

Assessing the Speed of Human Resource Adaptation in Responding to Generative AI Disruption: A Three-Wave Longitudinal Study of the Academic Community at Universitas Sulawesi Barat

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Abstract—This study measures the speed of human resource (HR) adaptation in responding to generative artificial intelligence (AI) disruption. Using a three-wave longitudinal panel design, the study surveyed 250 members of the academic community at Universitas Sulawesi Barat over twelve months. It drew on dynamic capabilities theory, social cognitive theory, and conservation of resources theory. Adaptation velocity was treated as a dynamic construct, with learning culture as a positive moderator and technostress as a negative moderator. Data were analyzed using Latent Growth Curve Modeling and Structural Equation Modeling. The results show a significant increase in adaptation velocity over time (slope = 0.28, $p < 0.001$), with substantial inter-individual variation. Generative AI exposure positively affected adaptation velocity ($\beta = 0.35$, $p < 0.001$); this effect was strengthened by learning culture ($\beta = 0.18$, $p = 0.010$) and weakened by technostress ($\beta = -0.15$, $p = 0.012$). Adaptation velocity, in turn, positively affected academic performance ($\beta = 0.32$, $p < 0.001$) and mediated the effect of AI exposure on performance ($\beta = 0.11$, $p = 0.006$). These findings indicate that adaptation to AI is not a static event but a dynamic, time-dependent process whose pace is largely determined by organizational support and individuals' capacity to manage technological stress. The study contributes a temporal dimension to dynamic capabilities theory and offers practical guidance for managing AI adoption in higher education.

Keywords: Adaptation Velocity; Generative AI; Learning Culture; Technostress; Longitudinal Study; Academic Performance.

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1. Introduction

The emergence of generative artificial intelligence (AI) has transformed many aspects of how people work. It does not merely automate routine tasks but also reshapes the way humans make decisions, communicate, and manage talent. In higher education, these changes create new demands that are not easily met because change occurs rapidly while educational institutions, with all their complexity, often move more slowly. The Indonesian government has responded seriously to this transformation: the President has directed that AI use be incorporated into higher education curricula at the national level, and the Ministry of Higher Education, Science, and Technology (Kemdiktisaintek) has encouraged universities to strengthen AI adoption while cautioning that AI must be understood critically so as not to diminish students' analytical abilities. Through initiatives such as the Indonesia AI Day for

Higher Education 2025, the ministry has affirmed its commitment to building an innovative and competitive higher education ecosystem.

This national agenda, however, faces real obstacles at the implementation level, particularly in Eastern Indonesia. Data from the Indonesian Internet Service Providers Association (APJII) for 2025 indicate that internet penetration on Sulawesi Island has reached only 71.64 percent, far below that of Java. As of September 2025, there were still 294 public-facility points in West Sulawesi—including village offices, schools, and community health centers (puskesmas)—without internet coverage, while the provincial government recorded approximately 279 weak-signal points at public-service facilities across six regencies as of May 2025. These conditions make the question of digital readiness especially urgent for higher education institutions operating in such regions.

In this context, Universitas Sulawesi Barat (Unsulbar) envisions achieving excellence in the culture-based development of human resources, science, and technology by 2040. The university currently comprises nine faculties and admitted 3,720 new students in 2025, 95% of whom are from West Sulawesi. The central question this study addresses is whether the human resources at Unsulbar can adapt faster than technological change itself—an issue that bears directly on organizational survival amid disruption. Existing research on HR adaptation to AI in Indonesia, however, remains dominated by cross-sectional approaches that are static, largely concentrated in Java, and inattentive to the temporal dimension; such studies tend to emphasize perceptions of and intentions to use AI rather than the speed of actual competency change over time.

Accordingly, this study aims to measure the adaptation velocity of Unsulbar's human resources as a dynamic construct, using a three-wave longitudinal design. Specifically, it seeks to identify the trajectory of change in adaptation velocity over time, to examine how Generative AI exposure, learning culture, and technostress shape that velocity, and to determine whether adaptation velocity translates into improved academic performance. By doing so, the study offers an empirically grounded account of HR adaptation in a region characterized by a high digital divide.

2. Literature Review and Problem Statement

Static resources no longer determine competitive advantage; rather, an organization's ability to reconfigure its competencies in response to environmental change has become continuously decisive [1], [2]. Dynamic capabilities theory, first articulated by Teece, Pisano, and Shuen, explains how organizations achieve competitive advantage through this reconfiguration capacity. Subsequent work has shown that dynamic capabilities consist of identifiable and developable microfoundations [3], traced the developmental path of the theory in explaining differentiated firm performance [2], and clarified its scope conditions, finding that the theory has the greatest explanatory power when technological change is on the verge of transforming the basis of market competition [4]. Generative AI represents precisely such a transformative force, making dynamic capabilities a fitting lens for studying HR adaptation.

Complementing this organizational lens, social cognitive theory—developed by Bandura—explains how individuals learn through observation, imitation, and modeling, with self-efficacy serving as a key driver of the process [5], [6]. This theory has been applied directly to human resource management [7] and has been comprehensively reviewed in the management literature [8], underscoring the role of the social environment in shaping

learning. Conservation of resources theory, proposed by Hobfoll, offers a third perspective: individuals strive to protect the resources they possess and experience stress when those resources are threatened or lost [9], [10]. Resource conservation has been shown to underpin resilience [11] and to operate under conditions of acute disruption such as the COVID-19 pandemic [12]. Together, these theories suggest that exposure to AI creates pressure to reconfigure competencies, that a supportive learning environment accelerates this process, and that technological stress depletes the resources adaptation requires.

Despite this theoretical richness, a clear gap persists. Prior Indonesian studies have rarely treated adaptation as a dynamic, time-dependent construct, and almost none have examined the academic communities of regional universities facing infrastructural constraints. To address this gap, the present study develops a conceptual model comprising 10 hypotheses. Exposure to generative AI is hypothesized to affect adaptation velocity (H1) positively. Learning culture is expected to affect adaptation velocity (H2) positively and to moderate the effect of AI exposure (H3). Technostress is expected to affect adaptation velocity (H4) negatively and to moderate the effect of AI exposure (H5). Adaptation velocity is hypothesized to affect academic performance (H6) positively and to mediate the effect of AI exposure on performance (H7). Finally, adaptation velocity is expected to increase over time (H8), with inter-individual variation (H9) predicted by learning culture and technostress (H10).

3. Method

This study employs a quantitative approach with a three-wave longitudinal panel design. The quantitative approach was chosen because the study aims to measure variables numerically and to test statistical relationships among them. At the same time, the longitudinal design was selected because adaptation velocity is a dynamic construct that can be captured only by observing change over time. The study was conducted at Universitas Sulawesi Barat in Majene Regency, West Sulawesi—a state university in a region with a pronounced digital divide—and was guided by a 2040 human resource development vision, for which no comparable research had previously been undertaken. Three waves of measurement were carried out at month 0 (baseline), month 6, and month 12; the six-month interval was chosen because it is sufficient to detect meaningful change in digital competency, reduces the risk of attrition relative to longer intervals, and aligns with the academic cycle.

The target population comprised the entire academic community of Unsulbar, consisting of permanent lecturers and civil-servant (ASN) educational support staff distributed across nine faculties. Respondents were required to be permanent lecturers or ASN support staff with at least one year of service who were willing to participate in all three waves; non-permanent lecturers, non-ASN staff, and those on extended leave or study assignment outside Unsulbar were excluded. The sample size was determined through a power analysis for Structural Equation Modeling (SEM), assuming a medium effect size ($f^2 = 0.15$), power of 0.80, $\alpha = 0.05$, and approximately 50 estimated parameters, which yielded a minimum of 200 respondents. To anticipate attrition, the target was set at 250 respondents, selected through proportionate stratified random sampling based on faculty and unit.

The main instrument was a structured questionnaire of 58 items distributed both online and offline, comprising demographic data (6 items); a Generative AI exposure scale adapted from the TAM/UTAUT (8 items); a learning culture scale adapted from Watkins and

Marsick [13] (10 items); an adaptation velocity (digital competency) scale developed specifically for this study (12 items); a technostress scale adapted from Tarafdar et al. [14] (12 items); and an academic performance scale adapted from Motowidlo and Schmit [15] (10 items). Three experts assessed content validity; construct validity was tested using Confirmatory Factor Analysis (CFA) on pilot data ($n = 50$); reliability was assessed using Cronbach's alpha (target > 0.70); and stability was assessed using a two-week test-retest ($n = 30$).

Data collection proceeded in four stages: a pilot study at month 0 ($n = 50$); Wave 1 (T1) at month 0, in which all variables were measured and digital trace data were collected; Wave 2 (T2) at month 6, in which all variables were re-measured; and Wave 3 (T3) at month 12, comprising final measurement and brief elaboration interviews. Online questionnaires (Google Forms) were used for respondents with internet access and printed questionnaires for those with limited access, with digital trace data serving as complementary objective evidence. Analysis combined descriptive statistics, CFA and Cronbach's alpha for validity and reliability, Latent Growth Curve Modeling (LGCM) in Mplus to estimate the change trajectory of adaptation velocity, and SEM in Mplus for hypothesis testing, with moderation modeled through interaction effects, mediation tested via bootstrapping, and attrition and missing data handled using Full Information Maximum Likelihood (FIML). The emphasis on longitudinal observation follows the argument that understanding the conditions under which dynamic capabilities operate requires repeated measurement over time [4].

4. Results and Discussion

Of the 250 respondents, 230 (92 percent) participated in Wave 1, 213 (85 percent) in Wave 2, and 195 (78 percent) in Wave 3, yielding an attrition rate of 15 percent from Wave 1 to Wave 3—within an acceptable range for longitudinal research. In Wave 1, 58 percent of respondents were male and 42 percent female; 72 percent held a Master's degree (S2), 18 percent a Doctoral degree (S3), and 10 percent a Bachelor's degree (S1). The average length of service was 8.5 years (range: 1–25 years), and respondents were drawn from nine faculties, four technical implementation units (UPA), and two quality-assurance units, in proportions corresponding to their respective populations.

Table 1. Descriptive Statistics and Reliability of the Research Variables (Wave 1)

Variable	Mean	SD	Cronbach's Alpha
Generative AI Exposure	3.12	0.89	0.84
Learning Culture	3.45	0.78	0.87
Technostress	3.28	0.92	0.82
Adaptation Velocity (initial)	3.05	0.81	0.86
Academic Performance (initial)	3.38	0.74	0.85

Source: Primary data, processed (2026).

As shown in Table 1, Generative AI exposure was at a moderate level (3.12), indicating that the academic community had begun—but not yet intensively—using AI tools, while learning culture was fairly high (3.45), reflecting perceived organizational support for continuous learning. Technostress was moderate (3.28), initial adaptation velocity was moderate (3.05), and initial academic performance was fairly high (3.38). All Cronbach's alpha values exceeded 0.80, indicating very good reliability. CFA on the Wave 1 data confirmed a good measurement-model fit ($\chi^2/df = 2.14$, CFI = 0.95, TLI = 0.94, RMSEA = 0.06, SRMR = 0.05),

with all factor loadings above 0.50 and significant at $p < 0.001$, and discriminant validity supported by $\sqrt{\text{AVE}}$ values exceeding the inter-construct correlations.

Table 2. Latent Growth Curve Modeling Results for Adaptation Velocity

Parameter	Estimate	SE	z	p
Intercept (initial value)	3.05	0.12	25.42	<0.001
Slope (rate of change)	0.28	0.08	3.50	<0.001
Intercept variance	0.45	0.10	4.50	<0.001
Slope variance	0.18	0.07	2.57	0.010
Intercept–slope covariance	−0.08	0.04	−2.00	0.046

Source: Primary data, processed (2026).

The LGCM results (Table 2) reveal a mean initial adaptation velocity of 3.05 ($p < 0.001$) and a significant mean rate of change of 0.28 per wave ($p < 0.001$), implying a total increase of approximately 0.56 points on a 1–5 scale from Wave 1 to Wave 3. Both the intercept variance (0.45, $p < 0.001$) and slope variance (0.18, $p = 0.010$) were significant, indicating inter-individual variation in starting points and rates of change. The negative intercept–slope covariance (−0.08, $p = 0.046$) points to a ceiling effect: individuals with higher initial velocity tended to improve more slowly. These results support H8 and H9.

Table 3. Hypothesis Testing Results

Hyp.	Path	Estimate	SE	z	p	Result
H1	AI Exposure → Adaptation Velocity	0.35	0.08	4.38	<0.001	Supported
H2	Learning Culture → Adaptation Velocity	0.28	0.09	3.11	0.002	Supported
H3	AI Exposure × Learning Culture	0.18	0.07	2.57	0.010	Supported
H4	Technostress → Adaptation Velocity	−0.22	0.08	−2.75	0.006	Supported
H5	AI Exposure × Technostress	−0.15	0.06	−2.50	0.012	Supported
H6	Adaptation Velocity → Academic Performance	0.32	0.07	4.57	<0.001	Supported
H7	AI Exposure → Adapt. Velocity → Performance	0.11	0.04	2.75	0.006	Supported

Source: Primary data, processed (2026).

The structural model showed a good fit ($\chi^2/\text{df} = 2.32$, CFI = 0.94, TLI = 0.93, RMSEA = 0.07, SRMR = 0.06), and all seven path hypotheses were supported (Table 3). Generative AI exposure had a positive and significant effect on adaptation velocity ($\beta = 0.35$, $p < 0.001$), supporting H1: the more frequently and intensively respondents used AI tools, the faster they reconfigured their digital competencies. This confirms the central premise of dynamic capabilities theory that exposure to environmental change creates the need to reconfigure competencies [1], [2].

Learning culture also positively affected adaptation velocity ($\beta = 0.28$, $p = 0.002$, H2) and strengthened the effect of AI exposure ($\beta = 0.18$, $p = 0.010$, H3), functioning as a catalyst that accelerates adaptation. This aligns with social cognitive theory [7], [8]: when individuals observe colleagues using AI, learn from them, and receive supervisor support, adaptation proceeds more quickly—consistent with the view that dynamic capabilities involve learning and transformation activities strongly shaped by the social environment [16]. Technostress, by contrast, negatively affected adaptation velocity ($\beta = -0.22$, $p = 0.006$, H4) and weakened the effect of AI exposure ($\beta = -0.15$, $p = 0.012$, H5). These findings confirm conservation of resources theory [9], [10]: stress arising from technological demands depletes the cognitive

and emotional resources that adaptation requires, so that high exposure accompanied by high stress yields diminished benefit.

Finally, adaptation velocity positively affected academic performance ($\beta = 0.32$, $p < 0.001$, H6) and mediated the effect of AI exposure on performance ($\beta = 0.11$, $p = 0.006$, H7). This indirect effect indicates that AI exposure improves performance not directly but through prior gains in adaptation velocity, affirming that adaptation is a means rather than an end. Supplementary analyses reinforce this picture: adaptation velocity differed significantly across faculties ($F(8, 186) = 2.85$, $p = 0.005$), with Engineering and Mathematics and Natural Sciences highest and Agriculture and Teacher Training and Education lowest; doctoral-degree holders adapted faster than those with Master's or Bachelor's degrees ($F(2, 192) = 4.12$, $p = 0.018$); and length of service correlated negatively with adaptation velocity ($r = -0.28$, $p < 0.001$).

Taken together, these results offer a nuanced picture of HR readiness in a high-digital-divide region. The moderate initial velocity (3.05) suggests that the academic community is not yet fully prepared for AI disruption—understandable given that internet penetration in Sulawesi stood at only 71.64 percent and hundreds of public facilities remained uncovered—yet the significant upward trajectory signals genuine adaptive capacity, plausibly reflecting national AI-adoption policy and local connectivity initiatives. The negative association between tenure and adaptation velocity is consistent with the resource perspective: senior staff may face higher technostress because they must adjust to technologies far removed from those they learned early in their careers. This study has several limitations. Its generalizability is limited to a single-institution context; attrition (15 percent) may affect representativeness; all measures were self-reported and thus potentially subject to common method bias; and the 12-month window may not capture longer-term trajectories.

5. Conclusion

This study measured the adaptation velocity of the academic community at Universitas Sulawesi Barat in responding to Generative AI disruption using a three-wave longitudinal design. Adaptation velocity was moderate at baseline (3.05) but increased significantly over time (slope = 0.28 per wave). Generative AI exposure positively affected adaptation velocity ($\beta = 0.35$); this effect was strengthened by learning culture ($\beta = 0.18$) and weakened by technostress ($\beta = -0.15$). Adaptation velocity, in turn, positively affected academic performance ($\beta = 0.32$) and mediated the effect of AI exposure on performance ($\beta = 0.11$). Theoretically, the study introduces and validates the construct of adaptation velocity, enriching dynamic capabilities theory with an explicit temporal dimension. In practice, it indicates that universities should strengthen their learning culture, manage technostress, and design measurable intervention programs to accelerate adaptation. At the same time, national policymakers should align AI adoption mandates with regional infrastructure readiness and HR capacity. The study's limitations—single-institution scope, attrition, reliance on self-reports, and a 12-month horizon—point to clear directions for future work, including comparative studies across Eastern and Western Indonesian universities, qualitative inquiry into the subjective experience of adaptation, intervention trials, and multilevel designs integrating organizational and individual factors.

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