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RESEARCH ARTICLE

Influence of Digital Work Capability on Workforce Agility among Generation Z IT Professionals

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Abstract

Purpose: This study examines the influence of perceived digital work capability on workforce agility among Generation Z IT professionals in Nepal. It addresses the limited empirical attention given to employee-level behavioural mechanisms through which digital capability is enacted in changing work systems.

Design/methodology/approach: Drawing on Dynamic Capabilities Theory and Sociotechnical Systems Theory, this study conceptualises workforce agility as a behavioural micro-foundation of digital work capability. Using survey data from 350 Generation Z IT professionals in Nepal and covariance-based structural equation modelling (SEM), the study examines the relationship between workforce agility and perceived digital work capability.

Findings: Results indicate that workforce agility is positively and significantly associated with digital work capability, accounting for 35.5% of the variance. The findings suggest that adaptive behavioural orientation, rather than demographic characteristics or formal credentials, is meaningfully associated with digital effectiveness within evolving work systems.

Implications: The study highlights the importance of employee-level adaptive capacity in supporting digital effectiveness within evolving work systems. For IT firms, the findings suggest that digital capability development should encompass adaptability, proactive problem-solving, resilience, and continuous learning, rather than focusing solely on technical skills.

Originality/value: This study contributes to the digital transformation literature by empirically operationalising employee-level micro-foundations and demonstrating how adaptive capacity facilitates the development and enactment of digital capabilities.

JEL Classification: M15, M12, O33

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Introduction

Digital transformation research has generated substantial knowledge regarding how organisations develop digital strategies, deploy infrastructures, and cultivate firm-level digital capabilities (Baiyere et al., 2025; Piccoli et al., 2022; Plekhanov et al., 2023). Yet digital capability is commonly conceptualised at the organisational level, while the employee-level adaptive processes through which digital systems are enacted remain less explicitly specified in empirical research (Ashrafi et al., 2025; Plekhanov et al., 2023). When digital capability is framed primarily as a structural or infrastructural property, the individual behavioural mechanisms that sustain performance during technological reconfiguration risk being underdeveloped in empirical analysis (Abhari, 2025; Ashrafi et al., 2025).

Nepal's expanding IT sector provides a relevant empirical setting for this inquiry. Recent industry evidence estimates Nepal's IT service exports at approximately USD 515 million in 2022, representing 64.2% growth from 2021 (Institute for Integrated Development Studies, 2023). This growth makes the sector a useful empirical setting for examining how early-career IT professionals sustain their effectiveness in digital work in technology-intensive roles.

The concern is particularly salient in IT work systems where technological change is continuous rather than episodic. Platform updates, workflow reconfiguration, and digital tool turnover require employees to repeatedly adjust routines under performance constraints (Ashrafi et al., 2025; John et al., 2025). In such contexts, digital work capability cannot be reduced to accumulated technical skill alone but instead reflects the capacity to sustain effective task performance as digital systems evolve (Petermann & Zacher, 2022; Vuchkovski et al., 2023). Although information system (IS) research acknowledges digital transformation as sociotechnical in nature (Iden & Bygstad, 2025; Plekhanov et al., 2023), empirical operationalisations frequently emphasise structural resources, technological readiness, or infrastructure investment (Ashrafi et al., 2025; Baiyere et al., 2025).

Despite these advances, a distinct research gap remains. Prior digital transformation studies explain digital capability mainly through organisational resources, digital strategy, technological readiness, and infrastructure. Less is known about the employee-level behavioural capacities through which digital work capability is enacted, particularly among Generation Z professionals working in an emerging IT-sector context (Abhari, 2025; Ashrafi et al., 2025; Iden & Bygstad, 2025).

In order to address this empirical and contextual gap, this study addresses the following research question: To what extent is workforce agility associated with perceived digital work capability among Generation Z IT professionals in Nepal?

Dynamic Capabilities Theory provides a framework for specifying the adaptive mechanism underlying sustained performance in changing environments (Teece, 2007). The theory emphasises sensing, seizing, and reconfiguring resources and highlights the importance of micro-foundations, individual behaviours, and capacities that enable higher-order reconfiguration (Felin et al., 2015; Teece, 2007). However, within digital transformation research, micro-foundational logic is often conceptually acknowledged but less frequently operationalised at the individual employee level (Abhari, 2025; Ashrafi et al., 2025).

Workforce agility represents a theoretically grounded micro-foundation in this context. It captures an individual's capacity to adapt to shifting demands, act proactively under uncertainty, recover from disruption, and engage in continuous learning (Petermann & Zacher, 2022). These dimensions correspond to the reconfiguration logic central to dynamic capabilities (Teece, 2007; Vuchkovski et al., 2023). In digitally transforming environments, agile individuals are more likely to adjust workflows and experiment with new tools in ways that stabilise performance during system transitions (Abhari, 2025; John et al., 2025). Such adaptive engagement is expected to support employees' perceived capability to manage complex and evolving digital tasks, particularly when work systems require repeated adjustment to new tools, workflows, and technical demands (Iden & Bygstad, 2025; Ulfert-Blank & Schmidt, 2022)

Sociotechnical Systems Theory further clarifies this mechanism by positing that performance depends on ongoing alignment between social subsystems and technical subsystems (Iden & Bygstad, 2025; Trist & Bamforth, 1951). In IT contexts characterised by continuous technological evolution, alignment must be repeatedly reconstructed (Ashrafi et al., 2025; Iden & Bygstad, 2025).

This study examines the relationship between workforce agility and digital work capability among Generation Z IT professionals in Nepal. By empirically modelling workforce agility as an individual-level behavioural micro foundation, the study clarifies how adaptive human capacities contribute to the enactment of digital work capability within evolving sociotechnical systems. The study advances the digital transformation literature by extending the understanding of employee-level behavioural micro-foundations that underpin the development of digital work capability in rapidly evolving organisational environments

The remainder of the paper reviews the relevant literature and theoretical foundations, describes the research methods, presents the results of the measurement and structural models, and discusses the theoretical, managerial, social, and research implications.

Literature Review

Digital Work Capability and Workforce Agility in Digital Work Systems

Digital capability has commonly been examined at the organisational level, where it is operationalised through infrastructure investment, digital strategy, technological readiness, or platform integration (Piccoli et al., 2022; Plekhanov et al., 2023). While such operationalisations are appropriate for analysing structural transformation, they provide limited insight into how digital effectiveness is enacted at the employee level during ongoing technological reconfiguration (Ashrafi et al., 2025). This creates a specific gap in explaining how individual employees sustain digital work effectiveness when tools, workflows, and technical systems continue to change (Abhari, 2025; Iden & Bygstad, 2025).

In IT-intensive environments, digital systems evolve continuously through platform updates, workflow redesign, toolchain modification, and system integration (Iden & Bygstad, 2025). Under these conditions, effectiveness depends not solely on accumulated technical knowledge but on the capacity to sustain performance while digital infrastructures shift. Accordingly, digital work capability is conceptualised here as perceived adaptive effectiveness, defined as the individual's belief in their capacity to manage complex and evolving digital tasks within changing technical systems (Compeau & Higgins, 1995; Ulfert-Blank & Schmidt, 2022).

This conceptualisation aligns with established IS traditions that treat perceived capability as a meaningful predictor of digital performance outcomes (Compeau & Higgins, 1995). While the construct is operationalised through perceived effectiveness, its theoretical framing emphasises adaptive enactment within dynamic work systems. The distinction between static technical skill and perceived adaptive effectiveness is particularly important in digitally transforming contexts where work demands are fluid rather than stable (Pulakos et al., 2000).

Workforce agility captures an individual's capacity to adapt to changing work demands, act proactively under uncertainty, recover from disruption, and continuously learn as conditions evolve (Petermann & Zacher, 2022). Unlike static competence, which reflects accumulated knowledge or task-specific expertise, workforce agility reflects behavioural flexibility in response to environmental shifts (Pulakos et al., 2000).

In IT contexts characterised by evolving digital architectures, employees frequently encounter new tools, altered processes, and shifting technical constraints (Iden & Bygstad, 2025). Individuals high in workforce agility are more likely to experiment constructively, modify routines when required, and persist during transitional instability. These behaviours align with the reconfiguration dimension of dynamic capabilities.

The rationale for linking workforce agility to digital work capability is therefore grounded in the gap between organisational-level digital capability research and employee-level enactment. Prior studies explain digital capability mainly through technological resources, digital strategy, or organisational readiness, but they provide less direct explanation of the behavioural capacities through which employees maintain effectiveness during digital change (Abhari, 2025; Ashrafi et al., 2025; Baiyere et al., 2025). Workforce agility addresses this gap by specifying an individual-level adaptive capacity that may help explain how digital work capability is enacted in daily IT work (Iden & Bygstad, 2025; Petermann & Zacher, 2022).

Directionality is grounded in the distinction between adaptive behavioural capacity and context-specific perceived effectiveness. Workforce agility represents an adaptive work orientation, whereas digital work capability reflects employees' perceived capacity to manage complex and evolving digital tasks (Petermann & Zacher, 2022; Ulfert-Blank & Schmidt, 2022). In changing IT work environments, employees who adapt routines, respond proactively to technical change, and continue learning are more likely to perceive themselves as capable of handling digital work demands. Although perceived capability may also shape behaviour, this study positions workforce agility as the antecedent because agility captures the behavioural adjustment through which digital work capability is enacted in changing digital environments (Abhari, 2025; Iden & Bygstad, 2025).

Theoretical Foundations

Dynamic Capabilities Theory explains sustained effectiveness in volatile environments through sensing environmental shifts, seizing emerging opportunities, and reconfiguring resources accordingly (Teece, 2007). Although originally articulated at the firm level, subsequent scholarship has emphasised the importance of micro-foundations individual-level behaviours and attributes that enable reconfiguration processes to occur in practice (Felin et al., 2015).

In digitally transforming IT environments, reconfiguration is enacted not only through strategic decision-making but also through daily adjustments in workflows, tool usage, and problem-solving practices (Iden & Bygstad, 2025). While digital transformation research increasingly acknowledges dynamic capabilities conceptually, empirical studies often focus on structural indicators or organisational outcomes, leaving individual behavioural drivers comparatively less directly specified (Ashrafi et al., 2025).

Applying the micro-foundations perspective to digital work systems, therefore, directs analytical attention to identifying specific employee-level capacities that operationalise reconfiguration under technological change.

Complementing the micro-foundational perspective of dynamic capabilities, Sociotechnical Systems Theory posits that effective performance in complex environments depends on the ongoing alignment between social and technical subsystems (Iden & Bygstad, 2025; Trist & Bamforth, 1951). In digitally intensive IT contexts, technical subsystems evolve continuously, disrupting previously stabilised patterns of interaction between employees and systems (Iden & Bygstad, 2025).

Digital work capability reflects the individual's perceived capacity to function effectively within newly configured sociotechnical arrangements (Compeau & Higgins, 1995; Ulfert-Blank & Schmidt, 2022). Workforce agility provides the behavioural mechanism through which alignment is reconstructed. By enabling individuals to reinterpret task demands, adjust routines, and sustain engagement during technological disruption, agility facilitates the restoration of sociotechnical fit. In the absence of adaptive behavioural capacity, misalignment between evolving technical systems and employee practices is more likely to persist.

Hypothesis Development

Digital transformation in IT environments requires continuous behavioural reconfiguration. Dynamic Capabilities Theory identifies reconfiguration as central to sustained effectiveness and highlights the role of micro-foundational behavioural capacities. Workforce agility captures adaptive flexibility and proactive adjustment, while digital work capability reflects perceived adaptive effectiveness within evolving digital systems. Sociotechnical Systems Theory further implies that adaptive individuals are better positioned to reconstruct alignment as technical subsystems change.

Together, these theoretical perspectives converge on the following expectation:

H1: Workforce agility positively influences digital work capability among IT professionals.

The conceptual framework derived from the preceding theoretical arguments is presented in Figure 1.

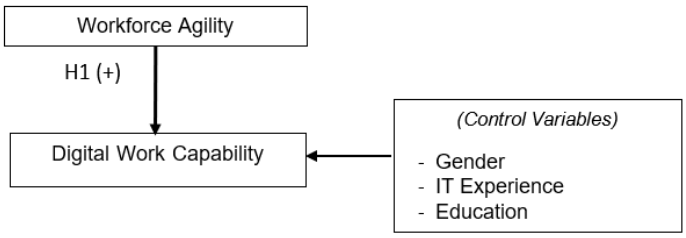

Figure 1: *Conceptual Framework*

Research Methods

Research Design, Context, and Data Collection

This study adopted a cross-sectional survey design to examine the relationship between workforce agility and digital work capability among Generation Z IT professionals. The unit of analysis was the individual employee. A survey-based design is widely used in Information Systems research to examine latent perceptual constructs such as self-efficacy and adaptive behavioural capacities (Gaskin et al., 2025; Hair et al., 2025).

The empirical context was the IT sector in Kathmandu, Nepal. The study focused on firms that had been in operation for at least five years to ensure organisational stability and reduce contextual volatility associated with newly established firms. Generation Z professionals were defined by year of birth (1997 or later), consistent with cohort-based definitions in workforce research (Al-Moteri et al., 2025).

Data were collected from employees of 30 IT firms in Kathmandu that had been operating for at least five years and were engaged in technology-intensive services. Eligible participants were Generation Z professionals (born in 1997 or later) employed in technical roles, including software development, quality assurance, data analytics, DevOps, IT support, and related functions. Employees in non-technical administrative roles were excluded to ensure alignment between the study's theoretical constructs and the technology-intensive work context. A total of 350 valid responses were obtained and retained for analysis. This sample size exceeds commonly recommended thresholds for covariance-based SEM (Buchberger et al., 2024; Hair et al., 2025). An online survey was administered through organisational contacts within these firms. Participation was voluntary and anonymous. A purposive sampling strategy was employed to ensure that respondents had direct exposure to IT-intensive work, digital tools, and changing technical tasks relevant to the constructs examined in this study. The purpose of this sampling approach was to obtain responses from participants positioned to evaluate workforce agility and digital work capability in actual IT work settings. Accordingly, the findings are analytically generalizable to comparable IT work contexts rather than statistically representative of the broader population (Hong & Fàbregues, 2026).

Measures and Common Method Considerations

All constructs were measured using previously validated instruments. Items were presented in English, which is commonly used as the working language within the IT sector in Kathmandu. All responses were measured using a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). The retained measurement items and corresponding codes are presented in Table A2 in the Appendix.

Workforce agility was measured using the 12-item multidimensional scale developed by Petermann and Zacher (2022) capturing adaptability, proactivity, resilience, and learning orientation. Click or tap here to enter text. Items were adopted with minimal adjustments to the contextual wording to reflect the IT work environment. Digital work capability was operationalised as perceived effectiveness in managing complex and evolving digital tasks. Measurement items were adapted from validated computer self-efficacy scales developed within Information Systems research (Howard, 2014). The initial digital work capability item pool included 12 items. Following CFA, the final retained measurement model used 11 DWC items because DWC11 did not meet the conventional standardised loading threshold, as reported in the Results section and Appendix A.

Three control variables were included: gender, years of IT work experience, and education level. These variables were included because prior IS and self-efficacy research indicates that demographic factors may influence perceived digital capability (Conte et al., 2025). Gender was coded as 0 = Female and 1 = Male; the education level was coded by degree attainment, and years of IT work experience were measured in years.

Because data were collected from a single source at a single point in time, procedural remedies were implemented to reduce potential common method bias. These included assurance of anonymity, psychological separation between independent and dependent variable sections, and neutral wording of items. These steps align with established recommendations for minimising common method variance in behavioural research (Podsakoff et al., 2024). Statistical assessment of common method bias was also conducted using established diagnostic approaches (Podsakoff et al., 2024). A single-factor confirmatory factor analysis model demonstrated substantially poorer fit than the proposed measurement model, suggesting that common method bias is unlikely to explain the observed relationships.

Analytical Strategy

Data were analysed using covariance-based structural equation modelling (CB-SEM). SEM is appropriate for theory-driven research involving latent constructs and allows simultaneous estimation of measurement and structural models while accounting for measurement error (Gaskin et al., 2025; Hair et al., 2025). Analyses were conducted in R using the lavaan package (version .6-21). The measurement model was estimated using maximum likelihood (ML) estimation with robust (sandwich) standard errors and the Yuan-Bentler scaled test statistic. Robust standard errors were used to mitigate potential deviations from multivariate normality in Likert-scale data. Model fit indices are reported based on the scaled solution derived from the sample covariance matrix.

The analysis proceeded in two stages. First, confirmatory factor analysis (CFA) was conducted to evaluate the measurement model. Reliability and validity were assessed using standardised factor loadings, composite reliability, average variance extracted, discriminant validity criteria, and overall model fit indices consistent with established SEM guidelines (Gaskin et al., 2025; McNeish & Wolf, 2023). The measurement model was re-estimated after removing DWC11 because its initial standardised loading was below .50. Second, the structural model was estimated to test the hypothesised relationship between workforce agility and digital work capability while including control variables. Standardised path coefficients and explained variance (R^2) were examined (Hair et al., 2025).

Results

Sample Characteristics

As shown in Table 1, the final sample comprised 350 Generation Z IT professionals. The gender distribution included 57.4% males and 42.6% females. Regarding educational attainment, 79.1% held a bachelor's degree, and 20.9% held a master's degree. Participants reported an average of 3.20 years of IT work experience (SD = 2.46), with values ranging from 0 to 10 years. No missing data were observed across the study variables.

Table 1: Sample Characteristics

Panel A. Categorical Variables

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	149	42.6
	Male	201	57.4
Education Level	Bachelor's	277	79.1
	Master's	73	20.9

Panel B. Continuous Variable

Variable	Mean	SD	Min	Max
Years of IT Experience	3.20	2.46	0	10

Note. *Based on the survey data collected by the authors.*

Descriptive Statistics and Measurement Model Assessment

Descriptive statistics and correlations are presented in Table 2. Workforce agility (WA) demonstrated a mean of 3.12 (SD = .72), while digital work capability (DWC) showed a mean of 3.12 (SD = .75). Both constructs exhibited near-zero skewness (WA = −.03; DWC = −.08) and acceptable kurtosis values (WA = −.35; DWC = −.66), indicating approximate univariate normality. The correlation between WA and DWC was positive and moderate (r = .506, p < .001), suggesting a meaningful association between the constructs.

Table 2: Descriptive Statistics, Correlations, and Reliability

Variable	Mean	SD	Skew	Kurtosis	1	2
1. Workforce Agility (WA)	3.12	.72	-.03	-.35	.854	
2. Digital Work Capability (DWC)	3.12	.75	-.08	-.66	.506***	0.852

Note. *Cronbach's alpha coefficients are reported on the diagonal. ***p < .001. Source: Survey data analysed by the authors.*

A CFA was conducted to evaluate the measurement properties of WA and DWC. During the initial CFA, DWC11 showed a standardised loading of .439, which was below the conventional .50 threshold. This item was therefore excluded, and the measurement model was re-estimated using 12 WA items and 11 DWC items. The revised two-factor model fit the data well: $\chi^2(229) = 216.713$, p = .710; CFI = 1.000; TLI > .999; RMSEA = .000; SRMR = .035.

As shown in Table 3, all retained standardised factor loadings were statistically significant ($p < .001$), ranging from .522 to .633 for WA and from .533 to .646 for DWC. Composite reliability (CR) exceeded recommended thresholds for both constructs (WA = .856; DWC = .853), indicating satisfactory internal consistency. Average variance extracted (AVE) values were .332 for WA and .347 for DWC. Although the AVE values were below the conventional .50 threshold, all retained loadings were statistically significant, and CR values exceeded .85. Convergent validity was therefore interpreted cautiously rather than treated as unequivocally established.

Table 3: Measurement Model Results

Panel A. Standardised Factor Loadings

Construct	Item	Loading
Workforce Agility (WA)	WA1	.614
	WA2	.591
	WA3	.543
	WA4	.522
	WA5	.564
	WA6	.606
	WA7	.622
	WA8	.544
	WA9	0.527
	WA10	.575
	WA11	.633
	WA12	0.555

Digital Work Capability (DWC)	DWC1	.584
	DWC2	.587
	DWC3	.600
	DWC4	.588
	DWC5	.596
	DWC6	.596
	DWC7	.533
	DWC8	.580
	DWC9	.600
	DWC10	.559
	DWC12	.646

Panel B. Construct Reliability and Validity

Construct	CR	AVE	√AVE
WA	.856	.332	.576
DWC	.853	.347	.589

Note. DWC11 was excluded from the revised measurement model because its initial standardised loading was below .50. Source: SEM output based on survey data.

Discriminant validity was assessed separately using the Fornell–Larcker criterion, HTMT, and model comparison. As shown in Table 4, the Fornell–Larcker criterion was marginal because the latent correlation between WA and DWC slightly exceeded the square root of AVE for both constructs. However, the HTMT value was below the commonly used .85 threshold. The constructs were therefore treated as closely related yet empirically distinguishable, with the interpretation further supported by the model comparison reported in Table 5.

Table 4: Discriminant Validity Assessment

Construct pair	√AVE WA	√AVE DWC	Latent correlation	HTMT
WA–DWC	.576	.589	.592	.595

Note. The Fornell–Larcker criterion was marginal because the WA–DWC latent correlation was slightly higher than the √AVE values. The HTMT value remained below .85. Source: SEM output based on survey data.

To further assess construct distinctiveness, the two-factor model was compared with a single-factor model. As reported in Table 5, the two-factor model demonstrated substantially better fit (CFI = 1.000; RMSEA = .000; SRMR = .035) than the single-factor specification (CFI = .825; RMSEA = .066; SRMR = .074). This comparison supported the decision to retain WA and DWC as separate latent constructs. Complete parameter estimates are provided in Table A1 in the Appendix.

Table 5: Model Fit Comparison

Model	χ^2 (df)	p	CFI	TLI	RMSEA	SRMR
One-factor model	584.903 (230)	< .001	.825	.808	.066	.074
Two-factor model	216.713 (229)	.710	1.000	> .999	.000	.035

Note. The two-factor model demonstrated substantially better fit than the one-factor model. TLI values above 1.00 are reported as > .999. Source: SEM output based on survey data.

Structural Model Results

The structural model also fit the data well (χ^2 (295) = 297.728, p = .445; CFI = .999; TLI = .999; RMSEA = .005; SRMR = 0.038). As shown in Table 6, WA was positively associated with DWC (*β = .592, p < .001*). The model explained 35.5% of the variance in DWC. None of the control variables, gender, education level, or years of IT work experience, was a statistically significant predictor. The final structural model with standardised estimates is illustrated in Figure 2.

Table 6: Structural Model Results

Path	B	SE(B)	β	z	p-value
WA → DWC	0.494	0.068	0.592	7.213	< .001
Gender → DWC	0.045	0.063	0.036	0.721	.471
Education → DWC	−0.022	0.078	−0.015	−0.285	.776
Experience → DWC	0.013	0.012	0.051	1.075	.282

Note. B, SE(B), z, and p are based on unstandardized estimates; β is the standardised estimate. Model fit: χ^2 (295) = 297.728, p = .445; CFI = .999; TLI = .999; RMSEA = .005; SRMR = .038. Explained variance: R^2 (DWC) = .355. Source: SEM output based on survey data.

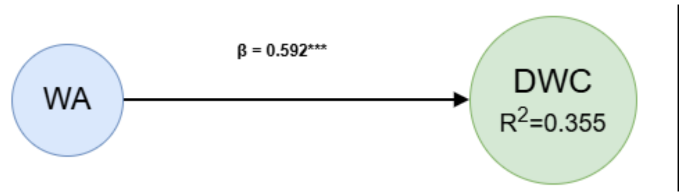

Figure 2: Structural model with standardised estimates

Note. *SEM outputs based on survey data.*

Alternative Model Specification

As a sensitivity check on directional specification, an alternative structural model that reverses the path (DWC → WA) was estimated. The reversed model demonstrated similar global fit indices: χ^2(295) = 298.353, p = .434; CFI = .998; TLI = .998; RMSEA = .006; SRMR = .038. The reversed model explained 35.4% of the variance in workforce agility (R^2 = .354). These findings indicate that, given the cross-sectional design, model fit statistics alone do not differentiate directional specifications. Accordingly, the hypothesised direction is interpreted on theoretical rather than statistical grounds.

Discussion

This study examined whether WA operates as an individual-level antecedent of DWC among Generation Z IT professionals. The findings indicate a positive and statistically significant association between WA and DWC, suggesting that adaptive behavioural capacities are closely linked to employees' ability to enact digital systems in practice.

Digital transformation research has generated substantial knowledge regarding how organisations design digital strategies, develop technological infrastructures, and cultivate firm-level digital capabilities (Basnet, 2025; Piccoli et al., 2022; Plekhanov et al., 2023). These capabilities are predominantly conceptualised as organisational or structural attributes, emphasising platforms, architectures, governance mechanisms, and resource orchestration (Ashrafi et al., 2025). The individual-level behavioural processes through which digital systems are interpreted, adjusted, and enacted in everyday work contexts remain comparatively under-specified (Abhari, 2025; Ashrafi et al., 2025).

By empirically modelling WA as a latent construct and linking it to DWC, this study specifies a behavioural micro-foundation of how such capabilities are enacted in practice. While micro-foundations theory has long argued that higher-order capabilities are grounded in individual-level actions and dispositions (Felin et al., 2015; Teece, 2007), empirical operationalisation at the employee level within digital transformation contexts remains limited (Ashrafi et al., 2025; Iden & Bygstad, 2025). The present findings provide evidence that adaptive behavioural orientations, rather than structural positioning alone, are meaningfully associated with the formation of digital capabilities at the individual level.

This study advances theory in three interrelated ways. First, it extends digital transformation research beyond infrastructural determinism. Whereas prior studies emphasise technological readiness, digital investment, and architectural alignment (Piccoli et al., 2022; Plekhanov et al., 2023), the present findings indicate that behavioural adaptability contributes independently to the enactment of digital capability. This shifts explanatory focus from what systems exist to how individuals mobilise those systems, reinforcing calls to incorporate micro-foundational perspectives into digital transformation research (Ashrafi et al., 2025; Iden & Bygstad, 2025).

Second, the study provides an empirical operationalisation of micro-foundations within a digital work context. Dynamic capability research frequently invokes individual-level processes as enabling mechanisms (Felin et al., 2015; Teece, 2007)yet direct empirical links between behavioural traits and digitally enabled capabilities remain comparatively sparse (Abhari, 2025). By demonstrating that WA accounts for a substantial portion of the variance in DWC, this study provides empirical support for micro-foundational logic within digital transformation scholarship.

Third, the findings refine conceptual distinctions between adaptability and digital competence. Although conceptually adjacent, the two constructs were empirically distinguishable and not reducible to a single factor. This distinction reinforces the idea that digital capability is not synonymous with adaptability; rather, adaptability may function as a precursor enabling digital capability enactment (Petermann & Zacher, 2022).

The focus on Generation Z IT professionals adds contextual nuance. Although Generation Z is frequently characterised as digitally immersed (Benítez-Márquez et al., 2022)digital immersion alone does not guarantee effective digital work capability. The findings suggest that adaptive behavioural orientation differentiates levels of digital capability even within a technologically experienced cohort. This observation refines generational narratives by indicating that behavioural agility, rather than mere exposure to technology, may shape digitally enabled performance among early-career professionals.

Importantly, digital work capability does not appear reducible to tenure or formal educational attainment. The absence of statistically significant demographic effects suggests that adaptive behavioural orientation may play a more central role than structural credentials in shaping how early-career professionals translate digital systems into functional work competence.

Conclusion and Implications

This study examined the relationship between WA and DWC among Generation Z IT professionals in Nepal. The findings indicate that WA is positively and significantly associated with DWC. Taken together, the results suggest that digital work capability is shaped not only by technological conditions but also by employee-level adaptive capacities that support effective engagement with evolving digital systems.

By empirically linking an individual-level adaptive construct to digital work capability, this study extends structural explanations of digital transformation that emphasise organisational-level technological and infrastructural capabilities. The findings suggest that digital capability is not solely an infrastructural or technological phenomenon but is also associated with behavioural capacities that shape how individuals respond to technological change. For future research, this implies that digital transformation studies should examine not only organisational resources but also employee-level behavioural mechanisms through which digital systems are used, adjusted, and sustained in daily work. The findings also support further investigation of WA as a potential micro-foundation of DWC across different occupational, organisational, and national contexts.

The findings carry practical implications for organisations engaged in digital transformation. Technological investments and digital infrastructures are necessary but may be insufficient if employees lack adaptive behavioural orientation. For IT firms, this means that digital capability development should not be limited to technical training.

Managers may also need to strengthen employees' adaptability, proactive problem-solving, resilience, and continuous learning. These capacities can be developed through structured onboarding, project rotations, digital problem-solving tasks, simulation-based training, and exposure to evolving tools and workflows. Such practices may be particularly relevant for Generation Z IT professionals, who may be familiar with digital technologies but still need workplace-based support to translate that familiarity into effective DWC.

Organisations may operationalise this insight through rotational problem-solving assignments, digital simulation-based training environments, and agile work design interventions that expose employees to iterative technological change. Integrating behavioural agility development into digital transformation efforts may help organisations translate digital infrastructure into more effective work outcomes.

The findings also offer cautious social implications for early-career digital workers in emerging IT labour markets. Because the study focused on Generation Z IT professionals in Kathmandu, the results should not be generalised too broadly. However, they suggest that digital employability may depend not only on technical familiarity but also on adaptive work behaviour. This is relevant to employers, training providers, and higher education institutions that prepare young professionals for digital work. Programmes that combine technical skill development with adaptability, learning orientation, and problem-solving under changing digital conditions may better support young workers entering technology-intensive workplaces.

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference and does not allow for the establishment of temporal ordering empirically. Future studies should use longitudinal or time-lagged designs to examine whether WA predicts later changes in DWC. Second, the use of self-reported measures introduces the possibility of common method variance, although diagnostic results suggest that such bias is unlikely to account for the observed relationship. Future research may incorporate supervisor ratings, task-based digital performance indicators, or system-use data to strengthen measurement. Third, the sample was restricted to IT professionals in Kathmandu, which may limit transferability across industries, occupational contexts, and geographic settings. Future studies should test the model across different sectors, regions, and generational cohorts. Finally, additional research could examine the separate effects of agility dimensions, such as adaptability, proactivity, resilience, and learning orientation, to clarify which aspects of workforce agility are most closely associated with digital work capability.

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Conflict of Interest

The author declares that there is no conflict of interest.

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Data Availability Statement

The data supporting the study are available from the corresponding author upon reasonable request and subject to appropriate ethical and confidentiality considerations.

Authors Contributions

Sanjaya Pudasaini: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Writing – Review and Editing, and Project Administration.

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Appendix A

Table A1: *Full Measurement and Structural Model Estimates, Revised Model (N = 350)*

Panel A. Measurement Model

Construct	Item	Std. Loading	SE	z	p
WA	WA1	0.614	—	—	—
	WA2	0.591	0.088	10.281	< .001
	WA3	0.542	0.094	8.970	< .001
	WA4	0.522	0.096	8.395	< .001
	WA5	0.564	0.088	9.562	< .001
	WA6	0.606	0.086	10.250	< .001
	WA7	0.622	0.093	9.677	< .001
	WA8	0.544	0.093	9.275	< .001
	WA9	0.527	0.110	8.291	< .001
	WA10	0.574	0.099	8.307	< .001
	WA11	0.633	0.083	11.910	< .001
	WA12	0.555	0.102	8.621	< .001
DWC	DWC1	0.586	—	—	—
	DWC2	0.586	0.132	9.426	< .001
	DWC3	0.599	0.122	8.768	< .001
	DWC4	0.589	0.118	9.357	< .001
	DWC5	0.596	0.125	9.244	< .001
	DWC6	0.596	0.107	9.626	< .001
	DWC7	0.533	0.121	8.597	< .001
	DWC8	0.580	0.127	8.810	< .001
	DWC9	0.600	0.113	9.611	< .001
	DWC10	0.558	0.129	8.613	< .001
	DWC12	0.646	0.130	9.795	< .001

Note. *Std. Loading refers to standardized factor loading. SE and z are based on the lavaan model estimates. DWC11 was excluded from the revised CFA/SEM because its initial standardized loading was below .50. Source: SEM output based on survey data.*

Panel B. Structural Model

Path	B	SE(B)	β	z	p
WA → DWC	0.494	0.068	0.592	7.213	< .001
Gender → DWC	0.045	0.063	0.036	0.721	.471
Education → DWC	−0.022	0.078	−0.015	−0.285	.776
Years of IT Experience → DWC	0.013	0.012	0.051	1.075	.282

Note. *B, SE(B), z, and p are based on unstandardized estimates; β is the standardized estimate. R^2 (DWC) = 0.355. Source: SEM output based on survey data.*

Table A2: *Measurement Items*

Construct	Code	Item
Workforce Agility	WA1	I can quickly adapt when changes occur in my work.
	WA2	I adjust my work methods in response to new demands.
	WA3	I handle unexpected work situations well.
	WA4	I take initiative to improve my work processes.
	WA5	I actively look for better ways to perform my tasks.
	WA6	I anticipate future work challenges.
	WA7	I remain effective even when facing difficulties at work.
	WA8	I recover quickly after setbacks.
	WA9	I stay positive when confronted with work pressure.
	WA10	I continuously develop my professional skills.
	WA11	I actively seek opportunities to learn new things.
	WA12	I apply newly acquired knowledge in my work.
Digital Work Capability	DWC1	I can always manage to solve difficult computer problems if I try hard enough.
	DWC2	If my computer is “acting up,” I can find a way to get what I want.
	DWC3	It is easy for me to accomplish my computer goals.
	DWC4	I am confident that I could deal efficiently with unexpected computer events.
	DWC5	I can solve most computer problems if I invest the necessary effort.
	DWC6	I can remain calm when facing computer difficulties because I can rely on my abilities.
	DWC7	When I am confronted with a computer problem, I can usually find several solutions.
	DWC8	I can usually handle whatever computer problem comes my way.
	DWC9	Failing to do something on the computer makes me try harder.
	DWC10	I am a self-reliant person when it comes to doing things on a computer.
	DWC12	I can persist and complete most any computer-related task.

Note. *All items were measured using a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Workforce Agility items were adapted from Petermann and Zacher (2022). Digital Work Capability items were adapted from Howard (2014). DWC11 was removed from* *the revised CFA/SEM because its initial standardized loading was below .50. Source: Survey instrument and SEM output based on survey data.*

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