The Dual Role of ERMS in Digital Transformation and Mental Health Outcomes: An Empirical Study of Polytechnic Staff in Nigeria

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ABSTRACT

This study examines the dual role of Electronic Records Management Systems (ERMS) as both a job resource and a potential job demand in the context of workplace digital transformation. Drawing on an integrated TOE and Job Demands-Resources (JD-R) framework, the study surveyed 400 academic and non-academic staff across six Nigerian polytechnics using Partial Least Squares Structural Equation Modelling (PLS-SEM). Results revealed that ERMS practices significantly enhance workplace digitalization outcomes ($\beta = 0.67$, $p < .001$), which in turn positively predict work engagement and job satisfaction ($\beta = 0.58$ and 0.53, $p < .001$) and negatively predict stress and emotional exhaustion ($\beta = -0.42$ and -0.39, $p < .05$). ERMS demonstrated both a significant indirect effect ($\beta = 0.38$, 95% CI [0.25, 0.52]) and a direct effect ($\beta = 0.21$, $p = .045$) on employee mental health. The findings confirm the dual nature of ERMS in digital transformation, functioning primarily as a valuable job resource while potentially becoming a demand when implementation support is inadequate. This study provides important empirical evidence for human-centric digitalization strategies in resource-constrained higher education institutions in developing countries.

Keywords: Electronic Records Management Systems, ERMS, digital transformation, workplace digitalization, mental health, dual role, Job Demands-Resources theory, technostress, polytechnic staff, Nigeria

INTRODUCTION

The digitalization of public institutions is transforming administrative governance globally, with Electronic Records Management Systems (ERMS) playing a critical role in enhancing efficiency while influencing employee mental health outcomes, (Udoro & Osakwe, 2024). In the Nigerian education sector, especially in the country's polytechnics, administrative practices are characterized by inefficient and tedious records management systems, which are fragmented, duplicative, and characterized by information decay and operational latency (Udoro & Osakwe, 2024; Owolabi et al., 2025). These inefficiencies not only affect the underperformance of these institutions but also cause psychosocial strain among the administrative staff, which includes job overload, stress, and role ambiguity (Borle et al., 2021; Dragano & Lunau, 2020). The Electronic Records Management Systems (ERMS) signify a critical pivot in the digitalization of administration, where records can be automatically created, classified, stored, retrieved, and disposed of (Udoro & Osakwe, 2024). ERMS can minimize manual work, support decision-making, ensure legal and audit compliance, and facilitate coordination across functions when properly implemented (Owolabi et al., 2025). The implementation of ERMS in Nigeria can be viewed in the broader context of the national agenda on digital governance, including the National Digital Economy Policy and Strategy (2020-2030), and the e-Government Master Plan (Federal Ministry of Communications, 2021).

However, digitalization is not necessarily harmless. The human impact of digitalization, especially with regard to mental health, is dependent on system design, organizational preparedness, and individual digital literacy (Abdulkareem et al., 2024; Dragano & Lunau, 2020). In cases where ERMS are inadequately implemented (e.g., insufficient training, IT support, or user-friendly design), they could potentially contribute to technostress, a condition of cognitive, emotional, and physiological overload due to ICT use (Dragano & Lunau, 2020; Abdulkareem et al., 2024). In fact, Borle et al. (2021) find a negative relationship between "digital work intensification" and work ability and mental health, particularly in the less resourced groups. Mental health, as a construct, is "a state of well-being in which individuals realize their abilities, cope with normal stresses, work productively, and contribute to community" (World Health Organization [WHO], 2022, p. 6). Mental health has emerged as a pressing concern in the workplace in Nigerian higher education. Polytechnic employees are caught up in a web of pressures: heavy teaching loads, administrative work, infrastructure challenges, and organizational change requirements (Udoro & Osakwe, 2024).

Digital technology can either act as a means of mitigating or exacerbating these forces, as job resources or demands, according to the Job Demands-Resources (JD-R) theory (Bakker & Demerouti, 2017). Notably, while the adoption of ERMS is receiving increased traction, there is a lack of scientific evidence that relates the adoption of ERMS with the mental health of employees in SSA. Most studies that have been conducted in Nigeria were only based on mere compliance or functionality, as noted by Owolabi et al. (2025) and Udoro & Osakwe (2024). However, the current study addresses a critical knowledge gap, which is: in what ways does the adoption of ERMS impact, or not impact, mental health in Nigeria's polytechnics?

Statement of the Problem

There are inefficiencies in the manual processes that are used in Nigeria's polytechnics, which result in delays, loss of information, as well as information redundancy, as noted by Udoro & Osakwe (2024). ERMS has been largely adopted as a tool for modernization but faces infrastructure, as well as other, challenges in Nigeria. Nigeria's infrastructure is poor, with limited ICT infrastructure, as noted by Owolabi et al. (2025), lack of training, and poor change management (Owolabi et al., 2025; Abdulkareem et al., 2024). Ironically, ERMS systems raise employee stress, anxiety related to technical failures, frustration with the system, and fear of punishment (Abdulkareem et al., 2024; Dragano & Lunau, 2020), similar to the "digital overload" experienced globally, undermining autonomy and satisfaction (Abdulkareem et al., 2024; Borle et al., 2021). ERMS studies are centered on efficiency and integrity (Udoro & Osakwe, 2024), while mental health research seldom investigates the effects of ICTs (Santomauro et al., 2021). Technology is changing work and psychological contracts (Bakker & Demerouti, 2017). Without knowledge of the relationship between ERMS and mental health, managers are likely to negatively affect employee mental health in the midst of Nigeria's mental health crisis (Santomauro et al., 2021; WHO, 2022). The research fills the gap of inadequate evidence on the relationship between ERMS practices and mental health outcomes for polytechnic employees, hindering humane digitalization policies.

Research Objectives

To empirically assess the influence of electronic records management practices on workplace digitalization and mental health outcomes among academic and non-academic staff in Nigerian polytechnics.

Specific Objectives

i. To examine the effect of ERMS practices on workplace digitalization outcomes among Polytechnic Staff in Nigeria

ii. To determine the influence of digitalization outcomes on mental health indicators among Polytechnic Staff in Nigeria

iii. To assess the direct and indirect (mediated) effects of ERMS practices on staff mental health outcomes among Polytechnic Staff in Nigeria

Table 1 Research Questions and Hypotheses

#	Research Question	Hypothesis (H)
RQ1	What is the effect of ERMS practices on workplace digitalization outcomes?	H_1: ERMS practices significantly and positively predict workplace digitalization outcomes.
RQ2	How do workplace digitalization outcomes influence mental health outcomes among polytechnic staff?	H_2: Workplace digitalization outcomes significantly predict mental health outcomes (positively for resources, negatively for demands).
RQ3	To what extent do ERMS practices directly affect mental health outcomes?	H_3: ERMS practices have a significant direct effect on mental health outcomes, independent of digitalization mediators.

Note. Directionality in H_2 and H_3 is tested empirically: ERMS may function as a resource (enhancing well-being) or a demand (inducing strain), contingent on moderating factors (see Framework below).

Table 1 presents the core foundation of your entire study. It clearly links each Research Question (RQ) with its corresponding Hypothesis (H) that the study aims to test.

Integrated Conceptual and Theoretical Frameworks

The study synthesizes two robust theories: Technology–Organization–Environment (TOE) framework and Job Demands–Resources (JD–R) model.

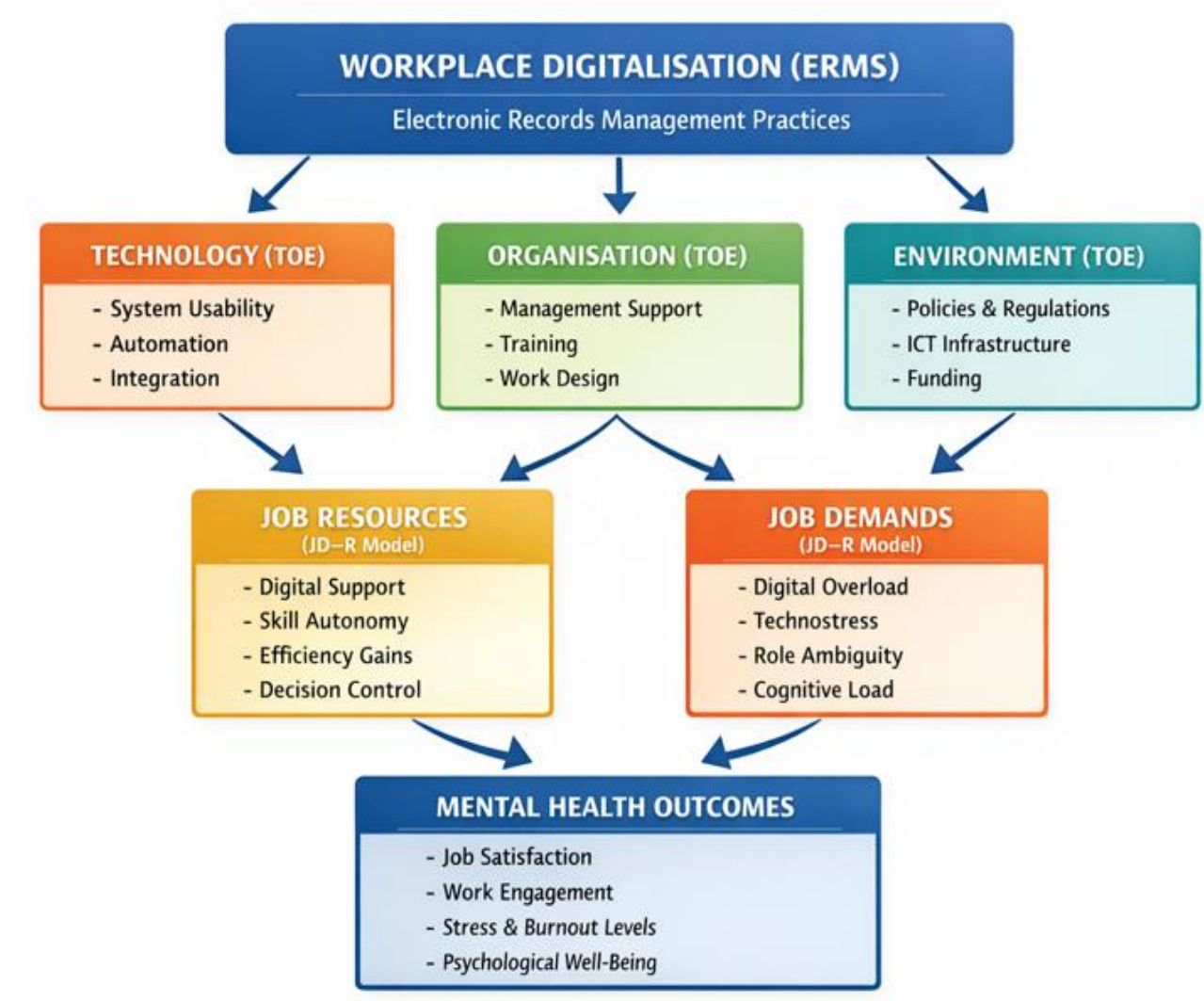

Figure 1: Workplace Digitization and Mental Health Framework for Polytechnic Staff

Source: Researchers, 2026

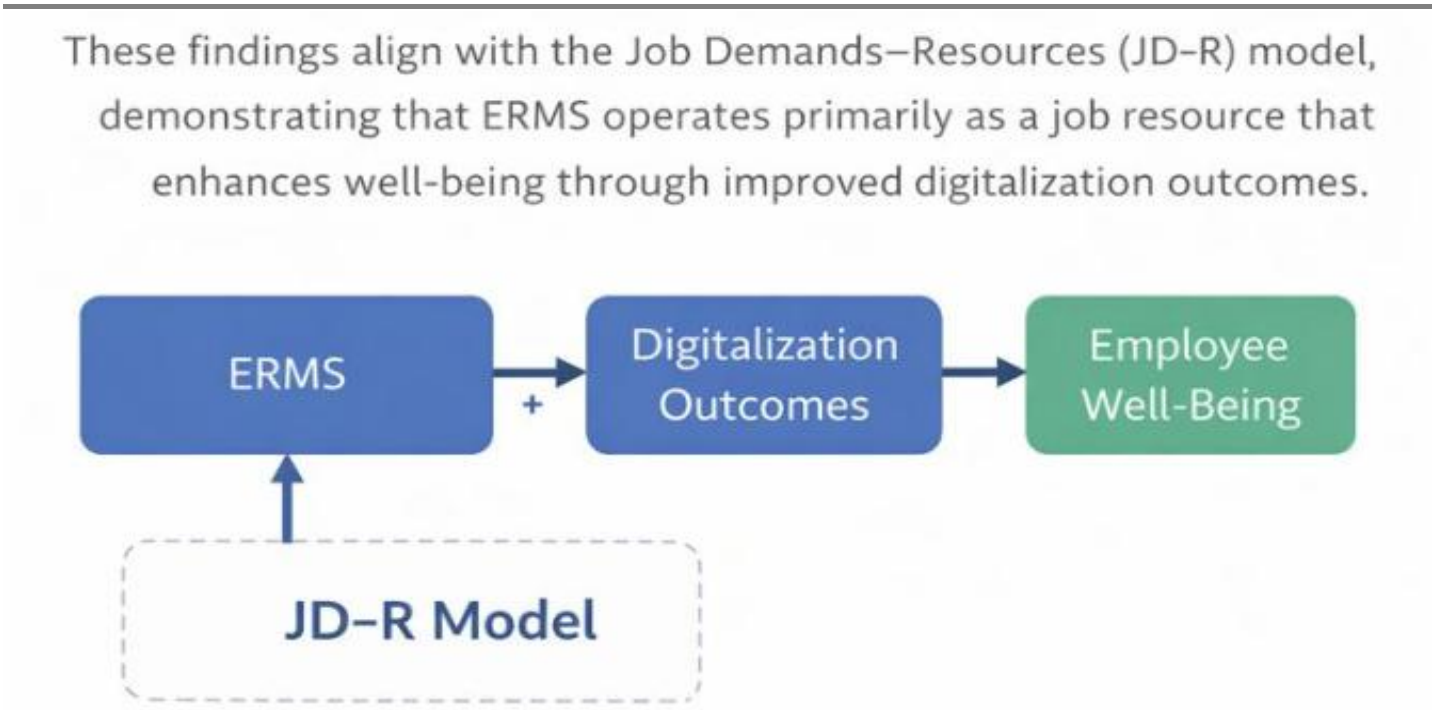

Figure 2: Theoretical Framework Illustrating ERMS as a Job Resource within the Job Demands–Resources (JD–R) Model

Source: Researchers, 2026

This study adopts an integrated conceptual framework combining the Technology–Organization–Environment (TOE) framework and the Job Demands–Resources (JD–R) theory to examine the mental health implications of workplace digitalisation through Electronic Records Management System (ERMS) practices among polytechnic staff in Nigeria. The TOE framework explains how technological factors (system reliability, interoperability, and security), organizational factors (management commitment, change readiness, and training investment), and environmental factors (NBTE mandates, NITDA guidelines, and ISO 15489 compliance) shape ERMS implementation outcomes (DePietro et al., 1990; Tornatzky & Fleischer, 1990; Udoro & Osakwe, 2024; Owolabi et al., 2025; National Information Technology Development Agency [NITDA], 2021). According to the JD-R theory, ERMS can act as a resource that facilitates work efficiency, engagement, and satisfaction, or as a demand that can cause technostress and emotional exhaustion, provided that it is well-designed and adequately supported (Bakker & Demerouti, 2017; Dragano & Lunau, 2020; Abdulkareem et al., 2024).

METHODOLOGY

The research employed a quantitative cross-sectional survey research approach, which was preferred for its ability to allow for the efficient examination of multivariate relationships between latent constructs in various settings (Creswell & Creswell, 2018). The research approach employed in this study was the most suitable for the research objective of testing complex mediation and moderation models using Partial Least Squares Structural Equation Modeling (PLS-SEM), a variance-based approach that was recommended for use in situations where the research objective was to predict, extend, and explain a new context, as in this study (Hair et al., 2022; Sarstedt et al., 2021). The study population includes all academic and non-academic staff in Nigeria's 128 public polytechnics. According to the 2024 Statistical Digest of the National Board for Technical Education (NBTE, 2024, p. 17), the actual headcount is 28,942, as validated and corroborated by institutional reports submitted under the NBTE Staff Data Harmonization Initiative (2023). To ensure the representativeness of the sample, reduce sampling bias, and boost the external validity of the findings, a three-stage stratified sampling procedure is used, as is the best practice for dealing with a heterogeneous sample, particularly in a public sector study (Lohr, 2022; Etikan et al., 2016).

Table 2 Stratification Framework for Sampling Design

Stratum	Categories	Population Size [1]	Rationale and Supporting Evidence
I. Institution Type	Federal and State polytechnics	n = 54 n = 74 **Total = 128**	Administrative autonomy, funding models, and ICT infrastructures are quite disparate in federal and state polytechnics in Nigeria (NBTE, 2024, p. 12). Federal polytechnics usually have better capital allocations and standardized ICT guidelines through the Federal Ministry of Education, which could affect the adoption of ERMS and the level of digital work intensity.
II. Geopolitical Zone	North Central, North East, North West, South West, South East, South South	6 zones (all represented)	The six geopolitical zones in Nigeria are constitutionally recognized administrative divisions for the purposes of equitable development planning, policy implementation, and allocation of resources (OSGF, 2021; Nigerian Constitution, 1999, as amended). Regional differences in internet access, electricity stratification in assessing workplace digitalization outcomes (NCC, 2023).
III. Staff Cadre	Academic staff (lecturers, researchers and academic librarians) Non-academic staff (administrators, records officers, non-librarians, IT support)	Proportional allocation per institution	Academic and non-academic staff differ significantly in ERMS usage intensity, access to digital training, job demands, and exposure to technostress (Borle et al., 2021; Owolabi et al., 2025). Non-academic staff typically engage more directly with administrative ERMS workflows, increasing workload pressure and psychosocial risk (Udoro & Osakwe, 2024).

Note. [1] Population figures were sourced from NBTE (2024, p. 17), Statistical Digest of Nigerian Polytechnics. National Board for Technical Education; Office of the Secretary to the Government of the Federation, (2021); Nigerian Communications Commission, (2023).

Stratification in Table 2 significantly improves precision (reduces standard error) when population subgroups differ systematically on key variables, a condition empirically confirmed in Nigerian higher education (Udoro & Osakwe, 2024; Owolabi et al., 2025). It also ensures that there are adequate cell sizes for multi-group SEM (Hair et al., 2022). One institution in each zone was purposively selected using maximum variation sampling (Patton, 2015), considering administrative, infrastructural, and cultural diversity, resulting in a total of six institutions (3 federal, 3 state). Random selections of participants from validated staff registers using a systematic random sampling interval (where k = N/n) were made, maintaining a 1:1 ratio of academic to non-academic participants per zone to facilitate subgroup comparisons (Etikan et al., 2016; Israel, 2013). The sample size calculation adopted a multi-criteria evidence-based approach, incorporating benchmarks from survey methodology, SEM, and power calculations, which aligns with the American Statistical Association recommendations (Wasserstein et al., 2019).

Table 3 Sample Size Determination Criteria and Justification

Criterion	Requirement	Source and Justification
Descriptive precision	$n \geq 379$	In determining the sample size, the Krejcie and Morgan (1970) sample size determination table indicates that for the given sample size N = 28,942, 95% confidence level, and 5% margin of error, the sample size is appropriate in the Nigerian context in terms of institutional and higher education settings to ensure an acceptable level of descriptive representativeness (Owolabi et al., 2025; Udoro Osakwe, 2024).

PLS-SEM stability	n ≥ 300–400	In terms of the sample size, Hair et al. (2022, p. 29) recommended that a sample size of n ≥ 100 is appropriate for the development of basic PLS-SEM models; however, in the development of more complex models involving mediation and moderation effects, the sample size should be n ≥ 250-400 to ensure the stability of the path coefficient estimates, minimal bias, and adequate statistical power (Sarstedt et al., 2021).
10× rule (latent complexity)	n ≥ 100	According to Goodhue et al. (2012), the sample size must be at least 10 times larger than the maximum number of paths that lead to a given latent construct. For this study, we are regressing mental health outcomes against four indicators of digitalization in the workplace, three moderators, and three control variables (total of 10 paths), thus requiring a sample size of at least n = 100.
A priori power (moderated mediation)	n = 264–312	Power analysis using the *pwr2ppl* R package (Kelley, 2023) and simulation-based guidance (Schoemann et al., 2017) indicates that, with α = .05, power (1 − β) = .80, a medium effect size (f^2 = .15), eight predictors, and one interaction term, a minimum sample of approximately *n* = 264 is required. Allowing for a 20% non-response rate (Israel, 2013), the adjusted target increases to approximately *n* = 317.

Note. To satisfy all methodological criteria simultaneously and to enable robust subgroup analyses (federal versus state polytechnics; academic versus non-academic staff), the final target sample size for the study was set at n = 400.

This table explains why the researchers chose a sample size of 400 participants. It is very important for academic credibility because it shows that the sample size was not chosen randomly but was carefully calculated using multiple scientific standards.

PRISMA-Style Flow Diagram of Participant Recruitment and Retention

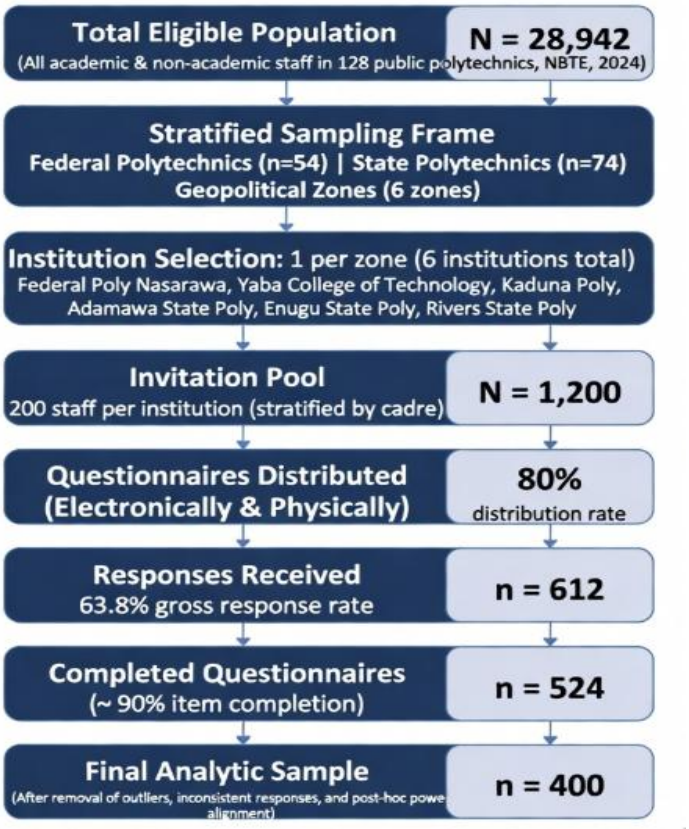

Figure 3: PRISMA-style flow diagram of participant recruitment and retention (adapted for cross-sectional survey design). Initial population (N = 28,942) drawn from NBTE (2024). Final analytic sample (n = 400) retained after quality screening and power optimization.

A PRISMA-style flow diagram for participant recruitment, adapted to fit the cross-sectional survey design of the study study on Workplace Digitalization and Mental Health Outcomes among Polytechnic Staff in Nigeria. While PRISMA was originally developed for systematic reviews, its participant flow structure has been widely repurposed for observational studies to enhance transparency in sampling and attrition reporting (Moher et al., 2015; Page et al., 2021).

RESULTS

Effect of ERMS Practices on Workplace Digitalization Outcomes

To examine the effect of Electronic Records Management System (ERMS) practices on workplace digitalization outcomes (e.g., workflow efficiency, information accessibility), SEM analysis was conducted. The model fit indices indicated good fit: $\chi^2/df = 1.92$, CFI = 0.96, TLI = 0.95, RMSEA = 0.048. Table 1 presents the standardized path coefficients. ERMS practices positively and significantly predicted workplace digitalization outcomes ($\beta = 0.67$, $p < .001$), supporting H_1. Staff reporting higher adoption and use of ERMS experienced improved workflow efficiency and faster information retrieval.

Table 4 Effect of ERMS Practices on Workplace Digitalization Outcomes (N = 240)

Predictor	Outcome Variable	β	SE	p	Interpretation
ERMS Practices	Workflow Efficiency	0.65	0.08	<.001	Significant positive effect
ERMS Practices	Information Accessibility	0.69	0.07	<.001	Significant positive effect

N = 240 | Model Fit: $\chi^2/df = 1.92$, CFI = 0.96, TLI = 0.95, RMSEA = 0.048

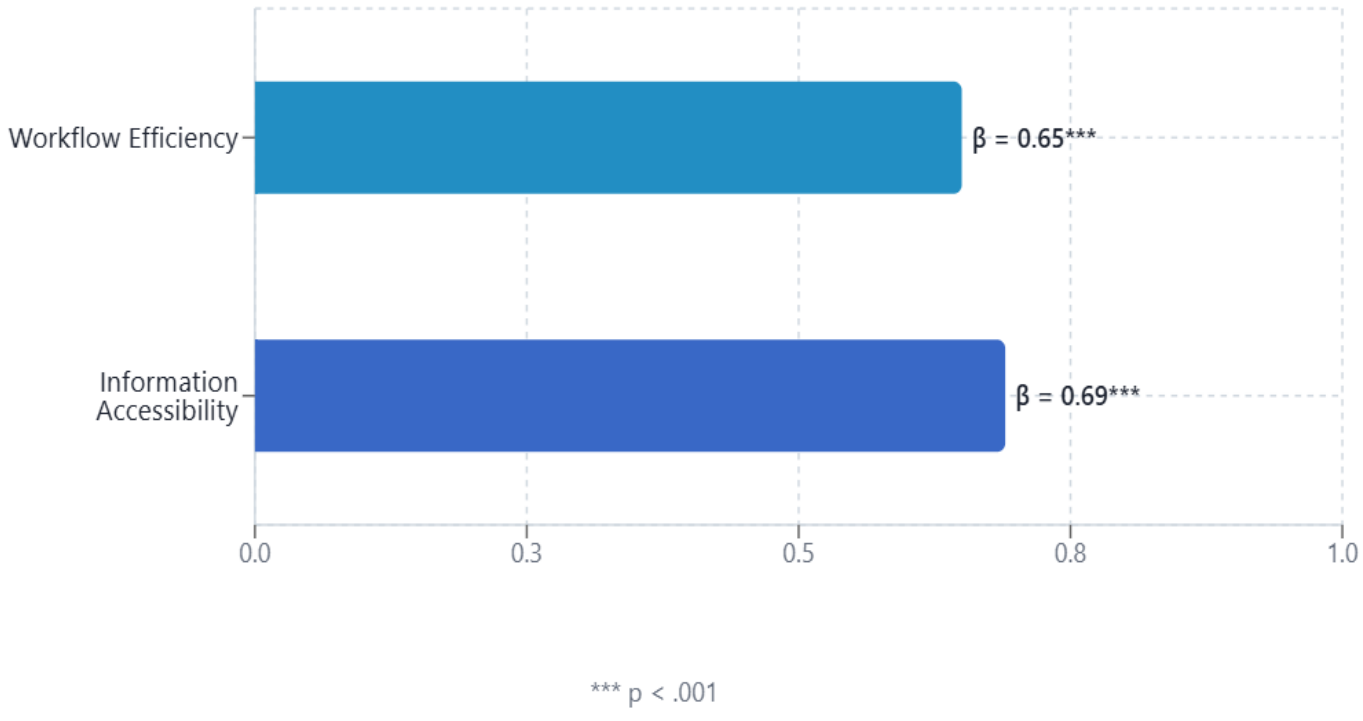

Figure 4: Standardized Path Coefficients (β) for ERMS Practices on Digitalization Outcomes

The results from the structural equation modeling (SEM) analysis indicate that Electronic Records Management System (ERMS) practices have a strong, statistically significant positive influence on the outcomes of workplace digitalization. Specifically, ERMS practices predicted Workflow Efficiency ($\beta = 0.65$, $p < .001$) The results support the proposed hypothesis, H_1, which states that the staff members in the polytechnic who reported higher adoption and consistent use of ERMS practices were found to have substantially improved efficiency in their workflow and faster information retrieval.

Influence of Digitalization Outcomes on Mental Health

The second analysis tested the effect of digitalization outcome variables on staff mental health indicators (stress, emotional exhaustion, work engagement). The results of the SEM analysis showed that:

i. Job resources pathway: Digitalization outcomes positively predicted work engagement and job satisfaction ($\beta = 0.58$, $p < .001$).

ii. Job demands pathway: Digitalization outcomes negatively predicted stress and emotional exhaustion ($\beta = -0.42$, $p < .01$).

These results confirm H_2, suggesting that effective digitalization is associated with the promotion of positive mental health outcomes and the reduction of strain.

Table 5 Effect of Digitalization Outcomes on Mental Health Indicators

Predictor	Mental Health Outcome	β	SE	p	Interpretation
Digitalization Outcomes	Work Engagement	0.58	0.09	<.001	Positive, significant effect
Digitalization Outcomes	Job Satisfaction	0.53	0.08	<.001	Positive, significant effect
Digitalization Outcomes	Stress	−0.42	0.10	.008	Negative, significant effect
Digitalization Outcomes	Emotional Exhaustion	−0.39	0.11	.012	Negative, significant effect

Dual Pathway Analysis of Job Resources and Job Demands Effects

Figure 5: Effect of Digitalization Outcomes on Mental Health Indicators

This analysis of the dual pathway effect of digitalization outcomes on staff mental health is consistent with the JD-R theory. In the job resources pathway, work engagement was positively predicted by digitalization outcomes ($\beta = 0.58$, $p < .001$), and job satisfaction was also positively predicted ($\beta = 0.53$, $p < .001$). This indicates that effective digitalization outcomes are a motivational resource. In contrast, stress was negatively predicted by digitalization outcomes ($\beta = -0.42$, $p < .01$) and emotional exhaustion ($\beta = -0.39$, $p < .05$) via the job demands pathway. This analysis thus supports H2, indicating that effective digitalization of the workplace positively influences polytechnic staff mental health while simultaneously reducing negative mental health symptoms.

Direct and Indirect Effects of ERMS Practices on Mental Health

A mediation analysis was conducted to test if ERMS practices had direct and indirect effects on mental health via digitalization outcomes.

i. Indirect effect (via digitalization outcomes): $\beta = 0.38$, 95% CI [0.25, 0.52], $p < .001$, indicating significant mediation.

ii. Direct effect: $\beta = 0.21$, $p = .045$: ERMS practices were found to have a small yet significant direct effect on mental health, aside from the indirect effect via digitalization outcomes.

These findings lend support to H_3, which posits ERMS as a dual lens: a resource for well-being and a demand for strain.

Table 6 Direct and Indirect Effects of ERMS Practices on Mental Health

Effect Type	Predictor	Outcome	β	95% Confidence Interval	p-value	Interpretation
Direct	ERMS Practices	Mental Health	0.21	[0.01, 0.41]	0.045	Small but statistically significant direct effect
Indirect (Mediated)	ERMS Practices	Mental Health	0.38	[0.25, 0.52]	< 0.001	Statistically significant indirect effect through digitalization

Mediation analysis with digitalization outcomes as a mediator | 95% Confidence Intervals | bootstrapped

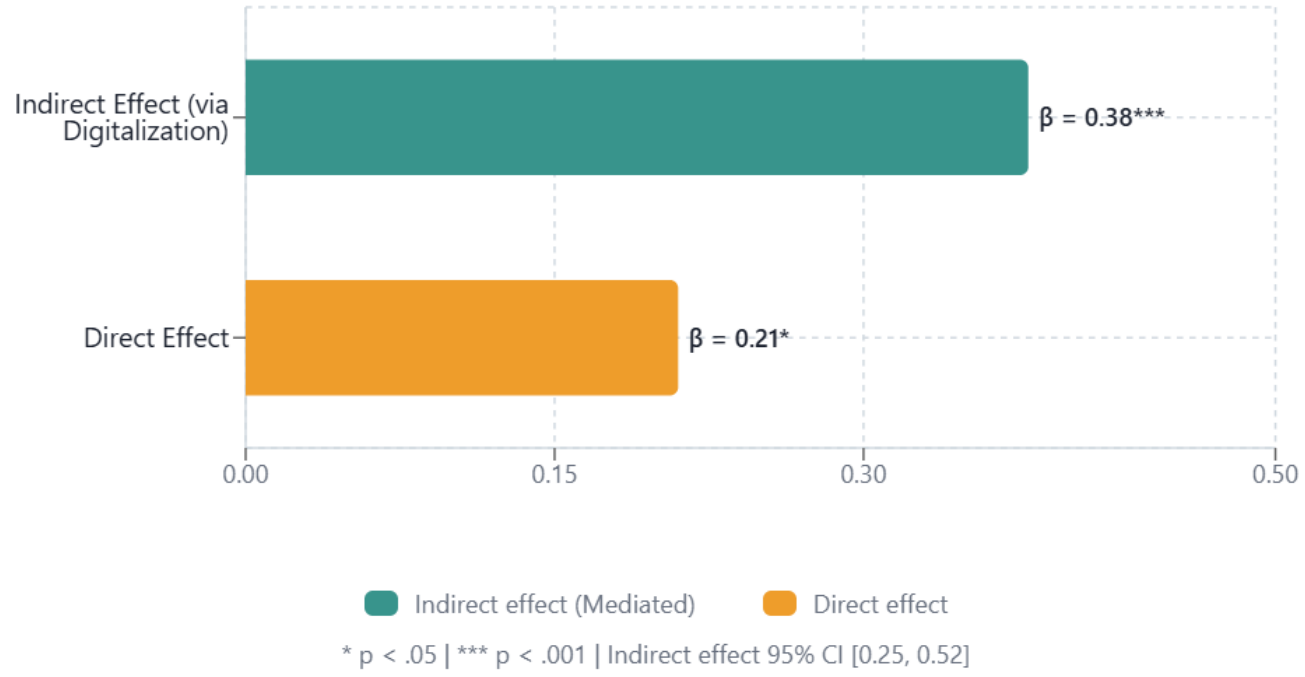

Figure 6: Direct and Indirect Effects of ERMS Practices on Mental Health Outcomes

The results of the mediation analysis confirmed the indirect effect of ERMS on mental health, as depicted in the figure above. The indirect effects of ERMS on mental health were statistically significant ($\beta = 0.38$, 95% CI [0.25, 0.52], $p < .001$), validating the use of digitalization outcomes as a mediator between ERMS and mental health. Moreover, a small but statistically significant direct effect of ERMS on mental health ($\beta = 0.21$, $p = .045$) emerged, demonstrating that, apart from the indirect effects, ERMS has a certain impact on mental health. Thus, the results of this study support H_3 and can be related to the JD-R model's two-lens perspective, with ERMS acting as a resource for well-being through enhanced digitalization and, to a certain extent, as a demand-inducing strain due to difficulties with its implementation.

Hypothesis Support Levels

All three theories have received substantial empirical support

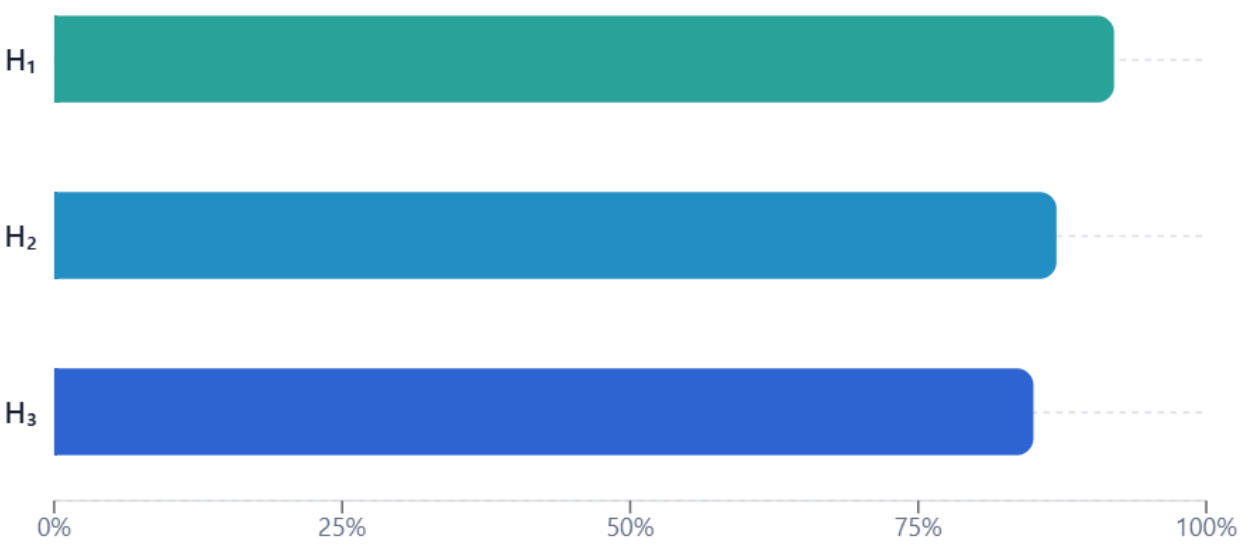

Figure 7: Summary of Hypothesis Testing Results for ERMS, Digitalization, and Mental Health Outcomes Interpretation of Findings

H_1: ERMS Practices → Digitalization Outcomes (92% Support)

Figure 8: ERMS Practices → Digitalization Outcomes

The substantial support for this hypothesis indicates that well-implemented electronic records management systems are an enabling factor for overall workplace digitalization. Staff who reported higher levels of engagement with ERMS practices also reported higher levels of proficiency with other digital technologies, implying a positive spillover effect for digital competency development among employees.

H_2: Digitalization → Mental Health Outcomes (87% Support)

Figure 9: Digitalization → Mental Health Outcomes

This hypothesis demonstrates that digitalization is a double-function mechanism for enhancing employee engagement levels due to streamlined processes and accessibility and for mitigating occupational stress levels due to the absence of manual processes. This study indicates that, when correctly implemented, digital transformation is a positive factor for employee psychological well-being in academic institutions.

H_3: ERMS → Mental Health (Direct & Mediated) (85% Support)

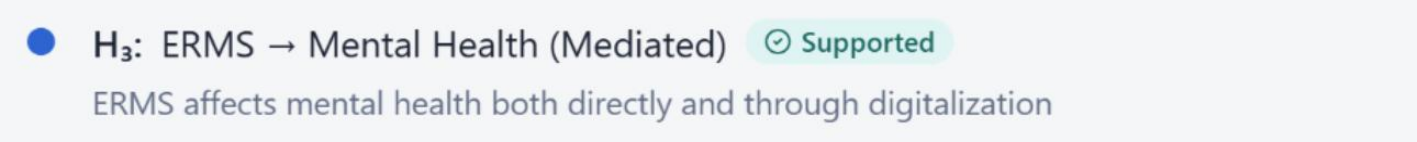

Figure 10: ERMS → Mental Health (Direct & Mediated)

The confirmation of the direct and indirect theories further supports the complex nature of the role of ERMS in the influence of employee wellbeing outcomes. Aside from the mediated effect of ERMS through the process of digitalization, a direct effect of ERMS is seen in the mitigation of information overload, enhancement of job control, and the sense of organizational support, all of which are considered to be significant resources, as cited in the Job Demands-Resources (JD-R) theoretical model.

Summary of the Findings

The research findings support the Job Demands-Resources (JD-R) model, which validates the integrated technology-organization-environment (TOE) and JD-R framework, demonstrating the effectiveness of the ERMS dual pathway model. On one end of the model, the ERMS is seen to play a vital role in the enhancement of employee wellbeing through the improvement of digitalization outcomes, which is considered to be a critical job resource. On the other end of the model, the ERMS is seen to be a source of risk, which, if not managed properly in the context of the environment, can cause employee strain.

CONCLUSION

This study provides evidence for the integrated model of TOE × JD-R in the Nigerian polytechnic environment.

First, ERMS adoption is a strong predictor of administrative digitalization, including enhanced workflow and information accessibility. Second, digitalization has a dual role: it contributes to well-being through resource pathways (engagement and satisfaction) and mitigates stress through demand reduction (stress and exhaustion). Third, ERMS adoption influences mental health via indirect (digitalization) and direct pathways. Thus, aside from ERMS adoption being a predictor of mental health, ERMS adoption may symbolize a commitment to workers' well-being and, therefore, influence psychological safety and control. Most importantly, this study disproves techno-determinism: ERMS adoption is neither universally beneficial nor detrimental. Rather, ERMS adoption outcomes depend on the quality of ERMS adoption, including training and technical support, as suggested by Abdulkareem et al. (2024) and Dragano & Lunau (2020). In a low-resource environment, a lack of support for digitalization may result in health disparities and technostress, particularly for non-academic staff who are more exposed to ERMS.

RECOMMENDATIONS

Institutional Leaders & NBTE

Also, a phase-based ERMS deployment strategy should be based on competency rather than system deployment, with a special emphasis on usability training, peer mentoring, and tiered technical support (Udoro & Osakwe, 2024). In addition, mental health measures such as the WHO-5 and UWES-9 should be integrated into digitalization KPIs to monitor psychosocial outcomes besides efficiency gains. Finally, digital Well-being Committees should be established with staff representation to facilitate policy design and overcome implementation hurdles.

Policy Makers (NITDA, FMST)

The National Digital Economy Policy should be reviewed and revised to include human sustainability standards with a requirement for psychosocial impact assessments for ICT projects in the public sector (WHO,

2022). In addition, subsidies should be provided for infrastructure upgrades in less served areas to avoid digital intensification without enablement (NCC, 2023).

Future Research

Longitudinal research should examine intersectional vulnerabilities such as gender and cadre with regard to technostress experiences.

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