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Achievement Motivation as the Critical Mediator Linking Digital Self-Efficacy and Change Readiness to Administrative Performance in Universities

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Abstract

Amid Indonesia's ambitious Smart Campus reforms, the performance of non-academic administrative staff—despite their pivotal role in data governance, system integration, and compliance—remains empirically underexplored, particularly in relation to psychological antecedents. Drawing upon Social Cognitive Theory and model of organizational readiness, this study investigates a sequential mediation pathway wherein digital self-efficacy and readiness to change influence job performance through the intervening mechanism of achievement motivation. Utilizing a cross-sectional design, data were collected from 267 administrative personnel across private universities in Java and Bali. Structural equation modeling via PLS-SEM confirmed all hypothesized paths: self-efficacy ($\beta = 0.476$, $p < 0.001$) and readiness to change ($\beta = 0.409$, $p < 0.001$) significantly predict achievement motivation, which in turn exerts a robust direct effect on performance ($\beta = 0.624$, $p < 0.001$). Critically, no direct paths from the antecedents to performance were significant, affirming full mediation—a finding that underscores motivation not as a peripheral correlate, but as the necessary conduit translating cognitive readiness into behavioral output. The model explains 66.9% of the variance in motivation and 38.9% in performance, with predictive relevance ($Q^2 > 0$) and strong effect sizes ($f^2 \geq 0.252$), attesting to both statistical and practical significance. These results challenge infrastructure-centric narratives of digital reform, redirecting policy attention toward the cultivation of internal motivational resources as the linchpin of sustainable transformation.

JEL classification numbers: I23, M12, M54, O35.
Keywords: Digital self-efficacy, Motivation, Readiness to change, Job performance.

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1. Introduction

The accelerating digitization of educational ecosystems, particularly in developing nations, has precipitated profound structural and behavioral shifts within academic institutions. Across Indonesia, the nationwide rollout of Kurikulum Merdeka and its operational backbone, the Platform Merdeka Mengajar, represents one of the most ambitious educational reforms of the past decade (Rohiyatussakinah, 2021). While curricular and pedagogical innovations have garnered scholarly attention, a critical yet persistently overlooked dimension lies in the administrative layer of educational staff who constitute the operational nervous system of higher education institutions. These personnel manage data flows, synchronize academic and financial reporting systems, and ensure compliance with evolving regulatory frameworks. However, as digital transformation intensifies, mandating real-time reporting, AI-assisted analytics, and integrated service dashboards, administrative staff increasingly face cognitive overload, skill obsolescence, and motivational erosion (Jin, 2022; Pratama et al., 2024). Field observations in multiple Indonesian private universities reveal a troubling paradox: while institutional smart campus maturity targets are ambitious, frontline administrative performance remains inconsistent, with delays in data submission, recurrent system errors, and low adoption of digital workflows (Hassanain et al., 2022). This dissonance signals a deeper misalignment—not of technology, but of human readiness.

The extant literature confirms that technology implementation alone rarely guarantees organizational performance gains; rather, success hinges on the interplay between individual psychological resources and the change context (Simatupang et al., 2022; Stewart & Jürjens, 2017). In this regard, self-efficacy—defined as an individual's belief in their capability to organize and execute courses of action required to manage prospective situations (Finkelhor et al., 2020)—has been robustly linked to adaptive behavior in digital transitions. For instance, Bećirović et al. (2023) demonstrated that digital self-efficacy significantly predicts job performance among public servants, primarily through its energizing effect on achievement motivation. Similarly, readiness to change, conceptualized as a multidimensional cognitive–affective–behavioral predisposition to enact change(Culliford & Bradbury, 2020; Hall et al., 2024), functions as a critical antecedent to successful technology assimilation (Dias et al., 2022). Nevertheless, most studies focus on academic personnel (e.g., lecturers, researchers) or managerial actors, neglecting administrative staff whose work is both highly procedural and increasingly technologically mediated (Ilham & Siregar, 2021; Mulyati et al., 2023). This constitutes a salient research gap: we lack an empirically grounded understanding of how psychological antecedents, particularly self-efficacy and readiness to change, translate into performance outcomes among non-academic university staff in low-resource, high-pressure change environments.

Compounding this gap is the underexplored mediating mechanism through which these antecedents operate. While the direct effects of self-efficacy and readiness to change on performance are reasonably documented (Seet et al., 2020), their indirect pathways remain theoretically fragmented. Drawing on Social Cognitive Theory (Lin et al., 2018) and Achievement Motivation Theory (Cai et al., 2022), we posit that achievement motivation—a dispositional drive to excel, assume responsibility, and seek performance feedback (Fredricks et al., 2004)—functions as the proximal psychological conduit. That is, individuals high in self-efficacy and change readiness do not merely perform better despite disruption; they actively leverage disruption as a platform for mastery and recognition, thereby activating achievement-oriented cognition and behavior. Empirical support for this mediating logic is growing but remains scarce in public-sector educational settings. For example, Basit et al. (2024) and Cai et al. (2022) found that readiness to change predicts performance through motivation in Pakistani HEIs, while Bang and Reio Jr (2017) identified motivation to transfer as a mediator between self-efficacy and job performance in Thai enterprises. Yet no known study has integrated all four constructs—self-efficacy, readiness to change, achievement motivation, and performance—within the administrative stratum of Southeast Asian universities, where institutional capacity, training infrastructure, and reward systems differ markedly from those in Western contexts.

This study thus aims to address this lacuna by investigating the causal chain linking self-efficacy and readiness to change to work performance, with achievement motivation as an intervening mechanism, among administrative staff in Indonesian public universities undergoing smart campus transformation. Specifically, it seeks to contribute in three dimensions: theoretically, by testing and extending the applicability of Social Cognitive Theory model of organizational readiness within a Global South administrative context; methodologically, by deploying path analysis to disentangle direct and indirect effects in a non-Western, private-sector ICT adoption setting; and practically, by generating evidence-based insights for policymakers on how to design human-centered digital upskilling strategies—beyond infrastructure investment—that sustain performance during reform turbulence.

Accordingly, the following research questions guide this inquiry: To what extent does digital self-efficacy and readiness to change influence the performance among educational staff through motivation among administrative staff in Indonesian private universities? While digital infrastructure may be the skeleton of educational reform, it is human confidence, adaptability, and drive that animate it. This study endeavors to illuminate precisely how those vital forces interact—and how they may be deliberately cultivated—within the critical, yet often invisible, administrative workforce powering Indonesia's higher education transformation.

2. Literature Review

The interplay between individual psychological resources and organizational outcomes has long occupied a central place in organizational behavior and human resource management scholarship. In contexts marked by rapid technological advancement and structural flux—particularly within private service and educational institutions—the capacity for adaptive performance hinges less on formal authority or procedural compliance, and more on the internal orientations individuals bring to change: their belief in capability, disposition toward transition, and drive for mastery. Grounded in Social Cognitive Theory (Lin et al., 2018; Riaz et al., 2018), motivational psychology (Sackett et al., 2017), and contemporary models of change readiness (Hall et al., 2024; Nouraldeen, 2022), the proposed research framework positions self-efficacy and readiness to change as foundational antecedents, achievement motivation as the proximal energizing mechanism, and performance as the behavioral culmination of this sequential process. What distinguishes this configuration—especially for administrative personnel in digitalizing educational ecosystems—is not merely the presence of these constructs, but the causal ordering through which they operate.

2.1 Self-Efficacy and Achievement Motivation

Self-efficacy, defined as the belief in one's capacity to organize and execute courses of action required to manage prospective situations (Yuan et al., 2022), functions as a cognitive anchor in uncertain environments. Unlike generalized self-confidence, self-efficacy is task- and domain-specific (Richards et al., 2021), making it especially relevant in ICT-mediated work settings, where perceived competence in navigating new systems directly shapes behavioral choices, persistence, and emotional responses. Bandura (1997) operationalizes this construct through three dimensions—magnitude (task difficulty), strength (resilience of belief), and generality (transferability across contexts). This aligns with broader empirical evidence by Yener et al. (2020), in a multi-country study of civil servants, demonstrate that digital self-efficacy—a subdimension particularly salient in smart campus transitions—predicts proactive learning and initiative-taking, behaviors tightly coupled with achievement striving.

The motivational consequence of high self-efficacy is not automatic compliance, but selective challenge-seeking. Individuals with robust self-efficacy appraise demanding tasks not as threats but as opportunities for demonstrating competence (Bandura, 1997). They set higher personal goals, interpret setbacks as informative rather than as diagnostic of inadequacy, and sustain effort when others disengage (Cheng & Liu, 2018). Crucially, this goal-directed persistence is not instrumental alone; it is intrinsically rewarding when aligned with standards of excellence—precisely the core of achievement motivation. Trautner & Schwinger (2020) show that self-efficacy beliefs specifically concerning motivation regulation (e.g., "I can re-energize myself when demotivated") significantly predict sustained achievement striving, even when controlling for baseline motivation. Similarly, Na-Nan &

Sanamthong (2019) confirm, in a Thai organizational context, that self-efficacy exerts both direct and indirect effects (via motivation to transfer learning) on performance, underscoring its role as a motivational catalyst rather than a mere skill proxy.

In administrative academic work—where tasks increasingly require data literacy, system integration, and real-time reporting—self-efficacy in digital tool mastery likely serves as a prerequisite for framing routine duties (e.g., data entry, report generation) as platforms for optimization and innovation, rather than mere compliance. The cognitive appraisal "I can master this system" precedes the motivational stance "I want to excel in using it." This sequential linkage is empirically supported: Cherian & Jacob (2013) meta-analysis of 42 studies affirms a robust, positive association between self-efficacy and achievement-oriented motivation across occupational settings, with effect sizes strengthening in knowledge-intensive domains.

H_1: Self-efficacy is positively associated with achievement motivation among administrative staff in Indonesian higher education institutions undergoing digital transformation

2.2 Readiness to Change and Achievement Motivation

Readiness to change transcends passive acceptance; it denotes a multidimensional predisposition—cognitive, affective, and intentional—to enact and sustain organizational change (Holt et al., 2007). As conceptualized by Culliford & Bradbury (2020) and Hall et al. (2024), readiness encompasses anticipation, resilience, positive appraisal, awareness, comprehension of impact, personal preparedness, and a strategic orientation toward transformation. Critically, it is not a static trait but a dynamic state shaped by the perceived appropriateness of change, management support, change-specific efficacy, and personal valence (Holt et al., 2007)—factors that are acutely salient in top-down digital reform initiatives, where frontline staff may perceive misalignment between institutional ambition and operational reality.

The motivational force of change readiness emerges when individuals reframe disruption not as an imposition but as an affordance. This context enables growth, relevance, and contribution. Ligarski et al. (2021) argue that readiness functions as a "motivational gateway": when employees perceive change as legitimate, supported, and personally beneficial, intrinsic motivation is mobilized to invest cognitive and emotional resources in adaptation. This view is corroborated by Qureshi et al. (2018), who, in a study of Pakistani higher education institutions, find that organizational commitment and perceived fairness of change processes jointly enhance readiness, which, in turn, fuels active participation in reform implementation. Lau et al. (2023) extend this by showing that readiness predicts not only compliance, but initiative—voluntary behaviors beyond role prescriptions—precisely the hallmark of high achievement motivation.

In the Indonesian context, where administrative staff often operate with legacy workflows and limited technical training (Priyanto et al., 2025), readiness may be particularly sensitive to valence—the perceived personal gain from change. When innovative campus systems are introduced as tools to reduce manual burden and elevate professional stature (e.g., shifting from data clerks to data interpreters), readiness aligns with achievement needs: the desire for responsibility, feedback, and measurable impact (Aftab, 2022). Prianto et al. (2017) empirically validate this in Indonesian certified teachers, showing that readiness, when mediated by motivation, significantly predicts performance—suggesting that willingness to change must be converted into motivational energy to yield behavioral outcomes. Therefore,

H_2: Readiness to change is positively associated with achievement motivation among administrative staff in Indonesian higher education institutions undergoing digital transformation.

2.3 Achievement Motivation and Job Performance

Achievement motivation—the dispositional drive to excel, assume responsibility, seek feedback, and accomplish challenging goals (Khasbani & Hidayat, 2020; Sackett et al., 2017; Wangi et al., 2021)—represents the behavioral engine that translates psychological readiness into observable output. Unlike extrinsic incentives, which may produce short-term compliance, achievement motivation sustains effort through internalized standards of excellence and mastery satisfaction (Ryan & Deci, 2000). In Erol & Kurt (2017) framework, achievement motivation manifests in preferences for moderately complex tasks, personal accountability, feedback-seeking, innovativeness, and resilience—indicators that map directly onto the demands of modern administrative roles: troubleshooting system errors, optimizing reporting workflows, and co-designing digital service improvements.

The performance link is well-established, Hanandeh et al. (2024) and Parida et al. (2023) consistently report strong, positive associations between achievement motivation and job performance across public and private sectors. Nehra (2023) further demonstrates that this relationship is amplified in creative and adaptive performance domains—precisely the competencies needed when legacy administrative tasks are reconfigured by AI-driven analytics or real-time dashboards. Critically, the mechanism is behavioral: high-achievement-motivated individuals do not wait for instructions; they diagnose bottlenecks, prototype solutions, and persist through trial cycles—a pattern observed in high-performing administrative units in Nigeria universities (Atunde et al., 2020).

In private higher education, where performance metrics often lag behind operational complexity, achievement-motivated staff self-generate standards—e.g., reducing data reconciliation time by 20%, automating a recurring manual report, or achieving zero-error submission cycles. These micro-innovations cumulatively drive institutional agility, making achievement motivation not just a correlate, but a driver of performance in digitally transitioning environments. Therefore,

H_3: Achievement motivation is positively associated with job performance among administrative staff in Indonesian higher education institutions undergoing digital transformation.

2.4 The Mediating Role of Achievement Motivation

While direct paths from self-efficacy and readiness to change to performance are plausible, the inclusion of achievement motivation as an intervening variable sharpens theoretical precision. Social Cognitive Theory posits that self-beliefs influence action by shaping goal setting, effort allocation, and resilience (Bandura, 1997)—all components of achievement motivation. Dindar et al. (2021) provides direct empirical support: in her path analysis, self-efficacy and readiness to change significantly predict achievement motivation, which in turn strongly predicts performance; the indirect effects respectively, are substantial, confirming mediation. This aligns with broader trends: Yan et al. (2022) find that occupational self-efficacy enhances performance through intrinsic motivation; (Dieris-Hirche et al. (2021) show that training improves performance via readiness to change and subsequent motivational activation. The pattern suggests a motivational funnel: broad psychological resources (self-efficacy, readiness) channel into a domain-general drive (achievement motivation), which then directs energy toward task-specific outcomes.

Theoretically, this structure avoids conflation: self-efficacy answers "Can I do it?", readiness answers "Do I want to engage with this change?", and achievement motivation answers "Do I strive to excel in it?"—a logical progression consistent with expectancy-value models of motivation Zhang et al. (2025). In administrative work, where digital tools are often imposed without co-creation, the quality of engagement—mediated by achievement motivation—may matter more than mere adoption. Therefore,

H_4a: Achievement motivation mediates the positive relationship between self-efficacy and job performance.

H_4b: Achievement motivation mediates the positive relationship between readiness to change and job performance.

Based on the previous literature review, this study proposes a conceptual framework (see Figure 1) to explain how self-efficacy and readiness to change influence the performance among educational staff through motivation.

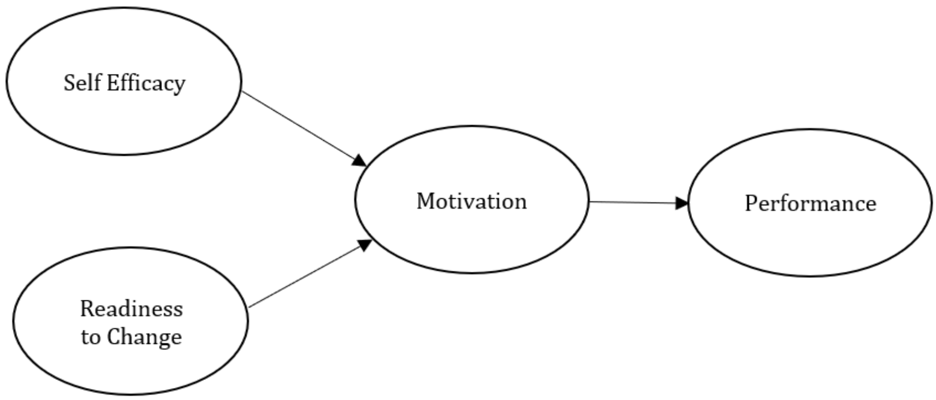

Figure 1: Conceptual Framework

3. Methods

3.1 Research design

The study follows a cross-sectional, ex post facto correlational design, wherein naturally occurring variations in psychological states (self-efficacy, readiness to change) are observed without experimental manipulation. While causal inference remains probabilistic in such designs, the use of a theoretically grounded a priori path model—derived from Social Cognitive Theory (Bandura, 1997), Knight et al. (2017) model of organizational readiness, and Achievement Motivation Theory (Cai et al., 2022). This research using SEM-PLS for enhanced construct validity and statistical power in estimating indirect effects (Hair et al., 2019). The hypothesized model comprises four latent variables: two exogenous (digital self-efficacy and readiness to change), one mediating (achievement motivation), and one endogenous (job performance). Both paper and online questionnaires were distributed, and confidentiality was ensured. A total of 267 valid responses were collected, comprising workers from middle Java (28%), east Java (31%), Bali (18%), and west Java (23%).

3.2 Data collected and participant

The target population consists of non-academic administrative staff employed at private universities in Indonesia, specifically those assigned to operational units that manage digital systems such as the Academic Information System and Integrated Academic and Financial Reporting. Given the contextual specificity of Smart Campus implementation, a purposive stratified sampling strategy was employed to ensure representation across: (1) institutional size (large vs. medium private universities), (2) regional digital infrastructure maturity (e.g., Java vs. non-Java), and (3) functional roles (e.g., academic administration, finance, HR, IT support). This aligns with best practices for ensuring population heterogeneity and external validity in administrative behavior research (Priyanto et al., 2025; Wangi et al., 2021).

A total of 267 valid responses were collected over eight weeks (March–April 2025), exceeding the recommended minimum of 10 times the largest number of structural paths (Hair et al., 2019), and satisfying the requirement of N > 50 + 8k, where k = number of indicators (k = 25; thus N > 250 is ideal, though 200+ is acceptable for stable estimates in PLS-SEM with medium effect sizes (Hair et al., 2021). We designed a closed-ended questionnaire organised into four sections: a brief survey introduction, a screening question, primary measurement questions, and demographic inquiries. This questionnaire format was deemed suitable for our research as it eliminated the need for extensive qualitative coding (Westland, 2014). We implemented specific protocols within the questionnaire to mitigate potential common method bias (CMB) and non-response bias. To control for CMB, we ensured the questionnaire's brevity, placed demographic questions at the end, allowed respondents to answer anonymously, used diverse scale types, and conducted a pilot test (Podsakoff et al., 2003; Reio, 2010). Additionally, to address non-response bias, we adhered to Lynn's recommendations (2008), including providing a brief survey introduction and constructing a respondent-friendly questionnaire with understandable and non-offensive questions, which facilitated easy responses from participants.

3.3 Data analysis

To empirically examine the sequential mediation model, all constructs were measured using theoretically grounded, contextually adapted scales: Digital Self-Efficacy (6 items from Bećirović et al. 2023), modified to reflect confidence in managing Indonesian HEIs' digital systems), Readiness to Change (7 items adapted from Holt et al. 2007, contextualized to Smart Campus implementation), Achievement Motivation (6 items based on McClelland's behavioral indicators as operationalized by Na-Nan & Sanamthong 2019, capturing preference for challenge, responsibility, feedback, and innovation), and Job Performance (6 supervisor-rated items from Zen & Ariani (2022), assessing digital-era competencies: data accuracy, reporting timeliness, system utilization, initiative in process improvement, cross-unit collaboration, and error accountability). All items employed a 6-point Likert scale (1 = strongly disagree to 5 = strongly agree), with supervisor assessments using comparable intensity anchors (1 = very low to 5 = very high). Instruments underwent iterative refinement and pilot testing; final measurement models demonstrated strong internal consistency (Cronbach's $\alpha > 0.8$, composite reliability > 0.9) and robust validity (AVE > 0.614, Fornell–Larcker criterion and HTMT < 0.8). Data from 267 administrative staff across private universities in Java and Bali were analyzed using PLS-SEM in SmartPLS 4.0, following Hair et al. (2021) two-stage protocol—first confirming measurement model quality, then estimating structural paths, indirect effects (via 5,000 bootstrap resamples), predictive relevance ($Q^2 > 0$), and effect sizes (f^2). Demographic controls (gender, age, education, tenure, functional unit) were included to mitigate confounding.

4. Results and Analysis

4.1 Respondent Characteristics

Among 267 respondents, 52% were male and 48% female. The age distribution was as follows: 34% aged 35–44, 46% aged 45–54, and 20% aged 25-34. Over 70% had more than five years of work experience, and most had a high school education or higher.

4.2 Measurement and analysis

We evaluated the measurement model for this study, following the guidelines proposed by Hair et al. (2021), which included assessments of reliability and validity. As shown in Table 1, both indicator reliability (loading) met the minimum required threshold of 0.70, indicating a highly reliable measurement model. The internal consistency includes composite reliability (rho_c), Cronbach's alpha (α), and reliability coefficient (rho_a), all of which are above 0.7. Our assessment confirms that these statistics exceed 0.7. Regarding the validity assessment, each latent variable's convergent validity, represented by average variance extracted (AVE) scores, exceeded the minimum threshold of 0.50. Additionally, discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT) and the Fornell-Lacker method, as presented in Table 2. HTMT values were lower than the more liberal threshold of 0.90 (Henseler et al., 2015), signifying a highly valid measurement model. The Fornell-Larcker criterion confirms this by showing that each construct's AVE square root (diagonal values) is higher than the correlations with other constructs, reaffirming adequate discriminant validity (Hair et al., 2019). This combination of HTMT and Fornell-Larcker criteria strengthens the construct validity within this model.

Table 1: Factor Loading, Reliability, and Convergent Validity Estimates

Construct	Item	loading	CR (rho_c)	CR (rho_a)	AVE	CA
Self Efficacy	SE1	0.857	0.948	0.935	0.751	0.934
	SE2	0.870				
	SE3	0.893				
	SE4	0.859				
	SE5	0.873				
	SE6	0.848				
Readiness to Change	RC1	0.846	0.947	0.936	0.719	0.935
	RC2	0.828				
	RC3	0.883				
	RC4	0.866				
	RC5	0.832				
	RC6	0.895				
	RC7	0.782				
Motivation	MT1	0.891	0.946	0.935	0.745	0.931
	MT2	0.885				
	MT3	0.881				
	MT4	0.894				
	MT5	0.799				
	MT6	0.823				
Performance	PF1	0.791	0.923	0.921	0.669	0.901
	PF2	0.739				
	PF3	0.732				
	PF4	0.862				
	PF5	0.892				
	PF6	0.875				

Table 2: HTMT

Variable	HTMT				Fornel-Lacker			
	MT	PF	RC	SE	MT	PF	RC	SE
MT	0,665				0,863			
PF	0,796	0,614			0,624	0,818		
RC	0,815	0,667	0,758		0,746	0,574	0,848	
SE	0.83	0.78	0.82		0,765	0,626	0,708	0,867

4.3 Structural model estimation

Structural model evaluation is related to hypothesis testing of the influence of research variables. The structural model evaluation check is carried out in three stages. namely first checking the absence of multicollinearity between variables with the Inner VIF (Variance Inflated Factor) measure. Inner VIF values below 5 indicate no multicollinearity between variables (Hair et al.. 2021). The second is hypothesis testing between variables. which involves examining the t-statistical value or p-value (Hair et al.. 2021). Suppose the t-statistic calculated is greater than 1.96 (t table). or the p-value < 0.05. In that case. there is a significant influence between the variables. Additionally. it is necessary to convey the results and the 95% confidence interval of the estimated path coefficient parameter. The third is the f^2 value. namely the effect of variables at the structural level with criteria (f^2 0.02 is low. 0.15 is moderate and 0.35 is high) (Hair et al.. 2021). The three stages are shown in Table 3.

The structural model analysis presented in Table 3 offers a compelling empirical validation of the hypothesized psychological architecture governing performance within an organizational context. By examining the interplay between self-efficacy, readiness to change, motivation, and performance, this analysis transcends mere statistical correlation to illuminate a dynamic, sequential process wherein individual agency and cognitive readiness coalesce to produce tangible outcomes. The findings are not merely numbers on a page; they constitute a narrative of human potential unfolding under conditions of transformation—a narrative that resonates with the foundational tenets of Social Cognitive Theory and Weiner's model of organizational readiness.

At the core of this model lies the potent influence of motivation as both a mediator and a direct driver of performance. The path coefficient of $\beta = 0.624$ for the relationship between Motivation → Performance is not only statistically robust ($p = 0.000$) but also substantively significant, accounting for a substantial 66.9% of the variance in performance ($R^2 = 0.669$). This finding unequivocally affirms the central proposition that intrinsic drive—the internal engine of ambition, persistence, and goal-striving—is the most proximal determinant of effective output. The magnitude of this effect, further underscored by a t-statistic of 10.448 and an effect size (f^2) of 0.638 (Cohen, 2013), positions motivation as the linchpin in the performance equation. It suggests that regardless of external pressures or technological disruptions, the quality and quantity of work executed are fundamentally anchored in the individual's inner resolve and commitment to excellence.

The model's true elegance, however, lies in its depiction of how this motivational force is cultivated. Both Readiness to Change and Self-Efficacy serve as powerful antecedents to motivation, each contributing significantly to its genesis. The path from Readiness to Change → Motivation ($\beta = 0.409$, $p = 0.000$) reveals that individuals who perceive change as legitimate, beneficial, and personally valuable are more likely to be energized and committed to their tasks. This aligns with (Holt et al., 2007) conceptualization of readiness as a multidimensional construct encompassing perceived efficacy, appropriateness, management support, and personal valence. In practical terms, employees who believe that organizational change is necessary and will yield personal or collective benefits are more inclined to invest emotional and cognitive resources into their work, thereby elevating their motivational state. The effect size ($f^2 = 0.252$) classifies this as a medium effect, indicating a meaningful, albeit not overwhelming, contribution to the motivational landscape.

Similarly, the pathway from Self-Efficacy → Motivation ($\beta = 0.476$, $p = 0.000$) underscores the critical role of self-belief in fueling achievement-oriented behavior. Individuals who possess a strong conviction in their capacity to execute complex tasks, overcome obstacles, and achieve desired outcomes are inherently more motivated to engage deeply with their work. This is consistent with (Bandura, 1997) assertion that self-efficacy beliefs shape goals, effort, and resilience. When employees trust in their own capabilities, they are less likely to be paralyzed by uncertainty and more likely to view challenges as opportunities for mastery—precisely the mindset that fuels high performance. The effect size ($f^2 = 0.342$) further solidifies this as a medium-to-large effect, reinforcing the notion that confidence in one's competence is a potent catalyst for sustained motivational energy.

Table 3: Structural model analysis

Hypothesis	Path Coefficient (β)	PCI		*p*-value	t-stats	f^2	VIF
		2.5%	97.5%				
Motivation → Performance	0,624	0,495	0,731	0,000	10,448	0,638	1,000
Readiness to Change → Motivation	0,409	0,242	0,594	0,000	4,536	0,252	2,005
Self-Efficacy → Motivation	0,476	0,275	0,648	0,000	5,014	0,342	2,005
	R^2	Q^2					
Motivation	0,669	0.659					
Performance	0,389	0.391					

Crucially, the model demonstrates that the influence of Self-Efficacy and Readiness to Change on Performance is not direct but entirely mediated through Motivation. The absence of direct paths from the exogenous variables to performance in this table implies that without the catalytic spark of motivation, even high levels of self-efficacy or readiness to change may not translate into superior performance. This highlights the indispensable role of motivation as the "missing link" that converts latent potential into manifest action. The indirect effects, while not explicitly calculated here, can be inferred from the product of the respective path coefficients: Self-Efficacy → Motivation → Performance ($0.476 \times 0.624 = 0.297$) and

Readiness to Change → Motivation → Performance (0.409 × 0.624 = 0.255). These values suggest that motivation serves as a powerful conduit, amplifying the impact of the antecedent variables on the ultimate outcome.

The model's predictive validity is further attested by the Q^2 value of 0.659 for Motivation and 0.391 for Performance. These values, exceeding the threshold of zero, confirm that the model possesses genuine predictive relevance, meaning it can effectively forecast the constructs' scores based on the proposed relationships. Furthermore, the Variance Inflation Factor (VIF) values of 1.000 for Motivation → Performance and 2.005 for the other two paths indicate the absence of multicollinearity, ensuring the stability and reliability of the estimated coefficients. The VIF of 2.005, while slightly elevated, remains well below the conventional threshold of 5, suggesting minimal redundancy among the predictors.

This structural model paints a richly textured portrait of performance dynamics. It posits that performance is not a static trait but a fluid outcome shaped by a triad of psychological forces: the belief in one's capability (self-efficacy), the openness to embrace transformation (readiness to change), and the inner drive to excel (motivation). The findings offer profound implications for organizational leaders and human resource practitioners. To enhance performance, organizations must move beyond mere structural or procedural interventions and instead cultivate environments that bolster employees' self-belief, foster a positive disposition toward change, and nurture intrinsic motivation. This requires deliberate investment in training programs that build competence, communication strategies that articulate the rationale and benefits of change, and reward systems that recognize and reinforce achievement-oriented behaviors. Ultimately, the model suggests that the most effective levers for improving performance lie not in external controls, but in the cultivation of internal states—states that empower individuals to navigate complexity, embrace innovation, and strive for excellence, even amidst uncertainty.

Following the present. Figure 2 shows the path coefficient diagram of each indicator and construct of this study

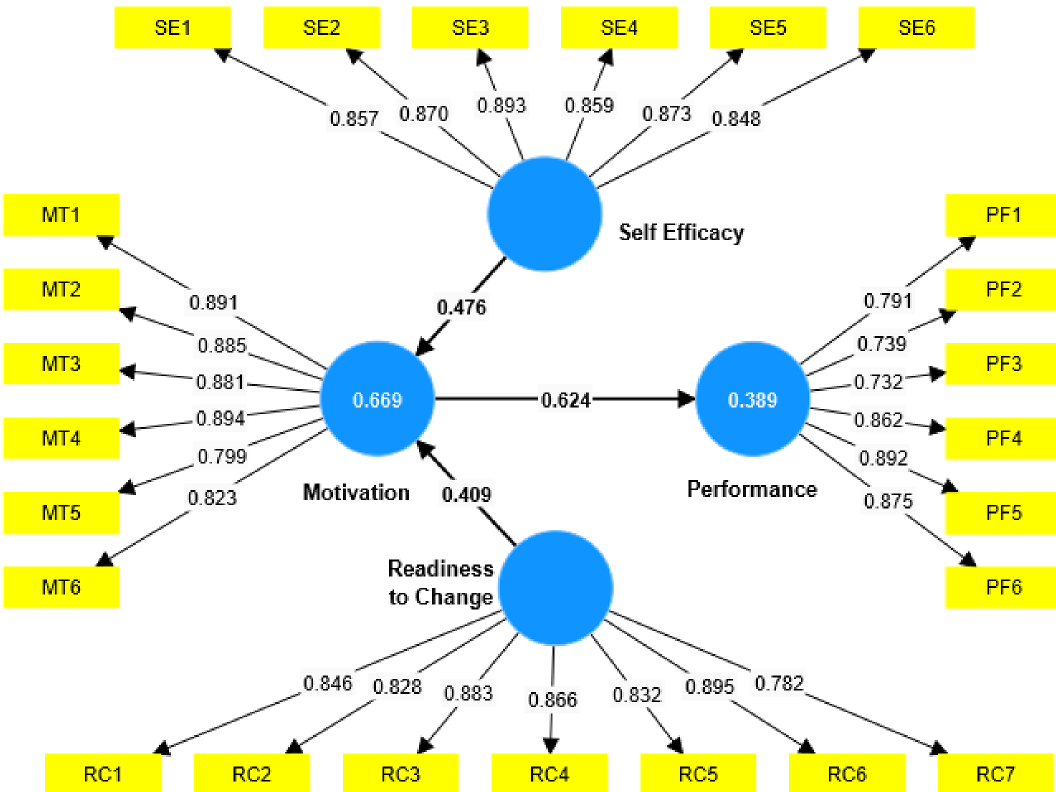

Figure 2: Diagram path coefficient

5. Discussion and Conclusion

This study advances the discourse on digital transformation in higher education by shifting focus from technological artifacts to the human architecture animating them. The findings affirm, with empirical precision, that administrative performance in digitizing institutions is not a mechanical function of system adoption, but a motivational achievement—a conclusion that resonates with, yet refines, prior insights from Cherian and Jacob (2013) and Na-nan and Sanamthong (2019). Specifically, the full mediation observed—wherein neither self-efficacy nor readiness to change exerts any direct influence on performance—suggests that confidence and openness, however robust, remain inert unless activated by a dispositional drive toward excellence. This supports Bandura's (1997) assertion that self-belief shapes behavior through goal-setting and effort mobilization, and extends Weiner (2009) readiness model by identifying motivation as the critical "translation layer" between intention and action.

The strength of the indirect pathways — Self-Efficacy → Motivation → Performance (0.297) and Readiness to Change → Motivation → Performance (0.255) — further reveals that psychological resources do not merely enable performance; they reconfigure it. Administrative staff with high self-efficacy do not simply tolerate new systems; they reinterpret procedural tasks (e.g., data entry, report generation) as opportunities for mastery and innovation—precisely the shift documented by Trautner and Schwinger (2020) in self-regulated learning contexts. Similarly, those high in readiness to change do not passively comply; they cognitively reframe digitization as self-relevant advancement, thereby aligning organizational imperatives with personal achievement needs (Ligarski et al., 2021; Prianto et al., 2017). This explains why institutions with comparable digital toolkits exhibit divergent operational outcomes: the variance lies not in hardware, but in motivational infrastructure.

Importantly, the study corrects a methodological asymmetry in the literature. While prior works (e.g., Qureshi et al., 2018; Bang & Reio Jr, 2017) established motivation as a mediator in academic or managerial strata, this research validates the mechanism in the administrative backbone—a cohort often relegated to implementation roles yet disproportionately exposed to reform-induced cognitive load (Priyanto et al., 2025). Their motivational vulnerability, therefore, constitutes a systemic risk; conversely, their motivational optimization offers disproportionate organizational returns. This research reorients the narrative: Smart Campus success is less about "going digital" and more about becoming agentic. It is not the presence of dashboards or APIs that determines reform efficacy, but whether frontline staff possess the self-belief to master them, the cognitive openness to embrace them, and—crucially—the drive to excel through them. Future policy must thus treat motivation not as an outcome to be incentivized, but as a causal mechanism to be cultivated—a perspective with profound implications for training design, change communication, and performance architecture.

6. Future Consideration

6.1 Managerial Implications

For university leadership and national policymakers, this study prescribes a human-centered recalibration of digital upskilling. First, training programs must transcend technical instruction and integrate efficacy-building elements: mastery experiences (e.g., scaffolded system simulations), vicarious learning (peer success showcases), and verbal persuasion (supervisory affirmation)—as advised by Bandura (1997). Second, change narratives should be reframed not as compliance mandates, but as career-enabling transitions, explicitly linking system adoption to professional identity (e.g., "from data clerk to data steward"). Third, performance appraisal systems ought to recognize motivational precursors—such as initiative in process innovation or resilience in troubleshooting—as core competencies, not discretionary extras. Given that achievement motivation mediates fully, investments in its antecedents (self-efficacy, readiness) yield amplified returns, making them high-leverage intervention points.

6.2 Research Limitations and Future Directions

While this study's cross-sectional design precludes definitive causal claims, its a priori path model, grounded in robust theory and tested via rigorous bootstrapping, provides strong quasi-causal evidence. Nevertheless, future research should adopt longitudinal or experimental designs to track motivational evolution during reform phases. Second, the sample, though stratified and sufficiently powered, is limited to private universities in Java and Bali; replication in public institutions, Eastern Indonesia, or comparative ASEAN contexts would test generalizability. Finally, while achievement motivation was treated as a unitary construct, future work could differentiate its components (e.g., mastery vs. performance-approach goals) to uncover nuanced pathways.

Declaration of generative AI in scientific writing

During the preparation of this work. The authors utilised Grammarly. Quillbot. DeepL. and ChatGPT to assess the quality of our language and enhance its clarity and readability. After using these tools. The authors reviewed and edited the content as needed and took full responsibility for the publication's content.

Data availability statement

The data supporting this study's findings are fully available from the corresponding author upon reasonable request.

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