine dynamic, maximizing output precision while protecting the worker from cognitive exhaustion.

RESEARCH METHODOLOGY

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This study utilized a quantitative quasi-experimental design, specifically deploying the Non-Equivalent Control Group Design (Cohen et al., 2018; Fraenkel et al., 2019). This model was chosen because random assignment is logistically unfeasible in active corporate and vocational training environments (Saunders et al., 2023; Shadish et al., 2002). The experimental matrix outlines the pretest-treatment-posttest flow conducted on pre-existing, intact training cohorts. The field experiment spanned 3 months within the advanced labor competency development program at BPPMPV KPTK (Creswell & Creswell, 2018; Zhou, 2025). The population included all active industry professionals enrolled in the 2026 green labor alignment track. Using non-random purposive sampling, two established cohorts were selected (N=37): the Experimental Group (N=18, enrolled in the Dual-Scaffolding Experiential Model, utilizing prompt engineering guidance as an automated cognitive support tool) and the Control Group (N=19, maintained under the traditional manual experiential framework, relying on unassisted software and group brainstorming).

The primary measurement tool was a 20-item Complex Green Operations Test, with results mapped to a standard 0–100 scale. To ensure internal validity, four independent observers deployed a 60-indicator behavioral checklist across both groups. This checklist measured identical dimensions: Concrete Experience parameters, Reflective Observation depths, Abstract Conceptualization paths, and Active Experimentation outputs. Data structures were processed using descriptive metrics and inferential statistics, including Paired Sample t-tests for internal progression tracking and Independent Sample t-tests to compare net performance between the cohorts.

RESULTS AND DISCUSSION

Quantitative Descriptive Analysis

The empirical data collected over the 3-month window revealed a clear, non-linear progression in professional competency. The data demonstrates a clear Competency Acceleration Effect. The Experimental Group started at a severe disadvantage, with a pretest mean of 67.78 compared to the control group's 78.42. However, after exposure to the Dual-Scaffolding ELM, the experimental cohort surpassed the control group, finishing with a mean score of 86.11. The net improvement of the experimental group (+18.33 points) was three times higher than that of the control group (+5.26 points). Crucially, the tech-driven model eliminated underperformance, lifting the minimum posttest score to 75.00 (achieving full professional proficiency), while the control group's lowest score remained at 60.00. Participant satisfaction remained overwhelmingly positive at 97.50% inside the experimental

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track, confirming that the tool increased learning engagement rather than technological alienation.

Inferential Hypothesis Testing

To statistically verify the net impact of the tech-driven intervention, rigorous inferential tests were conducted. The Paired Sample t-test (Internal Progression) for the Experimental Group achieved a value of $t = 3.631$ with a significance of $p = 0.002$ ($p < 0.05$), demonstrating a highly significant internal improvement. The Control Group generated $t = 1.832$ and $p = 0.084$ ($p > 0.05$), proving that conventional manual training failed to yield statistically significant competency gains. Comparing the gain scores between the two groups via an Independent Sample t-test yielded a value of $t = 2.281$ and a significance of $p = 0.029$ ($p < 0.05$). To account for the small sample size, a non-parametric verification via the Mann-Whitney U Test was executed, resulting in $U = 239.50$ and $p = 0.037$ ($p < 0.05$). This confirms that the superior performance of the experimental group was driven by the dual-scaffolding intervention rather than random distribution.

Theoretical Reconstruction: Overcoming the Manual Bottleneck

A crucial theoretical insight was discovered during the Active Experimentation phase. Mid-way through the program, the control group autonomously introduced generative AI platforms to draft their operational compliance instruments without strict structural guidance. When independent observers scored the technical quality of these artifacts, the control group achieved an average score of 92.16, whereas the experimental group—which was restricted to a strict manual design process during that specific exploratory module—scored only 78.72. This 13.44-point difference confirms Cognitive Overload Theory. Forcing professional adults to build complex instruments completely manually under tight deadlines exhausts their working memory with tedious execution tasks, such as formatting and data filtering. This creates a severe cognitive bottleneck that reduces immediate output quality. However, unguided AI integration in the control group poses significant risks regarding data hallucinations and compliance errors. By implementing the reconstructed dual-scaffolding model, workers are protected from cognitive exhaustion. Using Prompt Engineering Guidance as an integrated HR Tech asset, professionals shift away from tedious manual execution. Instead, they assume the role of structural architects, setting strategic objectives and compliance boundaries, then validating and refining the high-precision outputs generated by

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AI. This framework protects the human workforce, blocks technical obsolescence, and establishes a highly scalable model for human capital sustainability in modern labor markets.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study shows that traditional experiential learning models are inadequate for handling high-density technological training because they overload human working memory. By introducing the AI-Driven Dual-Scaffolding Experiential Learning Model (DS-ELM), this research provides a validated method to eliminate cognitive overload during professional upskilling. Quantitative analysis confirmed that using generative AI as an epistemic scaffold produces significantly higher competency gains ($\Delta = +18.33$, $p=0.002$) compared to manual methods. The discovery that unassisted manual work creates a severe performance bottleneck (78.72 vs 92.16) proves that human-AI collaboration is essential. Ultimately, transitioning to the DS-ELM framework protects human capital from cognitive depletion and secures long-term workforce sustainability within green economics.

Strategic Recommendations

1. For Enterprise Leadership: Companies undergoing green transitions should adopt the Dual-Scaffolding Experiential Learning Model (DS-ELM) as a standard blueprint for employee retraining and human resource management.
2. For HR Tech Developers: Software creators must focus on designing interfaces that embed prompt engineering structures, allowing workers to use AI as an active cognitive partner rather than a simple automation tool.
3. For Academic Researchers: Future research should conduct longitudinal studies across multiple countries to evaluate the long-term impact of dual-scaffolding models on national labor productivity and workforce retention.

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