

Bridging the Gap: How Digital Literacy Training Transforms Perceptions and Behaviours in the Digital Age

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This study investigates the influence of digital competence on workplace outcomes in resource-constrained service organizations in a developing economy. We hypothesize that enhancing supervisors' digital literacy increases their perceived technology adoption level, leading to a decrease to work alienation and an increase to innovative work behaviors. Using a sequential explanatory mixed-methods design, the study employed a quasi-experimental pre-post design with a control group, followed by qualitative interviews to explain the quantitative findings. Training led to an increase to technology adoption level, which in turn had a negative relationship with work alienation and a positive one with innovative work behaviors. This study offers guidance to organizations seeking to reduce administrative strain, improve employee wellbeing, and foster sustainable innovation by empowering leaders with foundational digital skills.

Keywords: digital literacy, perceived technology adoption level, innovative work behaviors, work alienation, healthcare

INTRODUCTION

Rapid evolution of Industry 4.0 Technologies (I4T) profoundly reshaped global economies (Hajoary, 2021; Holland et al., 2022), with implications for the service sector (Pandya & Kumar, 2023). I4T offers substantial opportunities for efficiency and innovation (Gupta & Jauhar, 2023), but adoption in service industries, particularly in developing economies, creates unique challenges (da Silva et al., 2023). Extant research overlooks the context of regions and individual employees' experiences, representing a knowledge

gap in I4T literature (Atieh et al., 2023; Leo et al., 2023; Meylemans et al., 2021) and creating a critical gap to understanding how technological integration influences human capital.

Comprehensive reviews of I4T adoption in service sectors have revealed significant barriers, including skill shortages and unreliable employee receptivity (Aceto et al., 2020; Mariani & Borghi, 2019), underscoring the need to enhance individual capabilities to leverage I4T. According to the World Economic Forum's Future of Jobs Report 2025 (World Economic Forum, 2025), 44% of workers will need reskilling or upskilling within the next five years, with 39% of core skills expected to be outdated by 2030. The report identifies broadening digital access as the most transformative trend, and it highlights technological literacy as a top-growing skill, making it a foundational competence (International Labour Organization, 2017; OECD, 2021). Building individual digital capabilities is therefore central to sustainable adoption and effective use of I4T.

Answering calls for balanced focus on individual and organizational dimensions during service technology adoption (Kim et al., 2022), social cognitive theory (SCT) offers a robust lens with which to understand how individual capabilities translate into behaviors. SCT describes a human agency model in which people proactively self-reflect, -regulate, and -organize (Martin et al., 2020), based on reciprocal determinism, during which personal influences (e.g., cognition and affect), the environment, and behavior interact and shape one another mutually (Bandura, 1997). A person's digital literacy (DL) is a personal factor that, within the SCT framework, represents a driver of behavioral outcomes and perceived environmental changes.

Preliminary qualitative research corroborates this gap. Leaders in Indonesian organizations with limited IT resources reported that their systems support structured, routine tasks such as data entry and reporting, but provide little support for strategy such as accreditation preparation. This disparity forces employees to contend with both supported and unsupported activities, creating perceptions that technology is inadequate. Recent research highlights that addressing the ease-of-use gap is critical to digital innovation readiness, since healthcare organizations must rethink their transformations by prioritizing technologies that are accessible and scalable (Brandsma et al., 2025). When digital technology lacks ease-of-use or fails to address operational complexities, employees disengage from systems, leading to perceived complexity, work alienation, and reduced organizational innovation (Handayani & Joeliaty, 2023; Henderikx & Stoffers, 2022), underscoring the need for targeted interventions that empower leaders in resource-constrained environments to implement practical, user-centric digital solutions (Chereka et al., 2024). One challenge lies in enhancing DL, particularly in organizations with resource constraints. Knowledge workers in such contexts are at the forefront of digital transformations (Kraus et al., 2021). They are increasingly exposed to I4T (Komalasari, 2024) and yet insufficient digital skills hamper their readiness, making them less likely to use technology fully. Addressing individual-level barriers is thus paramount, especially since the World Economic Forum (2025) recently reported that 85% of organizations are prioritizing reskilling and upskilling to navigate labor market transformations.

Beyond this practical contribution, the current study addresses several theoretical gaps. SCT is commonly applied to assess intentions to adopt technology (Yadegari et al., 2024), but no empirical research tests the interconnected paths among personal, environmental, and behavioral factors to explain the consequences of adoption. Our study extends SCT by examining this critical, circular relationship, demonstrating how interventions that target personal factors lead to changes to both environmental and behavioral factors. This study addresses this gap directly by proposing and evaluating a targeted intervention for supervisors and managers. We hypothesize that enhancing leaders' DL, a cognitive factor, through a structured program fosters greater technology adoption levels (TAL) within their organizations, an environmental factor. Increased adoption, in turn, simultaneously decreases individuals' work alienation (WA) and increases their innovative work behaviors (IWBs), both behavioral factors. These outcomes are treated as distinct behavioral paths through which enhanced DL contributes to better work performance in supportive digital environments. Recent research that highlights the dual, countervailing mechanisms of technology adoption that can either promote positive or attenuate negative employee behaviors supports this approach (Tang & Zhao, 2025). Conducted in Indonesian organizations with limited IT resources, this study used a pre- and post-test intervention to evidence the effectiveness of DL development in driving

positive organizational and individual outcomes. We therefore address whether DL training improves technology adoption levels, and whether greater technology adoption levels lower work alienation and improve innovative work behaviors. By investigating these relationships in a real-world context, this paper offers insights to policymakers and organizations striving for sustainable digital transformation and improved employee wellbeing in resource-constrained environments.

LITERATURE REVIEW

Industry 4.0, Digital Literacy, and Technology Adoption

Industry 4.0, a paradigm defined in 2011, integrates technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and Big Data analytics (BDA) to support or replace human decision-making (Haldorai, 2023; Xu et al., 2018). These advancements enable real-time collection and analysis of data, which enhances customer service, optimizes operations, and accelerates new product development (Ziora, 2015). They also foster digital integration, strengthening interconnectivity and information exchange to promote collaboration and learning across all organizational levels (Tortorella et al., 2020). To leverage these technologies fully, especially base technologies such as cloud computing, IoT, and BDA, and front-end technologies such as AI and robotics (Frank et al., 2019), workforces must acquire new skills, encompassing task-related, behavioral, cognitive, and social aspects (Ribeiro et al., 2022).

Integration of Industry 4.0 technologies into the service sector requires a digitally literate workforce that is not only proficient with digital tools, but adaptable to constantly evolving technological environments (Haleem et al., 2022; Zirar et al., 2023). DL is multifaceted, including technical abilities, cognitive capacities, and social-emotional skills that are essential to navigating new realities (Cetindamar Kozanoglu & Abedin, 2021). It empowers employees with the critical thinking and problem-solving skills needed to use technology effectively and responsibly (Bejaković & Mrnjavac, 2020), which in turn fosters collaborative work environments by facilitating seamless communication and cooperation. DL also enhances adaptability, allowing employees to learn new skills and succeed with emerging technologies, critical to cultures of continuous innovation and keeping pace with the rapid advancements of Industry 4.0 (Scuotto et al., 2021).

However, possessing such skills does not automatically lead to adoption of new technologies. The decision to integrate new digital tools is intentional and gradual, especially when employees enjoy autonomy (Thomas, 2024). Technology adoption level (TAL) reflects this process, indicating the extent to which an individual accepts and uses new technology in their professional role (Granić, 2024). A direct link is evident between DL and the likelihood of adopting new technologies (Adel, 2024). Employees with greater DL are more confident and capable of interacting with technology independently, reducing perceived barriers to adoption (Scuotto et al., 2021). According to the SCT, DL represents a personal factor that enhances self-efficacy, or the belief one holds regarding their ability to perform a task (Martin et al., 2020; Shamizadeh et al., 2019). Increasing self-efficacy influences perceptions of the work environment (Na-Nan et al., 2019), and thus greater self-efficacy strengthens the belief in an organization's capacity to accept change, increasing perceptions of a workplace's TAL and the willingness to engage with those technologies (Dubovi & Sheu, 2022; Stacey et al., 2015). Enhancing this ability through targeted interventions directly influences an employee's perceptions of their workplace's willingness and capacity to adopt new technologies, and therefore:

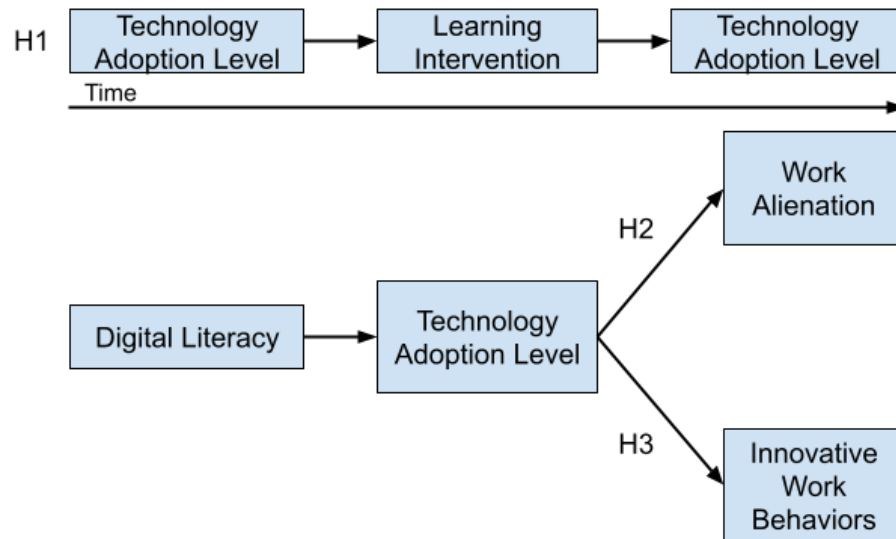
H1. Learning interventions designed to improve digital literacy lead to increased individual perceptions of a workplace's technology adoption level.

Proposed relationships are shown in the research model in Figure 1.

TAL, in turn, shape employees' psychological and behavioral responses to technological change. Under Industry 4.0, the extent to which people accept and use new technology influences their sense of professional integration in digitally enabled work systems. Greater TAL helps employees maintain a sense

of competence and relevance, and lower levels of adoption foster perceptions of professional obsolescence. TAL is thus an antecedent to emotional and behavioral outcomes, particularly in its potential to reduce WA and stimulate IWBs.

**FIGURE 1
RESEARCH MODEL**



Technology Adoption and Work Alienation

WA represents a state of estrangement characterized by feelings of powerlessness, meaninglessness, and social isolation at work (Howard & Cordes, 2010; Nair & Vohra, 2010). Rapid introduction of I4T, particularly as algorithms and automated systems begin to govern work processes, fosters feelings of displacement and a sense of being left behind (Wilkesmann & Wilkesmann, 2018), which in turn contributes to WA, an intrinsically negative phenomenon that has harmful consequences for both employees and organizations, leading to decreased job satisfaction, lower affective commitment, and increased turnover intentions (Lagios et al., 2023). It also causes physical and mental health problems, contributes to counterproductive work attitudes and behaviors, and impacts team dynamics and personal relationships negatively (Liu et al., 2025).

According to SCT, an organization's TAL represents an environmental factor that influences individual behaviors (Martin et al., 2020). Greater TAL leads to creation of digitally supportive environments, as demonstrated by positive digital climates that include user-friendly tools, efficient digital processes, and proactive digital leadership (Avtalion et al., 2025). Supportive environments reduce WA, a behavioral factor in SCT, since it represents a response to workplace conditions (Martin et al., 2020), achieved through two mechanisms—active engagement and sense of mastery. Active engagement with and use of new technologies give employees a sense of mastery and autonomy over work, transforming technology from a source of intimidation to a tool for empowerment (Hai et al., 2025; Haywood et al., 2025; Scuotto et al., 2021). Active engagement also leads to greater sense of connection to roles and reduces feelings of isolation from organizational processes (Bejaković & Mrnjavac, 2020). Therefore:

H2. *Perceptions of a workplace's TAL has a negative relationship with WA.*

Technology Adoption and Innovative Work Behaviors

IWBs are voluntary actions that contribute to creation and application of new ideas at work that improve performance (De Jong & Den Hartog, 2010). Such behaviors are essential to an organization's long-term success (Frate & Bido, 2024; Yang & Konrad, 2011), driving individual adaptability and responsiveness to

change (Ayoub et al., 2023; Lambriex-Schmitz et al., 2020). IWBs encompass a broad range of activities, including initial idea exploration/generation and promotion/implementation (Al Derei & Fam, 2023). Supportive cultures that value experimentation and creativity have been found to influence IWBs (Tian et al., 2018).

Despite their benefits, IWBs have both positive and negative consequences. They lead to improved individual, group, and organizational performance (Al Derei & Fam, 2023), but they paradoxically result in conflict with coworkers (Shih & Susanto, 2011), increased turnover intention (Choi, 2025), social ostracism that diminishes workplace wellbeing (Wang et al., 2022), and indirect inhibitions of innovation through organizational injustice (Turek & Wojtczuk-Turek, 2017). In a technology-driven environment, TAL is a precursor to IWBs (Dong et al., 2025), a relationship SCT supports, in which an organization's TAL represents an environmental factor that promotes IWBs (Martin et al., 2020). I4Ts, especially cloud computing, are catalysts for creativity, empowering people to explore new approaches and enhance work continuously (Nambisan et al., 2017). Employees who perceive high TAL leverage such tools to drive innovation, since technology transforms into support systems of creativity and supportive environments (Almogren & Aljammaz, 2022; Dennis et al., 2013). Such active engagement boosts self-efficacy, making employees more confident in their ability to innovate and solve problems using new tools (Stacey et al., 2015). Therefore:

H3. Perceptions of workplace TAL have a positive relationship with IWBs.

METHODS

Research Design

This study used a sequential explanatory mixed-methods design, an approach that involved two sequential phases. An initial quantitative phase used a quasi-experimental design (i.e., pre-post measurement with a control group) to test three hypotheses regarding the effects of DL training on TAL, WA, and IWBs. A subsequent qualitative phase used thematic analysis to collect and analyze in-depth interview data to explain and elaborate on mechanisms behind the quantitative results, providing rich contexts and participant perspectives (Braun & Clarke, 2006).

Quantitative Phase

Procedure and Sample

This quasi-experimental, pre- and post-test study examined the influence of a one-month learning intervention on 144 healthcare professionals. The study was conducted between a pre- (T1) and a post-test (T2), involving professionals in supervisory and managerial roles at C-class Indonesian hospitals. Participants were assigned randomly to either an intervention (n=72) or control (n=72) group. Participants were predominantly female (113 female, 31 male). Most held a Bachelor's degree (76), followed by diploma (50), senior high school (15), and Master's (3). Most began their careers after 2000 (123). The sample comprised Generation Y individuals (122), with smaller numbers of Generations X (11) and Z (11). The two groups were similar regarding demographics, with a few minor differences. The control group (n=72) was primarily female (61) and Generation Y (64), with most having a Bachelor's (34) or Diploma (28), and starting their careers during or after 2020 (36). The intervention group (n=72) was also predominantly female (52) and Generation Y (58), but this group had slightly greater Bachelor's degree holders (42), male participants (20), and those who began working before 2020 (48).

The Learning Intervention

The learning intervention was a focused DL training program designed to enhance participants' practical application and understanding of cloud computing as is relevant to healthcare. The curriculum addressed challenges from limited digital infrastructure at the participants' workplaces. The training was a single-session program that immediately followed the pre-test. The control group did not receive any training during this period, allowing comparisons of learning outcomes. The training modules were

designed to apply directly to participants' professional duties, particularly in supporting hospital accreditation. Participants were taught basic use of Google Drive, focusing on fundamental skills such as file organization, sharing, and access permissions, to establish a foundation in cloud-based storage. The intervention also taught use of Google Forms and Google Sheets for efficient document management and indexing, during which participants learned to create customized forms for data collection and then manage and analyze those data in Sheets. The training included learning how to sort, filter, and index information to create a searchable and organized system, which is crucial to document retrieval during audits.

The intervention followed a precise schedule to accommodate hospital staff groups. The training was administered to two separate groups of participants on different dates. The first group received the pre-test and training on 14 February 2025, and the second group on 25 February 2025. For both intervention groups, the training session was held immediately after the pre-test. A post-test was administered one month after each group's respective pre-test to assess the long-term impact of the training. The control group, which did not receive any training, also completed the pre- and post-tests, providing a baseline for comparison.

To verify the effectiveness of the training, a manipulation check was conducted using a mixed ANOVA on DL scores, with time (i.e., pre- vs. post-test) as the within-subjects factor and group (i.e., control vs. intervention) as the between-subjects factor. Results reported in Table 1 suggest a Time x Group interaction ($F(1,142)=7.226$, $p=0.008$, $\eta^2=0.048$), which means that the change in DL over time differed between the control and intervention groups. The intervention group showed an increase in DL from pre- (Mean = 3.42, SD = 0.64) to post-test (Mean = 3.61, SD = 0.60), resulting in a mean difference of +0.19. The control group showed a slight decrease in DL from pre- (Mean = 3.69, SD = 0.63) to post-test (Mean = 3.58, SD = 0.67), with a mean difference of -0.11. Neither the main effects of time ($F(1,142)=0.419$, $p=0.519$) nor group ($F(1,142)=1.803$, $p=0.182$) were statistically significant. Given the significant Time x Group interaction and the increase in DL in the intervention group in comparison to the control group, the manipulation check corroborated that the training affected participants' DL.

TABLE 1
MANIPULATION CHECK

Variable/effect	Group	Mean (pre)	SD (pre)	Mean (post)	SD (post)	Mean difference (post-pre)	F- value	df	p- value	η^2
Digital literacy										
	Control (n=72)	3.69	0.63	3.58	0.67	-0.11				
	Intervention (n=72)	3.42	0.64	3.61	0.6	0.19				
Effects										
Time							0.419	1, 142	0.519	0.003
Group							1.803	1, 142	0.182	0.013
Time x Group							7.226	1, 142	0.008	0.048

Measurement

TAL was assessed using a three-item scale adapted from Sütőová et al. (2020), Tortorella et al. (2020), and Zheng et al. (2021). The original scales measured I4T adoption, use, and knowledge. We adapted the scale to measure perceived adoption of foundational I4T, such as cloud computing, Big Data, and IoT, at participants' workplaces. Adaptation aligned with the context of the study, Indonesian organizations that typically have limited IT resources. Participants responded using a 5-point scale that ranged from "very low" (1) to "very high" (5). By assessing base technologies, the scale provided a relevant and accurate contextual measure of adoption, as opposed to assessing advanced front-end technologies such as AI and robotics. The measurement model for the construct demonstrated excellent reliability, with a Cronbach's alpha coefficient of 0.944 and a composite reliability (CR) of 0.944 (Table 2). Standardized factor loadings

for the three items were strong, ranging from 0.901 to 0.943, and the average variance extracted (AVE) was 0.85, exceeding the recommended 0.50 threshold (Cheung et al., 2024). This evidence supports the robustness and appropriateness of the adapted scale.

WA was assessed using a four-item scale adapted from a five-item scale from Miller (1967). Participants responded using a 5-point Likert-type scale that ranged from “strongly disagree” (1) to “strongly agree” (5). Adaptation was necessary due to the cultural sensitivity of the topic in the context of Indonesian organizations, in which negatively worded items impede data collection and limit organizational participation. To mitigate this risk and secure a broader sample, only positively phrased items (i.e., 2, 3, 4, and 5) from the original scale were used, a decision supported by the unsuitability of recent scales, such as that from Nair and Vohra (2010), which consists entirely of negatively worded items. Although the retained items were framed positively, they were reverse-coded before analysis such that a higher score reflected greater perceived WA. The measurement model for the adapted scale demonstrated strong psychometric properties, with a Cronbach’s alpha coefficient of 0.912 and CR of 0.912 (Table 2). Standardized factor loadings were robust, ranging from 0.828 to 0.872, and the AVE was 0.722, corroborating strong convergent validity. This evidence collectively supports the scale’s robustness and its appropriateness to the study.

IWBs were measured using a ten-item, second-order, four-dimensional scale from De Jong and Den Hartog (2010). Participants responded using a 5-point, Likert-type scale that ranged from “strongly disagree” (1) to “strongly agree” (5). The second-order construct demonstrated excellent reliability and psychometric properties, with a Cronbach’s alpha coefficient of 0.939 and CR of 0.939 (Table 2), corroborating the robustness of the comprehensive of the construct.

TABLE 2
FACTOR LOADINGS AND RELIABILITY MEASURES

Constructs	Item/Dimension	Factor Loading	Cronbach's Alpha	CR	AVE
Technology adoption level			0.944	0.944	0.85
	TAL_post_1	0.943			
	TAL_post_2	0.901			
	TAL_post_3	0.921			
Work alienation			0.912	0.912	0.722
	WA_post_2	0.857			
	WA_post_3	0.828			
	WA_post_4	0.872			
	WA_post_5	0.845			
Innovative work behaviors (second order)			0.939		
	Idea Exploration	0.904			
	Idea Generation	0.960			
	Idea Championing	0.848			
	Idea Implementation	0.969			
Innovative work behaviors dimensions (first order)					
Idea Exploration			0.632	0.632	0.462
	IWB_post_1.1	0.622			
	IWB_post_1.2	0.757			
Idea Generation			0.892	0.894	0.738
	IWB_post_2.1	0.831			
	IWB_post_2.2	0.847			
	IWB_post_2.3	0.898			

Idea Championing		0.881	0.882	0.789
IWB_post_3.1	0.882			
IWB_post_3.2	0.894			
Idea Implementation		0.894	0.895	0.74
IWB_post_4.1	0.881			
IWB_post_4.2	0.873			
IWB_post_4.3	0.826			

Data Analysis

Quantitative analysis began with calculation of descriptive statistics and correlations to characterize the sample and explore basic relationships between variables. To assess the validity of the measurement model, confirmatory factor analysis (CFA) was conducted and model fit indices were assessed. Prior to hypothesis testing, a comprehensive preliminary data analysis was conducted to examine assumptions of the statistical models. The univariate normality of continuous variables (i.e., TAL, WA, and IWB) was assessed using descriptive statistics (i.e., skewness and kurtosis) and visual inspection of histograms and Q-Q plots. The skewness and kurtosis values for TAL (0.12, 0.38), WA (0.46, -0.64), and IWBs (0.13, -0.30) lay within acceptable ranges, suggesting no severe univariate non-normality. Multicollinearity was assessed using variance inflation factors (VIFs) for predictor variables. VIF values for TAL (1.90), sex (1.16), and other control variables were below the threshold of 5, suggesting no concern of multicollinearity.

For the linear regression models that predict WA and IWBs, assumptions of linearity and homoscedasticity were assessed using diagnostic plots and the non-constant variance score test (ncvTest). For the model that predicts WA, the ncvTest yielded a borderline non-significant result ($p=0.0595$), suggesting slight heteroscedasticity. Due to observed non-normality in the WA dependent variable and its residuals, regression analyses that included WA used heteroscedasticity-consistent (HC3) standard errors to ensure reliable inferences (Pek et al., 2018). For the model that predicts IWBs, the ncvTest suggested no heteroscedasticity ($p=0.3745$), and diagnostic plots supported the assumption of homoscedasticity, and thus default OLS standard errors were used.

A multi-faceted approach was used to test the hypotheses. To compare the effects of DL training over time, a mixed ANOVA was conducted to examine TAL improvement between the pre- and post-test. To assess direct relationships between TAL and WA and between TAL and IWB, simple linear regression analyses were conducted.

Qualitative Phase

Procedure and Sample

The qualitative sample consisted of eight informants selected using purposeful sampling to provide deep insight into the training's implementation and impact. The sample included six participants who had undergone the DL training and two supervisors (R1 and R8; Table 3). The supervisors were those who managed participating groups and oversaw daily application of new skills. They were critical to contextualizing the organizational challenges and strategic rationale for the training. Semi-structured interviews were conducted following completion of the quantitative phase. An interview protocol was designed to explore participants' experiences with the DL training and its consequences. Interviews were transcribed verbatim and coded for analysis.

TABLE 3
QUALITATIVE SAMPLE DEMOGRAPHIC

Code	Age	Gender	Position
R1	45	Female	Director
R2	31	Female	Accreditation & Quality Head
R3	49	Male	Accounting Staff
R4	27	Female	Marketing Staff

R5	33	Female	Customer Relationship Staff
R6	25	Male	Administration Staff
R7	24	Male	Secretary Staff
R8	38	Female	Head of the Emergency Department

Qualitative Data Analysis

Following the systematic six-phase methodology that Braun and Clarke (2006) propose, we used thematic analysis to analyze the qualitative data. Analysis began with Phase 1: Getting Familiar with the Data, during which the interview transcripts were read and reread to achieve deep immersion. This was followed by Phase 2: Generating Initial Codes. Following an agreed-on protocol, the authors independently coded 25% of the transcripts to establish inter-coder consensus and a consolidated coding framework. Author 1 then coded the remaining transcripts. Examples of initial codes included “elimination of manual paper checking,” “fixed budget constraint,” and “future livelihood concern.”

Phase 3: Searching for Themes involved systematically grouping and linking the initial codes to form broader, potential themes. Phase 4: Reviewing Potential Themes was then conducted to assess whether the themes reflected the codes and the entire dataset accurately, leading to refinement of names and scopes. For example, codes “elimination of manual paper checking” and “reduced stress” were grouped under the theme of “mechanism of stress reduction—WA.” The process resulted in six themes (Table 4). During Phase 5: Defining and Naming Themes, the six themes were defined clearly in relation to the research questions and the overall narrative. Phase 6: Producing the Report involved integrating the themes to construct a coherent narrative, guided by the explanatory sequential design philosophy. The resulting narrative elucidated the process through which the DL intervention led to observed outcomes (H1, H2, and H3), thereby answering directly the “how” and “why” questions that underlay the quantitative relationships. Theme 2 explained mechanisms behind results for H1, Themes 3 and 5 provided the elaboration and context for H2, and Theme 4 provided explanatory evidence for H3.

TABLE 4
THEMES AND QUOTES FROM RESPONDENTS

Theme	Quotes	Respondent
Theme 1: Contextualizing the DL strategy	"A new system is almost impossible for us because the system outlined by our company owner is intended to be uniform... budget for it is fixed. So, a new system is not possible. Consequently, we switched to strengthening the ability of individuals for digitalization..."	R1
	"But most of the staff here whom I know find it quite difficult to find out things on their own. So, they are like, they just go day by day, indeed like their usual tasks, because they are all clinicians, so there is no one who... Truly administrative, let's say. So, they rarely hold computers, meaning other than to input patient data."	R8
Theme 2: Mechanism of perception shift (TAL)	For me, since the training yesterday, all those who may not have understood the ease of using current technology, it's easier for them, Sir. So, we, the younger ones today, can they adapt together between what is easy and what is... wow, like that, Sir. So, it's easier to give data, like that.	R4
	"Well, in my view, yes, before and after the training, it has changed my view quite a bit... previously, I was still, what, haven't... My view was still half-hearted, Sir, between digital knowledge and the still old system... it definitely broadened my perspective... I realized, oh, there is technology we can use. For us to try and implement it."	R6

Theme 3: Mechanism of stress reduction (WA)	"Training us to use technology makes all work easier. Specifically, the stress clearly decreased, Sir. Not like before when... don't mention things like Google Forms and so on... While previous work had to be handwritten, we stored it here, there, and eventually it was difficult to find. This training using technology is very helpful for finding documents or queries that were previously difficult to find."	R3
	"Previously, like, for example, recording incoming letter numbers, recording incoming letters, we usually used a book, still manual. Now, with technology, such as recording through Google Sheets, we can implement it... it turns out this can be done, and in the end, it's easier."	R6
Theme 4: Mechanism of innovation (IWBs)	"Administrative time decreases... then they focus on the patients. One, which means the quality of service to patients clearly improves..."	R2
	"Yes, it can be shifted to doing other tasks, deadlines in other [jobs], Sir."	R5
Theme 5: Cultural interpretation of alienation	"Our staff, yes, they do. Yes, yes, yes. Divided into two, you see. One side might be shy, or the Javanese culture of hesitation, of deference. The Javanese culture here is very strong, right, Sir, Jogja and we are in a village. So, the value of deference to leaders, the value of deference to nurses as seniors, is still high."	R1
	"Well, yes, I tend to... I still tend to hold back, Sir."	R6
Theme 6: Implementation and future strategy	"Actually, they were very enthusiastic, Sir. Maybe there were constraints with time or perhaps the duty schedule, and we were a bit tight on time. Meanwhile, our patient workload is increasing. We utilize the time well, Sir."	R3
	"In my opinion, it's more about policy, Sir. I mean, creating a policy such as: employees from each unit must attend the training, or, well, something like that, Sir."	R7

RESULTS

Quantitative Analysis

Analysis of post-test data revealed several notable relationships among the variables (Table 5). Descriptive statistics suggested moderate TALs ($M=3.30$, $SD=0.75$), high IWBs ($M=3.55$, $SD=0.68$), and low WA ($M=1.86$, $SD=0.72$). The sample was split between control and trained groups (Group $M=0.50$, $SD=0.50$) and was predominantly female (78%, Sex $M=0.78$, $SD=0.41$). Correlation analysis demonstrated interrelationships among core variables. TAL correlated positively with IWBs ($r=0.40$, $p<.001$) and negatively with WA ($r=-0.39$, $p<.001$). WA had a strong negative correlation with IWBs ($r=-0.55$, $p<.001$). Among the control variables, only sex (Female=1) had a positive correlation with TAL ($r=0.24$, $p<.01$). Group assignment, education (i.e., Edu1, Edu2, and Edu3), and generational categories (i.e., Gen1 and Gen2) did not correlate with TAL, WA, or IWB.

TABLE 5
DESCRIPTIVE STATISTICS AND CORRELATIONS

Variable	M (SD)	1	2	3	4	5	6	7	8	9
1. TAL (post-test)	3.30 (0.75)	—								
2. WA (post-test)	1.86 (0.72)	-0.39***	—							
3. IWB (post-test)	3.55 (0.68)	0.40***	-0.55***	—						
4. Group	0.50 (0.50)	-0.03	-0.01	0.12	—					
5. Sex	0.78 (0.41)	0.24**	-0.04	0	-0.15	—				
6. Edu1	0.35 (0.48)	0.07	-0.11	0.03	-0.09	0.06	—			

7. Edu2	0.53 (0.50)	-0.04	0.05	0.04	0.11	0.01	-0.77***	—		
8. Edu3	0.02 (0.14)	-0.04	-0.14	0.15	0.05	-0.16	-0.11	-0.15	—	
9. Gen1	0.85 (0.36)	0.02	-0.05	0.11	-0.12	0.01	-0.1	0.14	0.06	—
10. Gen2	0.08 (0.27)	0.06	-0.04	0.05	0.03	-0.1	0.12	-0.09	-0.04	-0.68***

Note. Dummy variables were coded as sex: female=1, male=0; group: trained=1, control=0; education: Edu1=diploma, Edu2=Bachelor's, Edu3=Master's, Edu0=senior HS (reference category); generation: Gen1=Gen Y, Gen2=Gen Z, Gen0=Gen X (reference category).

*p<0.05. **p<0.01. ***p<0.001

Based on fit indices, the overall measurement model demonstrated good fit with the data (Table 6), with a significant chi-square (χ^2 (112) = 195.607, p<0.001). More robust indicators supported the model's adequacy. The robust comparative fit index (CFI) of 0.954 and a robust Tucker-Lewis index (TLI) of 0.944 both exceeded thresholds of good fit (≥ 0.95 for CFI and ≥ 0.90 for TLI). The robust root mean square error of approximation (RMSEA) was 0.076 (90% CI: 0.058, 0.093), falling within the acceptable range (≤ 0.08), and the standardized root mean square residual (SRMR) was 0.062, suggesting good fit (≤ 0.08). Collectively, the fit indices corroborated that the measurement model aligned with the data.

TABLE 6
FIT INDICES FOR THE MEASUREMENT MODEL

Fit index	Value
χ^2 (df)	195.607 (112)
CFI	0.954
TLI	0.944
RMSEA	0.076 (90% CI [0.058,0.093])
SRMR	0.062

H1 suggests that a learning intervention that improves DL influences perceptions of a workplace's TAL positively. To test this, a 2 (Group: Control, Intervention) x 2 (Time: Pre-test, Post-test) mixed analysis of variance (ANOVA) was conducted to assess whether there were differences in perceived TAL between the two groups over time. The ANOVA revealed a significant Time x Group interaction, $F(1, 142) = 4.570$, $p = 0.034$, $\eta^2 = 0.031$ (Table 7). The intervention group reported an increase to perceived TAL from pre- (M=3.02) to post-test (M=3.27). In contrast, the control group reported a slight decrease (from M=3.42 to M=3.32). The main effect for Time was not statistically significant, $F(1, 142) = 0.853$, $p = 0.357$, $\eta^2 = 0.006$, and nor was the main effect for Group, $F(1, 142) = 4.946$, $p = 0.028$, $\eta^2 = 0.034$. These results support H1, suggesting that the learning intervention influenced how participants perceived their workplace's TAL. The significant interaction corroborates that the intervention caused a positive change in the intervention group's perception of TAL, closing the initial gap with the control group.

TABLE 7
MIXED ANOVA (H1)

Variable/effect	Mean					F-value	df	p-value	η^2
	Mean (pre)	SD (pre)	Mean (post)	SD (post)	difference (post-pre)				
TAL									
Control (n=72)	3.42	0.8	3.32	0.78	-0.1				
Intervention (n=72)	3.02	0.77	3.27	0.72	0.25				
Effects									
Time						0.853	1, 142	0.357	0.006
Group						4.946	1, 142	0.028	0.034

H2 suggests a negative relationship between perceptions of a workplace's TAL and WA. Linear regression was used to test this hypothesis, chosen to examine the predictive relationship between TAL and WA while controlling for other factors. Using heteroscedasticity-consistent standard errors, analysis suggested that TAL predicts WA negatively ($B = -0.3720$, $p < .001$, 95% CI $[-0.5171, -0.2269]$; Table 8). Thus, for every one-unit increase in perceptions of TAL, WA decreases by 0.3720 units, holding all other variables constant. The model was statistically significant, explaining 20.36% of the variance in WA ($R^2 = 0.2036$, $F(7, 136) = 7.0264$, $p < .001$). Control variables Edu1 and Edu3 correlated negatively with WA, and Sex, Edu2, Gen1, and Gen2 did not correlate with WA. These results support H2.

H3 suggests a positive relationship between perceptions of workplace TAL and IWBs. We used linear regression to test this relationship, chosen to determine the extent to which perceived TAL predicts IWBs while controlling for influences from other variables. Analysis suggested that TAL predicts IWBs positively ($B = 0.3714$, $p < .001$, 95% CI $[0.2324, 0.5104]$; Table 9). For every one-unit increase in perceived TAL, IWBs increase by 0.3714 units, holding all other variables constant. The overall model was significant, with predictors explaining 24.25% of the variance in IWBs ($R^2 = 0.2425$, $F(7, 136) = 6.2192$, $p < .001$). Control variables Edu2 and Edu3 correlated positively with IWBs, and Sex, Edu1, Gen1, and Gen2 did not correlate with IWBs. These results support H3.

Results supported the hypotheses, suggesting both relationships and directions between variables, including the effectiveness of DL interventions at raising perceived TAL, a negative relationship between TAL and WA, and a positive relationship between TAL and IWBs. Although these findings suggest what is happening, they do not explain how or why these effects occur. According with a sequential explanatory mixed-methods design, the final phase of this study involved qualitative analysis, investigating underlying mechanisms, contextual factors, and lived experiences that drove these results, and providing essential explanatory context to quantitative relationships.

TABLE 8
REGRESSION ANALYSIS RESULTS FOR OUTCOME VARIABLE: WA

Variable	B	SE (HC3)	t	p	95% CI	
					Lower	Upper
Constant	3.4654	0.3114	11.1269	<.001	2.8495	4.0813
TAL3post	-0.372	0.0734	-5.0707	<.001	-0.5171	-0.2269
Sex	0.0554	0.1494	0.3708	0.7114	-0.2401	0.3509
Edu1	-0.3802	0.178	-2.1363	0.0344	-0.7322	-0.0283
Edu2	-0.276	0.1757	-1.5713	0.1184	-0.6234	0.0714
Edu3	-1.031	0.2631	-3.9183	<.001	-1.5514	-0.5107
Gen1	-0.1329	0.2176	-0.6109	0.5423	-0.5632	0.2974
Gen2	-0.1611	0.283	-0.5695	0.57	-0.7207	0.3984
Model Fit						
R ²	0.2036					
F(7, 136)	7.0264	<.001				

TABLE 9
REGRESSION ANALYSIS RESULTS FOR OUTCOME VARIABLE: IWBS

Variable	B	SE	t	p	95% CI	
					Lower	Upper
Constant	1.7909	0.3082	5.8115	<.001	1.1815	2.4003
TAL3post	0.3714	0.0703	5.2838	<.001	0.2324	0.5104
Sex	-0.1066	0.1301	-0.8193	0.414	-0.364	0.1507
Edu1	0.3131	0.1807	1.7322	0.0855	-0.0444	0.6705
Edu2	0.347	0.174	1.9946	0.0481	0.003	0.6911
Edu3	1.029	0.3888	2.6465	0.0091	0.2601	1.7979
Gen1	0.3311	0.1954	1.6949	0.0924	-0.0552	0.7174
Gen2	0.3823	0.2653	1.4412	0.1518	-0.1423	0.907
Model Fit						
R ²	0.2425					
F(7, 136)	6.2192		<.001			

Qualitative Analysis

Mechanism of Perception Shift: From Apprehension to Self-Efficacy and Motivation

Training appears to have provided a direct boost to self-efficacy, in which the ability to use the tools replaced prior hesitations, and the training participants (R2–R7) universally reported a positive change to perceived TAL. R3 noted the direct link, stating, “Training us to use technology makes all work easier.” R7 similarly found that training resulted in work that was “easier, and more efficient.” Ease-of-use thus fueled a confidence boost, with R5 describing the training as something that “can improve my personal skill”, and R2 acknowledging, “I became aware of other knowledge, aware of other things...”

The change was not just about capability, but strengthening personal motivation and relevance. R6 reported a substantial change in outlook, noting, “Before and after the training, it has changed my view quite a bit.” R4 similarly confirmed this motivation, stating, “With the training yesterday, I was quite motivated.” Supervisors (R1 and R8) also recognized the importance of this shift, viewing digital mastery as essential to professional necessity. R1 saw the goal as “keeping up with the times,” and R8 agreed, stating that “their perception of something new about the technology that was explained earlier indeed increased.” These findings illustrate that the DL intervention shifted affective responses to digital tasks from apprehension or apathy to confidence and motivation, a process that represents a Mechanism of Perception Shift (Theme 2). This shift is not merely cognitive knowledge transfer but a profound change in self-efficacy and personal motivation regarding digital tasks. By providing participants with a broadened perspective and the confidence to master technology, the intervention fundamentally altered their emotional and professional link to digital adoption. This qualitative evidence explains the “how” and “why” behind the Time x Group interaction found during quantitative analysis.

Mechanism of Stress Reduction: Combating Alienation Through Administrative Efficiency

Primary evidence from training participants (R2–R7) highlights Elimination of Manual Paper Checking/Processing, which provided direct Mental Relief/Clarity. R3 discussed this change, stating, “Training us to use technology makes all work easier,” confirming the affective benefit, “Specifically, the stress clearly decreased.” R4 agreed, noting, “In my opinion, a decrease in stress, maybe yes.” This reduction in tedious work resulted in significant Time Saving for Rest/Reduced Effort. R6 affirmed, “Yes, correct, it saves more time,” and R7 shared a specific instance, “Now we also use Google Form for daily attendance. So, we don't need to....” R2 acknowledged that the improved process led to a clearer data collection system and easier retrieval, a factor critical to reducing stress related to accountability and compliance. Similarly, R4 appreciated that with the new digital process, “the storage is not scattered,” allowing easy retrieval. The supervisors (R1 and R8) corroborated such tangible benefits. R1 highlighted that digital archives meant documents could “just be retrieved” instead of involving manual checking,

which led to Reduced Stress of Accreditation Proof Retrieval. R8 confirmed such managerial benefits, noting that increased efficiency helped Reduce Overtime Cost, and stating, “They used to have to make people work overtime to do this.” TAL predicting WA negatively is explained directly through findings from Theme 3—Mechanism of Stress Reduction—which reveals how digital adoption mitigates alienation by structurally eliminating the volume of non-core administrative labor, freeing time and mental capacity for staff to focus on their primary, meaning-providing roles. Such efficiency directly mitigates the feelings of powerlessness and meaninglessness that characterize WA.

Qualitative analysis also revealed a strong cultural factor, Javanese Deference/Respect for Hierarchy, which complicates measurement of WA. This norm creates cultural reluctance to speak out directly, a phenomenon that both supervisors and staff confirmed. Supervisor R1 observed that if asked to voice complaints, “not many will. One side might be shy, or the Javanese culture of hesitation.” Training participant R2 described this as a “feeling of discomfort if they speak directly,” and R6 confessed to personally “holding back.” Consequently, staff often resort to indirect feedback, such as surveys (R5), rather than explicit communication. This cultural context is vital to understanding the link between TAL and WA. Employees are culturally conditioned to suppress outward signs of dissatisfaction or stress, and thus the administrative burden of manual work creates a silent form of alienation. Digital intervention not only reduces visible complaints, it alleviates the internal, unvoiced psychological strain that the Javanese cultural norm otherwise forces employees to carry in silence, explaining why the DL intervention was so impactful, even when reported alienation was low.

Mechanism of Innovation: Using Reallocated Time for Pragmatic, Bottom-Up Problem-Solving

The Mechanism of Innovation (Theme 4) explains fully the positive relationship found between TAL and IWBs, manifesting as reinvestment of time into new problem-solving and service improvements. Training participant R5 confirmed that the time digital tools save “can be shifted to doing other tasks,” time that can be refocused on core professional duties. R3 explained, “So with the reduced time spent on files/administration, the rest can be used for patient interaction.” One example of this team-level innovation was provided by participant R2, who noted that to solve a surgical scheduling issue, “finally, after discussion, we used Google Sheets to do what is called real time patient recording,” a classic example of pragmatic IWBs. Supervisor R8 corroborated this shift, reporting that the result represents energy reallocation to service for the staff. For the supervisors (R1 and R8), IWBs also involve strategic application. R1 reported that improving TAL was crucial to her core management responsibility, allowing her to “provide data and presentations that satisfy my superiors” and identify future innovation areas, such as “making patients satisfied regarding waiting for medicine.”

The “why” behind this innovation derives from system rigidity and budget constraints that compel employees with digital skills to engage in practical, bottom-up improvisation, an environment that forces active searches for low-cost solutions, without relying on an overhaul of expensive, existing hospital management information system (SIRS). Supervisor R1 summarized this necessity, explaining the goal is to find solutions in which “I won’t add much money, but it’s neat, it’s done. What technology can I use without having to change SIRS?” Such bottom-up innovations lead to the emergence of new ideas, which the hospital formally encourages through a formal innovation channel (Kaizen). Results from qualitative analysis demonstrate that the DL intervention equipped employees with the TAL to identify and solve operational pain points, converting organizational friction into innovative action.

DISCUSSION

This study used a sequential explanatory mixed-methods design to investigate the dynamic interplay among DL, TAL, and the critical employee outcomes of WA and IWBs in resource-constrained healthcare environments. Findings offer insights by not only confirming proposed relationships, but by detailing the psychological and operational mechanisms that drive them. Results for H1 suggest that targeted learning interventions increase an intervention group’s perceived TAL, evidenced by a significant Time × Group interaction. The control group’s perceptions either remained flat or declined slightly, but the intervention

group reported notable positive changes. Qualitative results explain that the success of the DL intervention was not merely cognitive knowledge transfer, but that it profoundly altered participants' emotional and professional link to digital adoption. Training provided a self-efficacy boost, in which the ability to use simple digital tools replaced prior hesitations, strengthening personal motivation for relevance since participants recognized that digital mastery was necessary to keep pace with innovation. The intervention equipped staff with skills to use existing, accessible digital tools, reshaping affective responses from apprehension and apathy to confidence and motivation, thereby establishing a stronger and more positive TAL.

As hypothesized, analysis suggested a negative relationship between TAL and WA. When employees perceive greater technology adoption at work, feelings of alienation decrease. A core issue identified from the interviews was a high volume of non-core administrative labor, such as manual paper processing for mandatory accreditation, which generated stress and helplessness. The DL intervention allowed staff to use simple digital tools to create a knowledge management system for documentation, eliminating manual paper checking and processing, and providing mental relief/clarity and significant time saving. When employees perceive that technology structurally eliminates tedious burdens, their sense of control is restored, leading directly to measurable reductions in WA. The managers corroborated that such efficiency also reduced overtime costs and stress associated with accreditation evidence retrieval, demonstrating a direct link between improved TAL and reduced operational friction.

Results for H3 suggested a positive relationship between TAL and IWBs, indicating that greater perceptions of technology adoption associate with increased individual innovation. Qualitative analysis revealed that the environment's rigidity (e.g., expensive hospital management information systems, or SIMRS) and budget constraints compel employees to engage in practical improvisation. Time saved through administrative efficiency was reinvested in core professional duties and service improvements, fostering IWBs. For example, staff repurposed simple tools to create real-time patient records. One supervisor explained that the goal was to find resourceful solutions with elegant execution, the essence of the pragmatic, bottom-up innovation that TAL encourages. Drawing from these results, we outline this study's theoretical contributions and practical implications.

Theoretical Contributions

This study contributes to theory by illustrating a practical application of SCT within the phased adoption model of Industry 4.0 in resource-constrained healthcare. Recent research suggests that service-sector digital transformations follow a sequence where base technologies (e.g., cloud computing and Big Data) form the essential infrastructure for future front-end (e.g., AI and Robotics) integration (Kornarius et al., 2025). Enhancing DL as a personal factor boosted self-efficacy, enabling employees to master these foundational tools, which in turn, improved perceptions of the workplace in the form of greater perceived TAL, reducing WA and encouraging IWBs. Findings extend extant research that suggests digital innovation in resource-limited hospitals is perceived risky (Maqdliyan & Setiawan, 2023) by demonstrating that targeted training reframes foundational base innovations as practical, low-risk solutions. These findings align with evidence that training enhances willingness to adapt technology, skills, and operations (Drydakis, 2022; van Laar et al., 2020), refining understanding of DL as a workplace resource that reshapes perceptions of organizational support (Nikou et al., 2022).

This study also shows that DL is not only a measurable competency, but a malleable resource that targeted interventions systematically enhance. Extant research commonly treats DL as a stable capability that predicts technology adoption and workplace adaptation (Hatlevik & Christophersen, 2013; van Laar et al., 2020). Current findings extend this view by demonstrating that modest, context-specific training elevates DL, which, in turn, reshapes perceptions of organizational technology adoption. DL is thus positioned as a dynamic workplace resource that enhances individual adaptability and catalyzes broader organizational outcomes when resources are constrained (Ilomäki et al., 2016; Spante et al., 2018).

This study contributes to workplace learning theory by showing that micro-level, problem-driven interventions drive organizational change. Workplace learning research traditionally emphasizes continuous development, formal training, and organizational learning cultures as drivers of performance

(Marsick & Watkins, 2003; Noe et al., 2014). Current findings extend this perspective by demonstrating that even modest, context-specific interventions that align with daily challenges (e.g., accreditation documentation) build digital confidence and capacity from the bottom up. Findings also suggest that the long-term viability of such bottom-up improvements depends on managerial reinforcement. As extant workplace learning research suggests (Haapatalo et al., 2023; Kang et al., 2020), the effects of micro-interventions diminish without formal institutionalization, positioning sustainability not merely as an operational concern, but a theoretical necessity for bottom-up digital transformations to move from isolated initiatives to embedded organizational practice.

This study advances WA theory, since classic alienation theory emphasizes that task fragmentation, lack of autonomy, and powerlessness generate estrangement (Nair & Vohra, 2010). Current results suggest that in resource-constrained healthcare settings, WA links to perceived technological insufficiency rather than to work itself, which employees continue to value, a finding that connects technology adequacy to employees' sense of estrangement. A negative relationship between TAL and WA highlights technology adequacy and perceived organizational support as critical, yet underexplored antecedents of reduced alienation (Haddad & Senter, 2017; Karayaman, 2024), a finding that corroborates research that suggests inefficient systems, rather than clinical duties, drive administrative strain in healthcare (Petitta & Ghezzi, 2023).

This study contributes to cross-cultural theorization of alienation, since low WA in the current context must be interpreted through lenses of Javanese deference and respect for hierarchy. Cultural values such as *malu* (social shame) and *tidak enak* (relational unease; Caparas & Hartijasti, 2014; Dhamanti et al., 2020) lead to internal reluctance to report negative feelings, such as alienation, to preserve group harmony. Integrating qualitative nuances, we argue that a reduction to WA, even if modest, is theoretically relevant, and we suggest that alienation in collectivist societies represents a silent drain on resources that requires context-sensitive measurement and qualitative depth to uncover fully.

This study also contributes to IWB theory. Extant IWB research suggests that autonomy, supportive climates, and resource abundance are enablers (Anderson et al., 2014; Janssen, 2000). Current findings suggest that when compliance-driven administrative tasks (e.g., accreditation) are supported by modest digital tools that enhance perceived TAL, employees redirect resources toward IWBs, turning routine duties into opportunities for innovation. This finding reframes IWBs as emerging not only from freedom and excess resources, but from creative repurposing of compliance to opportunities for proactive improvement (Srirahayu et al., 2023; Ye & Chen, 2024). Current findings also suggest a theoretical bridge between alienation and IWBs; adequate technology might reduce estrangement by freeing cognitive and emotional resources, which can then be redirected toward experimentation, problem-solving, and process improvement (Khan et al., 2019), a perspective that positions alienation as a cognitive-emotional resource drain and possible hidden inhibitor of innovation that future studies should address to unlock IWBs.

This study extends SCT, DL theory, workplace learning theory, and literature on WA and IWBs. It suggests that bottom-up DL interventions reshape environmental perceptions, reduce estrangement, and unlock innovation in resource-limited healthcare. More broadly, findings highlight that digital transformation in constrained settings can be achieved not only through large-scale investments, but by empowering employees with foundational skills that address everyday challenges directly.

Practical Implications

From a practical perspective, current findings highlight that targeted DL training represents a cost-effective strategy that advances digital transformation in resource-constrained hospitals. Rather than adopting a universal approach, organizations should prioritize tailored development opportunities that align training with specific professional needs and daily administrative challenges (Hoedemakers et al., 2026). By developing supervisors' and managers' skills that are modest but highly practical, such as digitalizing manual accreditation workflows, organizations not only enhance individual digital confidence, they strengthen daily operations. Supervisors and managers who can design tailored digital solutions independently signal that the organization is supporting its staff with workable, relevant tools. Such visible, problem-solving capacity improves employees' perceptions of TAL, reduces WA by restoring a sense of

control over administrative burdens, and fosters IWBs by freeing resources for experimentation and improvement, evidencing that leadership shapes technology acceptance and innovation climates (Chereka et al., 2024; Tarhini et al., 2015). This argument aligns with recent research that suggests digital leadership and supervisor digital communication skills strengthen innovation performance (Wang et al., 2025).

Commonly lacking the resources for large-scale projects, C-class hospitals' ability to routinely reinforce and integrate technology into daily operations will be essential to sustaining bottom-up improvements. Given their limited resources for large-scale projects, C-class hospitals must embed technology into routine daily operations to sustain bottom-up improvements. Similar to Kang et al.'s (2020) argument, management must formally institutionalize employee-led digital solutions to prevent them from remaining isolated initiatives, ensuring change is embedded both culturally and practically. For hospitals experiencing substantial operational and financial constraints, the most impactful strategy is not large-scale infrastructure spending, but empowering employees with foundational skills that allow them to leverage existing, low-cost technology. A human-centric approach creates supportive environments in which staff can adopt, rather than resist, technological change.

Limitations and Future Research

Findings are specific to a sample of supervisors and managers in C-class Indonesian hospitals, limiting generalizability to other healthcare settings, employee types, and cultural contexts. The duration of the intervention and the post-test measurement period was short, so the long-term sustainability of increases to TAL and effects on WA and IWBs remains uncertain. Future research should use longitudinal designs, tracking variables at extended intervals (e.g., 3, 6, and 12 months after an intervention) to assess both the sustainability and decay of observed effects (Haapatalo et al., 2023; Kang et al., 2020). Although participants were assigned randomly to intervention and control groups, minor baseline imbalances and information spillover between groups cannot be ruled out. Future research should strengthen causal inferences by using stratified or cluster randomization, monitoring contamination, and extending post-intervention follow-ups. A longitudinal study could track the long-term influences of such interventions. Qualitative research would provide richer insights into participants' experiences and the mechanisms through which DL reduces alienation and promotes innovation. A comparative study across types of hospitals (e.g., A- or B-class), and across Indonesia's service sectors, would help with understanding the findings' broader applicability.

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