Digital Transformation and Organizational Performance: Linking Employee Digital Competence, Customer Experience and Financial Outcomes

Babita Dosajh[1], Dr. Shafali[2], David Lalrochunga[3], Rama Manohar GVS[4]

[1]Professor, Chandigarh University; Email: bdosajh2@gmail.com

[2]Assistant Professor, University Institute of Legal Studies; Panjab University Chandigarh; Email: shafali088@yahoo.com

[3]Guest Faculty, North Eastern Regional Institute of Science and Technology; Email: lalrochunga@gmail.com

[4]Research Scholar, OPJU Punjipatra; Email: gvsramamanohar@yahoo.com

Abstract
Digital transformation creates organizational value only when technological resources are translated into employee capabilities, superior customer interactions, and ultimately stronger economic outcomes. This study develops and tests a three-construct model linking Employee Digital Competence (EDC), Customer Experience (CE), and Financial Outcomes (FO). PLS-SEM was applied to 200 complete survey cases using IIISR SEM v2.0.7. The reflective measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity. EDC positively influenced CE (beta = 0.545, p < .001), while CE positively influenced FO (beta = 0.545, p < .001). The indirect effect of EDC on FO through CE was significant (0.297, p < .001), supporting the proposed mediating mechanism. The model explained approximately 30% of the variance in both CE and FO and demonstrated positive predictive relevance. The findings position customer experience as an important market-facing pathway through which employee digital competence can be converted into financial value.

Keywords: digital transformation; employee digital competence; customer experience; financial outcomes; PLS-SEM

1. Introduction

Digital transformation has moved from a technology-adoption issue to a broader organizational challenge concerned with how firms create and capture value through digital technologies. Contemporary research describes digital transformation as a process in which digital technologies trigger strategic responses, changes in organizational structures and routines, and new pathways for value creation (Vial, 2019). Related work emphasizes that digitization, digitalization, and full digital transformation reshape business models, customer behavior, organizational capabilities, and performance metrics rather than merely automate existing activities (Verhoef et al., 2021). This shift is important because investments in platforms, analytics, artificial intelligence, cloud systems, and digital communication do not automatically produce organizational performance. Their value depends on whether people within the organization can use them productively and translate them into improved market outcomes.

Employee Digital Competence (EDC) is therefore a central but sometimes under-specified micro-level component of digital transformation. Digital competence encompasses the ability to locate and evaluate digital information, communicate and collaborate through digital technologies, solve problems, and use digital tools creatively in work settings (Van Laar et al., 2018). These capabilities matter because employees are the operational interface between digital infrastructure and day-to-day value creation. Even when organizations possess advanced technological resources, weak employee competence can limit adoption quality, slow response time, reduce service consistency, and prevent digital tools from being integrated into customer-facing processes. Conversely, digitally capable employees can use information more effectively, coordinate across channels, respond to customers faster, and adapt their work as technologies and customer expectations evolve.

A second issue concerns the mechanism through which employee-level digital capability becomes organizational value. Much of the digital transformation literature examines strategy, technology, business-model innovation, or firm-level digitalization, while customer experience research commonly focuses on the customer's journey, touchpoints, emotions, service encounters, and post-purchase evaluations (Lemon & Verhoef, 2016; Homburg et al., 2017). These streams are related but are not always integrated. This separation leaves an important explanatory gap: an organization may

possess digitally competent employees, yet the economic value of those competencies is likely to depend on whether they actually improve what customers experience. Customer Experience (CE) provides a useful market-facing mechanism because it captures the customer's assessment of the organization's ability to meet needs, deliver outcomes, reduce effort, respond to problems, and create dependable interactions (Klaus & Maklan, 2012, 2013).

The financial relevance of customer experience is supported by the service-profit logic, which links internal organizational conditions to customer responses and, subsequently, to economic outcomes. Empirical work has shown that customer satisfaction and related customer evaluations can be associated with financial performance and shareholder value (Anderson et al., 2004; Chi & Gursoy, 2009). A meta-analytic test of the service-profit chain further indicates that the links connecting internal service conditions, customer outcomes, and firm performance are generally significant, although their strength varies by context (Hogreve et al., 2017). In digital settings, the implication is that employee competence may become financially valuable not simply because employees can operate digital tools, but because those abilities help produce smoother, more responsive, and more valuable customer experiences.

Existing digitalization research also suggests that organizational resources do not always have a straightforward direct association with financial performance. For example, Eller et al. (2020) found that digitalization linked organizational resources to financial outcomes and cautioned against assuming that employee skills alone automatically create financial returns. Similarly, dynamic-capabilities research portrays digital transformation as an ongoing process of sensing, learning, adapting, and reconfiguring activities around new technologies and customer value (Warner & Wager, 2019; Matarazzo et al., 2021). This evidence strengthens the case for testing an explicit intermediate pathway rather than treating employee digital competence as a direct proxy for organizational performance.

Accordingly, this study examines a parsimonious three-variable model in which EDC influences CE, which in turn influences FO. The study addresses three questions: whether employee digital competence improves customer experience, whether customer experience improves financial outcomes, and whether customer experience carries an indirect effect from employee digital competence to financial outcomes. The study contributes by connecting a workforce-level digital capability with a customer-level value mechanism and an organizational economic outcome in one structural model. Practically, the model helps managers distinguish between technology training as an input and customer experience as the mechanism through which that input can be converted into financial value. The empirical analysis uses PLS-SEM on 200 complete cases and evaluates measurement quality, structural relationships, mediation, explanatory power, and predictive relevance.

2. Literature Review and Hypothesis Development

2.1 Theoretical foundation: digital capabilities and the service-profit mechanism

The conceptual model combines a digital-capabilities perspective with the logic of the service-profit chain. Digital transformation research increasingly treats technological change as an organizational capability problem rather than a hardware or software problem. Bharadwaj et al. (2013) argue that digital technologies blur the boundary between business strategy and information-technology strategy and create new possibilities for value creation and capture. Vial (2019) similarly conceptualizes digital transformation as a process in which digital technologies generate disruptions, strategic responses, structural changes, and altered value-creation paths. From a dynamic-capabilities perspective, organizations must continuously sense opportunities, learn, coordinate, and reconfigure resources so that digital technologies become embedded in operational routines (Warner & Wager, 2019). Matarazzo et al. (2021) further show how digital transformation can support customer value creation when sensing and learning capabilities translate technologies into new channels, interactions, and value propositions. Within this logic, employee digital competence can be understood as a micro-level capability that makes organizational digital resources usable in practice.

The service-profit perspective provides the complementary market-to-financial logic. Its core proposition is that internal organizational conditions influence employee behaviors and service delivery, which shape customer responses and subsequently financial results. Evidence has repeatedly linked customer satisfaction and customer-facing outcomes with economic performance (Chi & Gursoy, 2009; Anderson et al., 2004), and the meta-analysis by Hogreve et al. (2017) supports the broader chain while also showing contextual variation. The present study adapts this logic to digital transformation: employee competence is the internal capability, customer experience is the market-facing mechanism, and financial outcomes represent organizational value capture. This combination is useful because it avoids assuming that digital capability has value in isolation; instead, it proposes that capability must be translated into experiences that customers recognize and reward.

2.2 Employee Digital Competence and Customer Experience

Employee Digital Competence refers to employees'

capacity to use digital information, tools, communication channels, collaborative technologies, problem-solving approaches, and creative digital practices effectively in their work. Van Laar et al. (2018) developed and validated a digital-skills instrument for working professionals and identified information, communication, collaboration, critical thinking, creativity, and problem solving as core digital skill domains. These competencies are especially relevant in customer-facing environments because digital interactions increasingly require employees to retrieve information across systems, interpret customer data, coordinate with colleagues, solve non-routine problems, and communicate through multiple channels. Recent evidence also continues to associate employee digital competence with improved employee-level performance in technology-intensive organizational settings (Chai et al., 2026).

Customer experience is formed across multiple touchpoints and is affected by both functional and relational aspects of interactions (Lemon & Verhoef, 2016). Digital systems can improve those touchpoints only if employees can use them in ways that reduce customer effort, increase accuracy, personalize responses, and recover effectively from service problems. Homburg et al. (2017) describe customer experience management as an organizational resource requiring cultural orientations, strategic direction, and capabilities that continually renew customer interactions. Thus, digital competence should allow employees to convert technology into more reliable and responsive customer processes. The relationship is also consistent with the broader observation that digital transformation can create new channels and new forms of customer value when organizational capabilities are aligned with customer needs (Matarazzo et al., 2021). Therefore, the first hypothesis is proposed:

H1: Employee Digital Competence has a positive and significant effect on Customer Experience.

2.3 Customer Experience and Financial Outcomes

Customer Experience represents the customer's holistic evaluation of interactions with an organization, including the extent to which needs are understood, desired outcomes are achieved, interactions require minimal effort, problems are handled effectively, and the provider is dependable. Klaus and Maklan (2012) developed the EXQ scale to capture experience beyond conventional service-quality or satisfaction measures, and later work showed that experience quality can predict important customer outcomes such as loyalty and recommendation (Klaus & Maklan, 2013). Customer experience therefore has economic relevance because it can influence retention, repurchase, advocacy, price tolerance, and the stability of future customer relationships.

The link between customer evaluations and financial value has a strong empirical foundation. Anderson et al. (2004) reported a positive association between customer satisfaction and shareholder value, arguing that customer satisfaction influences the level, timing, and risk of future cash flows. Chi and Gursoy (2009) found that customer satisfaction had a positive effect on financial performance and could transmit employee-related effects to financial outcomes. At a broader level, Hogreve et al. (2017) found meta-analytic support for the service-profit chain and highlighted the role of customer responses in connecting internal service conditions to firm performance. Although customer experience is conceptually broader than satisfaction, the same economic logic applies: when customers perceive interactions as easy, responsive, trustworthy, and outcome-oriented, the organization is better positioned to retain demand and realize financial benefits. Hence:

H2: Customer Experience has a positive and significant effect on Financial Outcomes.

2.4 Mediating role of Customer Experience

The mediation argument follows from the distinction between organizational capability and realized market value. Employee digital competence is an internal resource: it can improve information processing, coordination, technology use, and problem solving, but these benefits become economically meaningful only when they alter outcomes valued by customers. This reasoning is consistent with studies showing that digitalization can mediate resource-performance relationships (Eller et al., 2020) and with service-profit research in which customer outcomes carry internal organizational effects toward financial performance (Chi & Gursoy, 2009). A mediation model is therefore theoretically preferable to an assumption that employee digital competence must directly produce profit or revenue. In the present model, customer experience is the mechanism through which digitally capable employees contribute to financial outcomes. The indirect pathway also aligns with dynamic-capabilities thinking because resources create value when they are deployed and reconfigured around market needs rather than merely possessed (Warner & Wager, 2019). Accordingly:

H3: Customer Experience positively mediates the relationship between Employee Digital Competence and Financial Outcomes.

Figure 1. Proposed conceptual model

3. Methodology

3.1 Research design and analytical sample

The study used a quantitative, cross-sectional explanatory design to test the proposed relationships among Employee Digital Competence, Customer Experience, and Financial Outcomes. The analytical dataset contained 200 complete cases. The SEM export reported that no case was excluded for missing or non-numeric values on model indicators or control variables. The model contained 17 observed indicators: six for EDC, eight for CE, and three for FO. All indicators were coded on a five-point response metric, with the observed values spanning 1 to 5. The analytical export available for manuscript preparation does not retain sector, geographic location, respondent demographics, sampling-frame information, or recruitment metadata. Accordingly, the study does not make population-specific claims that are not supported by the supplied analysis record; this limitation is revisited in the discussion.

A sample of 200 is adequate for estimating this parsimonious PLS-SEM model, which has only one predictor for each endogenous construct. Contemporary PLS-SEM guidance discourages exclusive reliance on the traditional '10-times rule' and recommends considering statistical power and model characteristics instead (Kock & Hadaya, 2018; Hair et al., 2019). The present sample provides a substantial ratio of observations to indicators and structural paths and is well above levels typically encountered in minimum-sample discussions for a model of this simplicity. No control variables, moderators, higher-order constructs, or multi-group comparisons were specified in the estimated model.

3.2 Measures

All three constructs were specified as reflective Mode A constructs. Employee Digital Competence was measured with six adapted indicators based on the working-professional digital-skills framework of Van Laar et al. (2018). The indicators capture information search and evaluation, digital communication and collaboration, creative use of digital technologies, and digital problem solving. Customer Experience was represented by eight adapted indicators informed by the EXQ framework of Klaus and Maklan (2012, 2013), focusing on need fulfilment, ease, desired outcomes, flexibility, problem resolution, confidence, and dependable interaction. Financial Outcomes was measured with three perceptual business-economic performance indicators - sales/revenue growth, net-income/profit growth, and return on investment - based on Venkatraman and Ramanujam (1987). The use of perceptual financial measures is consistent with strategy research when comparable objective accounting data are not available across respondents or organizations.

Table 1. Construct operationalization and measurement sources

Construct	Codes	Items	Measurement focus	Source
Employee Digital Competence	EDC1-EDC6	6	Digital information, evaluation, communication, collaboration, creativity and problem solving	Van Laar et al. (2018)
Customer Experience	CE1-CE8	8	Need fit, ease, outcome focus, flexibility, problem handling, confidence and dependable interaction	Klaus & Maklan (2012, 2013)
Financial Outcomes	FO1-FO3	3	Revenue/sales growth, net-income/profit growth and ROI	Venkatraman & Ramanujam (1987)

3.3 PLS-SEM procedure

The model was estimated with partial least squares structural equation modeling using IIISR SEM v2.0.7. PLS-SEM was selected because the study is prediction-oriented, uses latent composite scores, and evaluates both the explanatory and predictive performance of a compact mediation model. The reporting sequence followed established PLS-SEM recommendations: assessment of reflective

measurement quality, discriminant validity, structural paths, explanatory power, mediation, effect sizes, and predictive relevance (Hair et al., 2012, 2019). Reflective indicator loadings were screened against the commonly used .708 guideline. Internal consistency was evaluated using Cronbach's alpha and composite reliability, and convergent validity using average variance extracted (AVE), with AVE above .50 indicating that a construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981).

Discriminant validity was evaluated through the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT). Because the Fornell-Larcker criterion can fail to detect discriminant-validity problems in some settings, HTMT was treated as the primary complementary diagnostic (Henseler et al., 2015). The export reported HTMT values and bootstrap confidence intervals based on 500 HTMT resamples; values below .85/.90 and upper confidence limits below 1.00 were interpreted as supportive. Structural paths were evaluated using standardized coefficients, standard errors, t statistics, p values, and 95% bootstrap confidence intervals. Inner VIF values were inspected for collinearity, while R-squared and f-squared were used to describe explanatory power and effect magnitude.

The mediating hypothesis was tested from the specific indirect effect EDC -> CE -> FO. Modern mediation analysis emphasizes direct inference on the bootstrapped indirect effect rather than relying on a sequence of separate significance tests (Nitzl et al., 2016). Importantly, the structural model did not include a direct EDC -> FO path. Consequently, the analysis can establish whether the specified indirect mechanism is significant, but it cannot distinguish partial from full mediation or compare the indirect pathway with an estimated direct effect. Predictive assessment included Q-squared and a construct-level PLSpredict procedure, comparing PLS prediction errors with a benchmark. Shmueli et al. (2019) recommend such out-of-sample-oriented checks to complement explanatory PLS-SEM assessment. Composite-model indices including SRMR, d_ULS, NFI, and RMS_theta were also reported as descriptive screening diagnostics; because definitions can vary across PLS-SEM implementations, these indices were not treated as stand-alone proof of model validity.

4. Results

4.1 Descriptive statistics and measurement model

All 200 observations were retained in estimation. Indicator means ranged from 2.810 to 3.125 and standard deviations ranged from 1.052 to 1.196, showing substantial use of the five-point response range. The reflective measurement model demonstrated strong indicator reliability. EDC loadings ranged from .806 to .837, CE loadings from .751 to .852, and FO loadings from .845 to .871. Thus, every retained indicator exceeded the .708 screening guideline. Internal consistency was also satisfactory: Cronbach's alpha was .904 for EDC, .921 for CE, and .818 for FO; composite reliability values were .926, .935, and .891, respectively. AVE values of .677 for EDC, .644 for CE, and .732 for FO all exceeded .50, supporting convergent validity.

Table 2. Reliability and convergent validity

Construct	Loading range	Cronbach alpha	Composite reliability	AVE
Employee Digital Competence	.806-.837	.904	.926	.677
Customer Experience	.751-.852	.921	.935	.644
Financial Outcomes	.845-.871	.818	.891	.732

Discriminant validity was supported by both reported approaches. The square roots of AVE were .823 for EDC, .802 for CE, and .856 for FO, each exceeding the relevant inter-construct correlations. HTMT values were .594 for EDC-CE, .442 for EDC-FO, and .624 for CE-FO. These values were below .85, and their bootstrap confidence intervals - [.479, .683], [.302, .575], and [.508, .722], respectively - remained below 1.00. The evidence therefore indicates that the three constructs are empirically distinguishable.

Table 3. Discriminant validity

Construct pair	Correlation	HTMT	HTMT 95% CI
EDC - CE	.545	.594	[.479, .683]
EDC - FO	.380	.442	[.302, .575]

CE - FO	.545	.624	[.508, .722]

4.2 Structural model and hypothesis testing

The structural model produced two positive and statistically significant direct relationships. EDC had a positive effect on CE (beta = .545, SE = .047, t = 11.544, p < .001, 95% CI [.452, .634]), supporting H1. The associated f-squared value was .422, indicating a large effect within the estimated model. CE, in turn, positively affected FO (beta = .545, SE = .048, t = 11.306, p < .001, 95% CI [.449, .639]), supporting H2; its f-squared value was .421, also classified as large. Inner VIF was 1.000 for both structural paths, so collinearity was not a concern in this one-predictor-per-equation model.

The model explained 29.7% of the variance in CE (R-squared = .297; adjusted R-squared = .293) and 29.6% of the variance in FO (R-squared = .296; adjusted R-squared = .293). The specific indirect effect EDC -> CE -> FO was .297 (SE = .042, t = 7.119, p < .001, 95% CI [.220, .385]). Because the confidence interval excluded zero, H3 was supported. The result demonstrates a statistically reliable indirect pathway from employee digital competence to financial outcomes through customer experience. However, the direct EDC -> FO path was not estimated in the specified model, so the result should not be labeled partial or full mediation.

Table 4. Structural relationships and hypothesis decisions

Hypothesis / path	Effect	SE	t	p	95% CI	Decision
H1: EDC -> CE	.545	.047	11.544	< .001	[.452, .634]	Supported
H2: CE -> FO	.545	.048	11.306	< .001	[.449, .639]	Supported
H3: EDC -> CE -> FO (indirect)	.297	.042	7.119	< .001	[.220, .385]	Supported

4.3 Predictive assessment and model diagnostics

Predictive diagnostics were favorable. CE showed Q-squared = .292 and construct-level Q-squared_predict = .290. Its PLS RMSE (.847) was lower than the benchmark RMSE (1.005), and PLS MAE (.701) was lower than the benchmark MAE (.826). FO showed Q-squared = .294 and Q-squared_predict = .288; its PLS RMSE (.849) was lower than the benchmark RMSE (1.006), and its PLS MAE (.688) was below the benchmark MAE (.840). These results indicate that the model possesses predictive relevance for both endogenous constructs in the implementation used. The importance-performance analysis for FO assigned CE an importance of .545 and performance of 49.7, while EDC had indirect importance of .297 and performance of 49.3, suggesting that customer experience is the more immediate leverage point for the financial-outcome target.

Composite-model screening diagnostics were SRMR = .0482, d_ULS = .0070, NFI = .9906, and RMS_theta = .0696. The SRMR value is below the frequently cited .08 screening threshold (Hu & Bentler, 1999), while NFI was high and RMS_theta low in the software output. These indices are reported descriptively rather than treated as universal goodness-of-fit tests, because the supplied IIISR SEM output explicitly notes that composite-model diagnostics and their definitions may differ across PLS-SEM implementations. Figure 2 presents the estimated model and standardized coefficients.

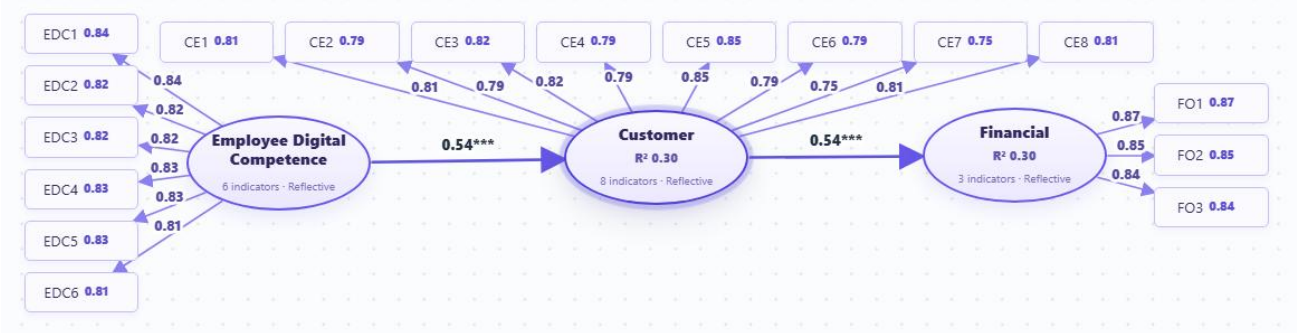

Figure 2. Estimated PLS-SEM model

5. Discussion

The results provide consistent support for the proposed capability-experience-performance chain. First, Employee Digital Competence had a substantial positive association with Customer Experience. The standardized coefficient of .545 and large f-squared effect indicate that employees' ability to use digital information, tools, communication channels, collaborative technologies, and problem-solving

practices is closely connected with the quality of customer-facing outcomes. This finding extends the digital-skills literature beyond employee task performance. Van Laar et al. (2018) established digital skills as a multidimensional set of capabilities for working professionals; the present results suggest that these capabilities also matter for how customers experience organizational processes. The result is consistent with digital-transformation research emphasizing that technologies create value only when they are embedded in organizational routines and capabilities (Vial, 2019; Warner & Wager, 2019). It also aligns with current evidence linking employee digital competence to improved employee performance (Chai et al., 2026), while showing a different downstream consequence: customer experience.

Second, Customer Experience was positively associated with Financial Outcomes. The effect was again .545 and was statistically precise, with the 95% confidence interval remaining well above zero. This finding supports the central economic logic of customer-experience management. Customers who perceive that an organization understands needs, delivers desired outcomes, reduces interaction effort, responds flexibly, and resolves problems effectively are more likely to produce behaviors that support revenue stability and profitability. The result is consistent with work demonstrating links between customer satisfaction and shareholder value (Anderson et al., 2004), with evidence that customer satisfaction predicts financial performance (Chi & Gursoy, 2009), and with the broader service-profit-chain meta-analysis (Hogreve et al., 2017). The present study contributes by using a broader customer-experience construct rather than treating satisfaction alone as the market-facing outcome.

Third, the indirect effect from EDC to FO through CE was significant. This is theoretically important because it clarifies how an internal digital capability can be connected with an organizational financial outcome. Digital competence does not generate revenue merely because employees possess technical skills. Its business value emerges when employees use those skills to improve customer-relevant processes and interactions. This mechanism is consistent with the dynamic-capabilities perspective, in which resources must be deployed and reconfigured around changing market requirements (Matarazzo et al., 2021), and with findings that digitalization can transmit the effects of organizational resources to financial performance (Eller et al., 2020). It also parallels the service-profit-chain logic in which customer outcomes carry internally generated improvements toward financial results. The model therefore offers a concise micro-to-market-to-financial explanation of digital transformation value creation.

The study makes three theoretical contributions. First, it places employee digital competence at the microfoundation of digital transformation. Digital transformation studies often operate at the level of strategy, technologies, business models, or organizational architecture (Bharadwaj et al., 2013; Hanelt et al., 2021; Verhoef et al., 2021). By explicitly modeling employee competence, the study shows that the human ability to use digital resources is a necessary analytical layer between organizational digital investment and market performance. Second, it connects the digital-capabilities literature with customer-experience theory. Customer experience is frequently treated as the result of customer journeys and touchpoints (Lemon & Verhoef, 2016), but the results emphasize that employee competence is one organizational antecedent capable of shaping those touchpoints. Third, the mediation result connects these literatures with financial performance and supports a mechanism-based interpretation rather than a simple technology-performance association.

The explanatory and predictive evidence strengthens this interpretation. EDC explained 29.7% of the variance in CE, and CE explained 29.6% of the variance in FO. These values indicate meaningful but incomplete explanatory power, which is realistic because customer experience and financial outcomes are affected by many factors beyond the two modeled constructs. The positive Q-squared and Q-squared_predict values, together with lower PLS prediction errors than the benchmark, also indicate that the model is not solely descriptive within the observed sample. This is important because PLS-SEM is increasingly evaluated as a causal-predictive approach in which explanation should be accompanied by predictive assessment (Shmueli et al., 2019). At the same time, the findings should not be interpreted as proving causality because the data are cross-sectional.

For managers, the findings imply that digital-transformation programs should not evaluate employee training only through completion rates, technology-adoption counts, or system usage. Training and capability development should be tied to customer-facing tasks: retrieving the right information at the point of service, coordinating across digital channels, solving customer problems without unnecessary transfers, using digital data to personalize responses, and maintaining consistent communication across touchpoints. The importance-performance results reinforce this point because CE had the strongest total importance for FO. Managers can therefore treat customer-experience indicators as intermediate performance measures that reveal whether digital competence is being converted into value. If competence rises but customer experience does not, the problem may lie in process design, system usability, incentives, or cross-functional coordination rather than in skill alone.

The financial-outcome findings also have implications for measurement. Because FO was captured through perceptual indicators of revenue or

sales growth, profit growth, and ROI, managers should ideally complement survey-based assessments with objective accounting data where access permits. This would allow researchers and practitioners to examine whether improved customer experience precedes measurable changes in revenue, margins, repeat purchases, or customer lifetime value. It may also reveal time lags. Service-profit-chain research has shown that internal actions, customer responses, and financial effects do not necessarily occur simultaneously. Longitudinal performance dashboards linking employee digital competence, customer experience metrics, and financial indicators would therefore provide a stronger basis for managerial learning than a single snapshot.

Several limitations qualify the conclusions. First, the analysis is cross-sectional and cannot establish temporal causality. Second, the analytical export used for manuscript preparation does not contain sector, geography, respondent demographics, or sampling-frame information, restricting claims about generalizability. Third, the model contains no controls, moderators, or group comparisons; industry conditions, firm size, digital maturity, employee role, and customer-contact intensity could alter the observed relationships. Fourth, financial outcomes are perceptual rather than directly audited accounting values. Fifth, the supplied SEM output does not report a dedicated common-method-bias test, so method variance cannot be ruled out. Future studies should use multi-source designs in which employees report digital competence, customers provide experience evaluations, and financial outcomes are drawn from organizational records. Temporal separation and marker-variable or method-factor approaches could further strengthen inference.

A final modeling limitation is especially important for interpreting H3. The specified structural model does not contain a direct EDC -> FO path. Therefore, the significant indirect effect establishes the proposed mediated pathway but does not permit a statistical conclusion that mediation is 'full' rather than 'partial.' Future research should estimate the direct path alongside the indirect path and compare competing models. Additional work could test whether digital maturity, service climate, leadership support, organizational agility, or task interdependence strengthens the EDC-CE relationship. Multi-group analysis could examine whether the mechanism differs across service versus manufacturing contexts or across high- and low-digital-intensity sectors. These extensions would preserve the parsimonious logic of the present model while improving boundary-condition knowledge.

6. Conclusion

This study examined how employee-level digital capability can be connected with organizational performance through a customer-facing mechanism. The proposed model positioned Employee Digital Competence as the internal capability, Customer Experience as the mediating pathway, and Financial Outcomes as the organizational result. Using 200 complete cases and PLS-SEM, the analysis found strong measurement quality and support for all three hypotheses. Employee Digital Competence positively influenced Customer Experience, Customer Experience positively influenced Financial Outcomes, and the indirect EDC -> CE -> FO effect was statistically significant. The model explained about 30% of the variance in each endogenous construct and also demonstrated positive predictive relevance.

The central implication is that digital transformation should be understood as a value-conversion process rather than a technology-acquisition process. Employees may possess digital skills, but those skills become strategically meaningful when they improve the way customers interact with the organization. Customer experience is therefore not merely a marketing outcome; it is a mechanism through which workforce digital competence can be translated into financial value. This interpretation integrates insights from digital transformation, dynamic capabilities, customer-experience management, and the service-profit chain.

For practice, the findings support investment in digital capability development that is explicitly connected to customer journeys and service processes. Organizations should identify which employee digital behaviors reduce customer effort, improve responsiveness, strengthen problem resolution, and increase confidence, and then monitor whether improvements in those experience indicators precede stronger financial results. For research, longitudinal, multi-source, and multi-industry studies are needed to establish temporal ordering, test the omitted direct EDC-to-FO relationship, incorporate objective financial measures, and identify boundary conditions. Within these limits, the study provides a parsimonious empirical explanation of how the human side of digital transformation can contribute to organizational performance through customer experience.

Reference

1. Anderson, E. W., Fornell, C., & Mazvancheryl, S. K. (2004). Customer satisfaction and shareholder value. Journal of Marketing, 68(4), 172-185. https://doi.org/10.1509/jmkg.68.4.172.42723
2. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471-482. https://doi.org/10.25300/MISQ/2013/37:

2.3

3. Chai, M., Wong, D. H.-T., & Yuan, M. (2026). Employee digital competence, financial technology, and enhancement of employee performance in enterprises. Finance Research Letters, 100, 109993. https://doi.org/10.1016/j.frl.2026.109993
4. Chi, C. G.-Q., & Gursoy, D. (2009). Employee satisfaction, customer satisfaction, and financial performance: An empirical examination. International Journal of Hospitality Management, 28(2), 245-253. https://doi.org/10.1016/j.ijhm.2008.08.003
5. Eller, R., Alford, P., Kallmunzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. Journal of Business Research, 112, 119-127. https://doi.org/10.1016/j.jbusres.2020.03.004
6. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50. https://doi.org/10.1177/002224378101800104
7. Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40(3), 414-433. https://doi.org/10.1007/s11747-011-0261-6
8. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203
9. Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. Journal of Management Studies, 58(5), 1159-1197. https://doi.org/10.1111/joms.12639
10. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43, 115-135. https://doi.org/10.1007/s11747-014-0403-8
11. Hogreve, J., Iseke, A., Derfuss, K., & Eller, T. (2017). The service-profit chain: A meta-analytic test of a comprehensive theoretical framework. Journal of Marketing, 81(3), 41-61. https://doi.org/10.1509/jm.15.0395
12. Homburg, C., Jozic, D., & Kuehnl, C. (2017). Customer experience management: Toward implementing an evolving marketing concept. Journal of the Academy of Marketing Science, 45, 377-401. https://doi.org/10.1007/s11747-015-0460-7
13. Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1-55. https://doi.org/10.1080/10705519909540118
14. Klaus, P., & Maklan, S. (2012). EXQ: A multiple-item scale for assessing service experience. Journal of Service Management, 23(1), 5-33. https://doi.org/10.1108/09564231211208952
15. Klaus, P., & Maklan, S. (2013). Towards a better measure of customer experience. International Journal of Market Research, 55(2), 227-246. https://doi.org/10.2501/IJMR-2013-021
16. Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, 28(1), 227-261. https://doi.org/10.1111/isj.12131
17. Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69-96. https://doi.org/10.1509/jm.15.0420
18. Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. Journal of Business Research, 123, 642-656. https://doi.org/10.1016/j.jbusres.2020.10.033
19. Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial Management & Data Systems, 116(9), 1849-1864. https://doi.org/10.1108/IMDS-07-2015-

0302

20. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189
21. Van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2018). 21st-century digital skills instrument aimed at working professionals: Conceptual development and empirical validation. Telematics and Informatics, 35(8), 2184-2200. https://doi.org/10.1016/j.tele.2018.08.006
22. Venkatraman, N., & Ramanujam, V. (1987). Measurement of business economic performance: An examination of method convergence. Journal of Management, 13(1), 109-122. https://doi.org/10.1177/014920638701300109
23. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889-901. https://doi.org/10.1016/j.jbusres.2019.09.022
24. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003
25. Warner, K. S. R., & Wager, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. Long Range Planning, 52(3), 326-349. https://doi.org/10.1016/j.lrp.2018.12.001