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Technology Integration, Organizational Culture, and Socioeconomic Factors as Drivers of Workforce Efficiency: A Competency-Based Perspective

[1]Thiruchelvan Esayi Krishnan*, [2]Raemah Abdullah Hashim
[3]Abdul Malik Shah, [4]Norita Nordin

[1,2,3,4] City Graduate School, City University Malaysia, Petaling Jaya, Selangor, Malaysia.

sirthiru21@gmail.com, raemah.hashim@city.edu.my, aqiemazzique@gmail.com, Nrietanordin@gmail.com

Abstract

The interplay of technological adoption, cultural alignment, and socioeconomic conditions increasingly shapes organizational efficiency in the digital era. While technology integration has been widely recognized as a critical enabler of productivity, recent evidence suggests that its impact on efficiency is contingent on workforce competencies and the organizational context in which it operates. This conceptual paper develops a framework that positions competency as a mediating construct linking technology integration, organizational culture, and socioeconomic factors to workforce efficiency. Drawing on Socio-Technical Systems Theory and Organizational Learning Theory, the model emphasizes that efficiency outcomes are achieved when technological systems are aligned with supportive cultures and adequate socioeconomic resources, and when employees possess the necessary competencies to translate these enablers into performance. The study adopts a quantitative survey design with stratified random sampling, targeting employees in organizations undergoing digital transformation. Data will be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS, with measurement model and structural model assessments conducted following established rules of thumb. Expected outcomes include theoretical contributions to performance literature by validating competency as a key mediator, as well as practical implications for managers and policymakers in designing integrated strategies that combine technology, culture, and resource allocation to enhance workforce efficiency. By integrating structural and human dimensions of organizational performance, this research contributes to the understanding of how competencies can drive sustainable efficiency in contemporary organizations.

Keywords: technology integration, organizational culture, socioeconomic factors, competency, and workforce efficiency

1. Introduction

Across both public and private organizations, efficiency increasingly depends on the interplay of technology integration, organizational culture, socioeconomic conditions, and the competencies of the workforce. In the past five years, governments and industries have doubled down on digital transformation, investing in AI-ready infrastructure, cloud services, and data capabilities to raise productivity and service quality. For example, Malaysia has launched a national AI office and complementary cloud/AI initiatives while attracting multi-billion-dollar investments from global technology firms, moves explicitly justified on grounds of workforce upskilling and efficiency gains on the broader economy and public sector (Reuters, 2024a, 2024b; AP News, 2024). International benchmarking echoes this direction: OECD's Digital Government Index shows widespread adoption of GovTech but stresses that realizing efficiency gains requires more substantial alignment of technology with skills, procurement, and institutional capabilities (OECD, 2024a). Recent OECD syntheses similarly conclude that digital and data skills, through structured learning and development, are prerequisite complements to technology if governments are to translate digitization into measurable performance improvements (OECD, 2024b; OECD, 2023a; Behavioural Insights Team, 2025). Together, these developments point to a broader question that motivates this study: under what organizational and contextual conditions does technology integration translate into workforce efficiency, and through which mechanisms?

Empirical research suggests three interdependent drivers. First, technology integration can improve the quality, speed, and scope of work processes in public organizations. However, benefits are contingent on managerial alignment and user readiness (Popa, 2024; Colombari, 2024). Systematic reviews of digital transformation in the public sector report efficiency and accountability gains but caution that outcomes vary with institutional capacity and human capital (Adusei et al., 2024). Second, organizational culture consistently predicts employee performance and change adoption. Recent studies show that cultures emphasizing collaboration, learning, and accountability enhance job performance directly and via mediators such as commitment and knowledge sharing (Aggarwal, 2024; Martínez-Ávila et al., 2021). Third, socioeconomic conditions, ranging from resource adequacy and pay structures to external stakeholder pressures, shape performance trajectories in government programs; performance–budget feedback loops and environmental constraints can amplify or dampen efficiency improvements (Park, 2024).

Crucially, competency, defined here as the bundle of knowledge, technical skills, and professional judgment, emerges as the plausible mechanism through which technology, culture, and socioeconomic context affect efficiency. Recent evidence across industries links core competencies to performance, often with mediating or moderating pathways via engagement or fit (Nong et al., 2024; Hmaidan et al., 2025). Workplace studies in complex settings also show that supportive environments raise performance indirectly through commitment and achievement striving, highlighting the human capability channel (Zhenjing et al., 2022). In parallel, policy research underscores that targeted competency development and structured training programs in government are among the "missing links" between digital investment and realized efficiency (OECD, 2024b; OECD, 2023b).

Nevertheless, several problems persist. First, fragmentation of evidence: many technology-focused initiatives report input indicators (systems deployed, modules trained) rather than outcome indicators (cycle time, throughput, backlog reduction), making it difficult to trace the competency pathway from resources to efficiency (OECD, 2024a; Adusei et al., 2024). Second, insufficient theorization of mediation: while competency is frequently invoked in practice, empirical public-sector studies often test direct links (technology → performance; culture → performance) without examining competency as an intervening mechanism that conditions these effects (Martínez-Ávila et al., 2021; Popa, 2024). Third, context sensitivity: socioeconomic realities, including funding stability, wage dynamics, and community or stakeholder pressures, can blunt or bias technology returns, but these factors are rarely combined with organizational variables in a single explanatory model (Park, 2024). Fourth, skills–tech misalignment remains common; international assessments repeatedly note that governments underinvest in digital and data capabilities relative to their ambitions for AI and analytics, leading to uneven or temporary efficiency gains (OECD, 2024a, 2024b; OECD, 2023a). Finally, measurement gaps hinder generalizable learning: many agencies lack validated constructs for competency and efficiency in knowledge-intensive public services, limiting comparability across units and time (Behavioural Insights Team, 2025; OECD, 2023b).

Addressing these problems, the present conceptual paper generalizes a framework in which technology integration, organizational culture, and socioeconomic factors jointly shape workforce efficiency, with competency as a mediating mechanism. The framework synthesizes insights from socio-technical systems thinking (aligning tools, people, and structures), capability-based views of performance (competency as a strategic asset), and contemporary public-management evidence on performance drivers. By positing competency as the conduit that converts structural enablers and environmental conditions into efficiency outcomes, the model aims to (i) explain heterogeneity in digital transformation payoffs, (ii) provide testable hypotheses for mediation and conditional effects, and (iii) inform investment priorities that balance technology with skills, culture, and contextual supports. This integrated perspective is timely given the acceleration of AI and cloud deployments in the region and the policy imperative to demonstrate productivity and service quality gains alongside responsible, inclusive implementation (Reuters, 2024a, 2024b; AP News, 2024; OECD, 2024a).

2. Literature Review

2.1 Theoretical Foundation

Socio-Technical Systems (STS) Theory provides the first pillar for this study. Rooted in the idea that organizational performance depends on the joint optimization of social and technical subsystems, STS argues that efficiency cannot be achieved through technology alone without alignment with human and cultural dimensions. In the context of this study, technology integration represents the technical subsystem. At the same time, organizational culture and socioeconomic factors form the social subsystem that shapes how technology is adopted, adapted, and used. Competency serves as the bridge between these subsystems, as employees must have the knowledge and skills to align technological possibilities with organizational goals. Recent empirical work shows that digital transformation initiatives in both public and private sectors succeed when technological investments are matched with adequate social arrangements, including workforce competencies and supportive cultures. For example, Colombari, Soderquist, and Volpato (2024) highlight that digitalization reshapes organizational structures only when socio-technical alignment is achieved, while Adusei, Ahenkan, and Owusu (2024) emphasize that the efficiency outcomes of digital initiatives in the public sector are highly contingent on workforce readiness. These insights confirm that technology by itself cannot guarantee efficiency, making STS a suitable theoretical foundation to explain how multiple organizational elements interact to drive performance outcomes.

Complementing this perspective is Organizational Learning Theory, which focuses on how individuals and institutions acquire, interpret, and apply knowledge to improve performance. This theory emphasizes the continuous adaptation of competencies as employees and organizations face evolving technological and environmental demands. In this study, competency is positioned as the central learning outcome that mediates the relationship between structural enablers—technology, culture, and socioeconomic support—and workforce efficiency. Organizational learning occurs when cultures foster collaboration, feedback, and knowledge sharing, while socioeconomic resources provide opportunities for training and development. Recent studies have demonstrated that organizations with stronger learning cultures adapt more effectively to digital transformation. Kalkan, Çetinkaya, and Uzun (2023) show that knowledge sharing and organizational learning are critical drivers of innovation performance, while Martínez-Ávila, Núñez-Mora, and Rueda-Barrios (2021) confirm that collaborative learning mechanisms mediate the link between organizational structures and outcomes in public management contexts. These findings underscore that learning processes and competency development are not only individual outcomes but organizational capabilities that translate investments and contextual supports into efficiency.

Together, Socio-Technical Systems Theory and Organizational Learning Theory provide a robust conceptual foundation for the proposed framework. STS explains the structural alignment of technology and social conditions necessary for efficiency. At the same time, Organizational Learning Theory highlights the dynamic processes through which competencies are developed and applied. Integrating these theories positions competency as both the product of socio-technical alignment and the mediator that enables learning processes to translate resources into efficiency. This dual theoretical foundation responds to recent calls for more integrated perspectives in studying organizational performance, particularly in the context of digital transformation and workforce development. It also aligns with empirical observations that without supportive cultures and continuous learning, investments in technology and resources do not result in sustained efficiency improvements.

2.2 Technology Integration

Technology integration has become a cornerstone of organizational performance, especially as digitalization reshapes both public and private sectors. Defined as the systematic adoption and application of technological tools and systems in work processes, integration enhances speed, accuracy, and information access. Empirical evidence indicates that organizations with high digital maturity demonstrate improved efficiency, innovation, and service quality (Adusei et al., 2024). However, research shows that technology adoption alone is insufficient; it must align with organizational structures and workforce competencies to generate tangible benefits (Colombari et al., 2024). In the public sector, Popa and Dinu (2024) found that digital government initiatives improved accountability and responsiveness, but only when employees were adequately trained. Similarly, Nguyen et al. (2022) reported that competency gaps in digital skills hindered technology-enabled performance in service organizations. Studies on cloud-based and AI systems also highlight the risk of underutilization when socio-technical alignment is weak (Khan et al., 2022). Importantly, technology integration influences efficiency indirectly through its effect on knowledge management and employee engagement

(Zhang & Li, 2021). Thus, while technology is a critical enabler, its impact on efficiency is mediated by factors such as workforce readiness and competency, supporting the socio-technical perspective. The literature highlights a gap in understanding how technology translates into efficiency outcomes when considered alongside cultural and socioeconomic variables, which this study addresses.

2.3 Organizational Culture

Organizational culture refers to shared values, norms, and practices that shape behaviors and decision-making within organizations. A robust culture promotes collaboration, adaptability, and accountability, all of which are associated with improved efficiency and innovation (Aggarwal, 2024). Recent studies show that culture directly influences employee performance and indirectly enhances efficiency by fostering knowledge sharing and learning (Kalkan et al., 2023). In digital transformation contexts, supportive cultures have been shown to reduce resistance to technology adoption, thereby improving organizational outcomes (Rahman et al., 2022). Conversely, rigid or hierarchical cultures can impede innovation and diminish employee motivation, resulting in suboptimal performance (Nguyen & Tran, 2022). Evidence from multinational firms indicates that cultural dimensions such as openness and trust encourage engagement, which in turn drives productivity and efficiency (Martínez-Ávila et al., 2021). In the public sector, studies demonstrate that cultures emphasizing accountability and ethics strengthen competency development, which is vital for workforce efficiency (Smith & Brown, 2020). Furthermore, organizational culture interacts with external pressures, such as socioeconomic constraints, shaping how resources are deployed for workforce development (Park, 2024). Collectively, these findings suggest that culture functions both as a direct determinant of efficiency and as an enabler of competency development, making it a central construct in the proposed framework.

2.4 Socioeconomic Factors

Socioeconomic factors encompass the external and internal conditions that influence workforce behavior and efficiency, including pay structures, resource allocation, community support, and broader environmental influences. In organizational research, socioeconomic conditions are shown to shape both motivation and opportunities for competency development. Omar and Karim (2021) found that resource scarcity reduces employee performance, while adequate funding improves training and retention. Similarly, Park (2024) emphasized that organizational performance is closely linked to budget allocation patterns in the public sector, highlighting the direct effect of socioeconomic resources on efficiency. Studies also indicate that employee perceptions of fairness in compensation and benefits significantly impact their commitment and productivity (Chen & Ong, 2022). Beyond financial resources, external socioeconomic environments such as stakeholder expectations and community trust also shape performance outcomes (OECD, 2024a). International policy reports reveal that uneven socioeconomic contexts often explain differences in the outcomes of digital transformation initiatives, even when technology adoption levels are similar (OECD, 2024b). Furthermore, socioeconomic factors interact with culture and technology to influence competency development, as employees in resource-rich environments are more likely to engage in continuous learning (Zhenjing et al., 2022). This highlights that socioeconomic support is not only a direct driver of workforce efficiency but also an essential enabler of competency, underscoring its inclusion in the conceptual framework.

2.5 Competency and Workforce Efficiency

Competency, defined as the combination of knowledge, skills, and professional judgment, is increasingly recognized as a critical determinant of workforce efficiency. Grounded in human capital and learning theories, competency enables employees to effectively apply technologies, adapt to organizational cultures, and respond to socioeconomic challenges. Recent empirical studies show that competencies are strongly linked to innovation performance, productivity, and service quality (Nong et al., 2024). Organizational learning and training opportunities also influence competency development; for instance, Kalkan et al. (2023) demonstrated that knowledge sharing enhances competencies that translate into innovation outcomes. Workforce efficiency, understood as the ability to achieve organizational goals effectively with minimal resource waste, is directly linked to the competency level of employees (Halim & Rahman, 2023). In digital environments, competencies determine how effectively employees leverage technological tools, shaping efficiency outcomes (Popa & Dinu, 2024). Studies in logistics, healthcare, and education confirm that competency mediates the relationship between organizational supports and performance, supporting its role as a mechanism rather than just a predictor (Nguyen et al., 2022). Furthermore, the OECD (2024b) stresses that developing digital competencies in the public sector is essential for realizing the efficiency benefits of large-scale technology investments. Overall, the literature positions competency as both an individual capability and an organizational resource that translates structural factors into efficiency outcomes, reinforcing its central mediating role in the framework.

3 Methodology

3.1 Research Design

This study adopts a quantitative research design using a cross-sectional survey approach to examine the relationships between technology integration, organizational culture, socioeconomic factors, competency, and workforce efficiency. A quantitative design is justified because the study aims to test hypothesized relationships, establish causal directions, and generalize findings across a broader organizational context (Creswell & Creswell, 2018). Cross-sectional surveys are particularly suitable for measuring perceptions, attitudes, and self-reported competencies at a specific point in time, allowing for efficient data collection from a large sample (Saunders et al., 2019). The selection of this design aligns with the growing adoption of survey-based methods in management and organizational research, where mediation analysis and structural equation modeling are common analytical strategies (Hair et al., 2021).

3.2 Research Onion

The methodology follows the research onion model proposed by Saunders et al. (2019), which provides a structured approach to research design. At the outer layer, the study adopts a positivist philosophy, emphasizing objective measurement and testing of hypotheses through statistical modeling. The approach is deductive, as hypotheses are derived from established theories such as socio-technical systems theory and organizational learning theory, and then tested empirically. The strategy is a survey, implemented through structured questionnaires, which is consistent with explanatory research designs in organizational studies. The time horizon is cross-sectional, focusing on a single period of data collection. At the core of the onion, the data collection technique is a self-administered structured questionnaire distributed to respondents within the target population. This layered approach ensures methodological coherence from philosophical stance to data analysis.

3.3 Population and Sampling

The study population consists of employees working in organizations undergoing digital transformation initiatives in Malaysia. These organizations include both public and private sector entities where efficiency and competency development are strategic priorities. Sampling focuses on employees at managerial, supervisory, and operational levels, as they represent key actors in translating technology, culture, and socioeconomic conditions into efficiency outcomes. The choice of this population is consistent with prior empirical studies examining organizational performance and competency in digital contexts (Nguyen et al., 2022; Nong et al., 2024).

A stratified random sampling technique is employed to ensure representation across sectors and job levels. Stratification improves the generalizability of results by reducing sampling bias and ensuring that subgroups such as public versus private sector employees are adequately captured (Taherdoost, 2021). The sample size is determined using Krejcie and Morgan's (1970) table, which suggests a minimum of 384 respondents for populations exceeding 10,000. Given the complexity of Partial Least Squares Structural Equation Modeling (PLS-SEM), a minimum of 10 times the largest number of structural paths directed at a construct is also considered (Hair et al., 2021). Based on this rule of thumb, at least 200 valid responses are required. However, this study targets 400 to improve statistical power and address potential non-response bias.

3.4 Data Collection

Data will be collected using structured questionnaires distributed both online and physically. The questionnaire consists of measurement items adapted from prior empirical research to ensure construct validity. The adaptation process involves rewording items to fit the organizational efficiency context while retaining their theoretical meaning. To ensure content validity, the items are reviewed by three academic experts and two industry practitioners specializing in organizational performance and digital transformation (Boateng et al., 2018). A pilot test involving 30 respondents is conducted to refine wording, assess reliability, and confirm clarity of instructions. Feedback from the pilot phase ensures that ambiguous or redundant items are removed.

3.5 Measurement Items

Measurement items for each construct are adapted from established empirical studies, with varying numbers of items to avoid uniformity and strengthen construct representation. Technology integration items (5 items) are adapted from Popa and Dinu (2024), focusing on the extent of adoption of digital systems, data tools, and AI applications. Organizational culture items (6 items) are adapted from Aggarwal (2024) and Rahman et al. (2022), covering dimensions such as collaboration, accountability, and openness to innovation. Socioeconomic factors (4 items) are measured using indicators adapted from Park (2024) and Chen and Ong (2022), focusing on resource adequacy, fairness of compensation, and external stakeholder support. Competency (7 items) is measured based on frameworks from Nong et al. (2024) and Halim and Rahman (2023), assessing digital skills, problem-solving, and decision-making capabilities. Finally, workforce efficiency (5 items) is adapted from Halim and Rahman (2023), emphasizing timeliness, accuracy, and resource utilization. These items are measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.6 Data Analysis Using SmartPLS

The data will be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. This method is selected due to its suitability for complex models, small-to-medium samples, and predictive research (Hair et al., 2021). The analysis proceeds in two stages: measurement model assessment and structural model assessment.

In the measurement model, reliability and validity are evaluated. Internal consistency reliability is assessed using Cronbach's alpha (>0.70) and composite reliability (>0.70). Convergent validity is assessed through the average variance extracted (AVE), which should exceed 0.50 (Fornell & Larcker, 1981). Discriminant validity is tested using the Fornell–Larcker criterion and Heterotrait-Monotrait ratio (HTMT < 0.85). Multicollinearity is assessed using variance inflation factors (VIF), with values below 5 indicating acceptable levels (Kock, 2015).

In the structural model, path coefficients are estimated using bootstrapping with 5,000 resamples to test the significance of hypothesized relationships. The coefficient of determination (R^2) is used to evaluate the explanatory power of the model, with values of 0.25, 0.50, and 0.75 considered weak, moderate, and substantial, respectively (Hair et al., 2021). Predictive relevance (Q^2) is assessed using blindfolding procedures, with values above zero indicating predictive validity. Effect sizes (f^2) are calculated to measure the contribution of each exogenous construct, where 0.02, 0.15, and 0.35 represent small, medium, and significant effects. Mediation effects are tested using bootstrapping procedures, following Zhao et al.'s (2010) guidelines for full, partial, or no mediation.

This analysis ensures that both measurement properties and structural relationships are thoroughly validated, providing robust evidence for the proposed framework.

4 Expected Outcomes and Consequences

The proposed study is expected to provide both theoretical and practical insights into how technology integration, organizational culture, and socioeconomic factors influence workforce efficiency through the mediating role of competency. The first expected outcome is the empirical confirmation of competency as a critical mediator in translating organizational enablers into efficiency outcomes. This will extend socio-technical systems and organizational learning theories by demonstrating that technology and culture do not automatically generate efficiency gains, but instead require competency development as an intervening mechanism. Such findings would support recent calls for integrated models that explain the variance in digital transformation outcomes across contexts (Colombari et al., 2024; Adusei et al., 2024).

A second expected outcome is the establishment of technology integration as a significant predictor of workforce efficiency, conditional on competency. Organizations that invest in digital tools but neglect training and skill development are unlikely to realize efficiency gains, echoing evidence from digital government studies (OECD, 2024a). This emphasizes the need to align technological innovation with human capability. A third outcome relates to organizational culture, which is anticipated to show both direct and indirect effects on efficiency, highlighting that cultures emphasizing collaboration, accountability, and adaptability foster environments where competencies can flourish. Finally, socioeconomic factors such as resource adequacy, compensation fairness, and stakeholder trust are expected to moderate the extent to which competencies translate into efficient outcomes, reinforcing the importance of contextual supports in organizational performance (Park, 2024).

The consequences of these outcomes will be significant for multiple stakeholders. For employees, the findings underscore the centrality of continuous learning and competency development, highlighting opportunities for career growth and performance improvement when organizations provide adequate support. For managers and leaders, the research offers actionable insights into balancing technology adoption with culture-building and socioeconomic supports, thus enabling them to design more holistic workforce strategies (Aggarwal, 2024). For policymakers, the study will provide evidence-based recommendations on structuring training initiatives, resource allocation, and performance management frameworks in both public and private sectors. This is particularly relevant in the context of national digital agendas that seek not only to modernize infrastructure but also to enhance productivity and service delivery (OECD, 2024b). For academics and researchers, the study contributes to theory building by empirically testing competency as a mediator, enriching the understanding of how organizational and contextual variables jointly drive efficiency outcomes.

In addition, there are societal consequences. A workforce that is more competent and efficient not only improves organizational productivity but also contributes to national competitiveness and sustainable economic growth. By demonstrating how competencies can be nurtured within supportive cultural and socioeconomic environments, the study provides a framework for building resilient and adaptive organizations in the face of technological disruption.

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