

The Influence of Digital Procurement Transformation on Procurement Performance: The Mediating Roles of Procurement Transparency and Process Agility in Pakistani Organizations



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Abstract: Digital technologies are increasingly central to procurement modernization efforts worldwide; however, empirical evidence on their actual contribution to procurement performance remains scarce, particularly in developing economies. This study examines the effect of digital procurement transformation on procurement performance among Pakistani organizations, with procurement transparency and process agility investigated as sequential mediating mechanisms. Grounded in the dynamic capabilities perspective and information transparency theory, a conceptual model was developed to explain this relationship. A quantitative, cross-sectional design was adopted, with data collected from 250 procurement professionals and supply chain managers across Pakistani organizations via a structured questionnaire. Hypothesized relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess both direct and indirect effects. Results indicate that digital procurement transformation significantly and positively influences procurement performance, with this relationship partially mediated by procurement transparency and process agility. Organizations adopting digital procurement solutions demonstrate greater sourcing visibility and enhanced process flexibility, both of which contribute to improved performance outcomes. These findings extend the digital procurement literature by clarifying the mechanisms underlying value creation and offer practical implications for managers and policymakers seeking to strengthen procurement capabilities in emerging markets. The study further establishes a foundation for future research examining additional mediators and moderators within the digital procurement–performance nexus.

Keywords: Digital Procurement Transformation, Procurement Performance, Procurement Transparency, Pakistani Organizations, Digital Technologies

Introduction

To enhance overall Procurement Performance, businesses must initially transform technological investments into intermediate operational capabilities such as Process Agility and Procurement Transparency. Herold et al. (2022) studied “Dynamic capabilities for digital procurement transformation: a systematic literature review”; the paper’s aim was to establish a shared comprehension of the skills necessary for the transformation of digital procurement (DP). Design/methodology/approach – The writers situate the theoretical framework concerning dynamic capabilities (DCs) to consolidate the disjointed body of research on procurement digitalization through a systematic literature review. Through the extraction and clustering of skills, alongside validated performance results from current situation.

Findings – The authors initially present and explain DPT along with the associated motivations that drive companies to allocate resources in cutting-edge digital technologies. Secondly, through the adoption of the

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DC perspective, the authors offer a summary of nine micro-foundations essential for DPT and underscore the strategic choices procurement leaders may employ when planning on integrating various digital technologies. Teo et al. (2009) studied “Adopters and non-adopters of e-procurement in Singapore: An empirical study” and said that the Technology–Organization–Environment (TOE) framework offers a valuable organizational viewpoint for comprehending the reasons behind firms' adoption of technological innovations. Teo, Lin, and Lai (2009) utilized the framework to investigate the implementation of e-procurement by firms in Singapore. Employing survey data from 141 organizations and logistic regression analysis, the research examined technological, organizational, and environmental elements linked to adoption. The results showed that company size, support from top management, perceived indirect advantages, and influence from business partners were significantly linked to the adoption of e-procurement. The research shows that technology adoption is influenced not just by the features of a technology; organizational abilities and external connections are also significant factors.

Supporting Theory

This article supports two theories, i.e., Technology–Organization–Environment (TOE) Framework and ii. Dynamic Capabilities Theory.

Technology–Organization–Environment (TOE) Framework

The Technology–Organization–Environment (TOE) Framework is an organizational-level theory, developed in 1990 by Louis G. Tornatzky and Mitchell G. Fleischer, that explains how and why a firm selects to adopt and implement new technological innovations. It suggests that the decision to accept an innovation is prejudiced by three distinct contexts: Technology, Organization, and Environment.

Holistic Perspective: Unlike frameworks that concentrate solely on personal psychology or user perceptions (such as consumer technology adoption frameworks), the TOE model examines the complete enterprise environment, integrating internal strengths with external market influences.

Strategic Planning: It aids decision-makers in recognizing obstacles prior to initiating a project—like discovering that an organization possesses the technology and market demand, yet lacks the internal capabilities or leadership backing to implement it. A systematic review of cloud-technology adoption in organizations investigated the application of the TOE framework in classifying and elucidating factors that influence organizational choices to adopt cloud-based technologies.

Wang et al. (2010) applied the TOE framework to examine the elements affecting the adoption of radio-frequency identification (RFID) within the manufacturing sector. The research identified nine elements encompassing technological, organizational, and environmental aspects, such as relative advantage, compatibility, complexity, support from top management, company size, technological capability, information intensity, competitive pressure, and pressure from trading partners. Logistic regression was applied to data from 133 manufacturing companies in Taiwan. The results indicated that factors from each of the three TOE contexts played a role in clarifying RFID adoption. The research emphasizes the significance of taking into account technological traits alongside internal organizational assets and external competitive and inter organizational influences. It thus demonstrates how the TOE framework can be applied to analyze the integration of new technologies in manufacturing companies. Skafi, Yunis, and Zekri (2020) examined the factors influencing cloud computing adoption in small and medium-sized enterprises (SMEs) in Lebanon by merging the TOE framework with contextual theory.

Dynamic Capabilities Theory

The Dynamic Capabilities Theory is a key strategic management model that elucidates how companies modify, incorporate, and reorganize their internal and external abilities to respond to swiftly evolving landscapes. Created as an extension of the Resource-Based View (RBV) of the firm, it tackles a significant

limitation of RBV: although RBV clarifies how valuable, rare, and inimitable resources offer a competitive edge in stable markets, it finds it difficult to explain how firms endure and succeed in volatile, hyper-competitive, and disruptive markets.

Theoretical Roots and Evolution

The Impact of Evolutionary Economics: Heavily based on the research of Richard Nelson and Sidney Winter (1982), which examined firms from an evolutionary perspective, emphasizing organizational routines and their transformation over time.

The expression "dynamic capabilities" was introduced and established by David Teece, Gary Pisano, and Amy Shuen in their influential 1997 article, "Dynamic Capabilities and Strategic Management." David Teece later significantly elaborated on it in his influential 2007 paper, "Explicating Dynamic Capabilities: The Nature and Micro-foundations of (Sustainable) Enterprise Performance."

Core Definition and Distinctions

David Teece characterized dynamic capabilities as "the organization's capacity to combine, develop, and modify internal and external skills to respond to swiftly evolving contexts." A key difference in the literature (further explained by researchers such as Sidney Winter in 2003) is the separation of Ordinary Capabilities and Dynamic Capabilities and Basic (Operational/Zero-Order) Capabilities. These refer to the necessary routines to "make a living" in the immediate future. They manage daily administrative, operational, and technical tasks (e.g., performing standard accounting, regular manufacturing, or fundamental supply chain implementation). They respond, "Are we doing this correctly?" Dynamic (Higher-Order) Capabilities: These are elevated routines that alter, expand, or change basic capabilities.

The Three Pillars: Sensing, Seizing, and Transforming

In his refined framework, Teece (2007) broke dynamic capabilities down into three distinct operational processes (often called "micro-foundations"):

Sensing (Opportunities and Threats): Companies cannot sit back and wait for changes to come to them; they need to proactively observe, analyze, and understand the outside environment. What it entails: Customer analysis, observing technological changes, keeping an eye on competitors, and leveraging local and global scientific/market connections. Main Goal: Identifying hidden customer demands or upcoming market changes ahead of rivals.

Seizing (Mobilizing Resources): When an opportunity or threat is detected, the organization needs to create a feasible business model and invest financial, physical, and human resources to seize value. What it entails: Choosing product frameworks, creating client solutions, defining the firm's limits (make-or-buy choices), and fostering commitment via strategic investments and collaborations. Main Goal: Converting insights into a marketable product, service, or procedure.

Transforming (Continuous Renewal and Reconfiguration): As companies expand, they encounter structural inertia, silos, and "core rigidities" (practices that were once beneficial but now hinder their progress). Dynamic capabilities necessitate ongoing organizational rejuvenation. What it entails: Decentralizing organizational frameworks, coordinating co-specialized resources, readjusting internal incentives, discarding outdated legacy assets, and promoting a culture of ongoing organizational learning.

Main Goal: Avoiding outdated-ness and sustaining flexibility across various generations of products and technologies.

Literature Review

Digital transformation is progressively altering procurement processes through the incorporation of electronic procurement systems, data analysis, automation, cloud platforms, and digitally supported decision-making within the procurement cycle. This research examines how digital procurement transformation affects procurement performance in organizations in Pakistan, focusing specifically on the mediating roles of process agility and procurement transparency. Utilizing the Technology–Organization–Environment (TOE) framework and existing literature on digital transformation, the research suggests that transforming digital procurement can enhance procurement efficiency by boosting the visibility, traceability, and availability of procurement data, while also allowing organizations to adapt more swiftly to evolving purchasing needs. Current empirical studies suggest that digital procurement skills and data analysis are linked to enhanced operational and supply-chain performance, whereas e-procurement enhances transparency, coordination, and efficiency studied by Kumar, N., & Ganguly, K. K. (2021). Recent findings suggest that digital procurement may shorten administrative processing durations and enhance access to procurement information. In Pakistan, new findings on e-procurement suggest possible enhancements in efficiency, transparency, cost savings, and audit-ability, despite ongoing issues like partial automation, digital literacy, and institutional preparedness.

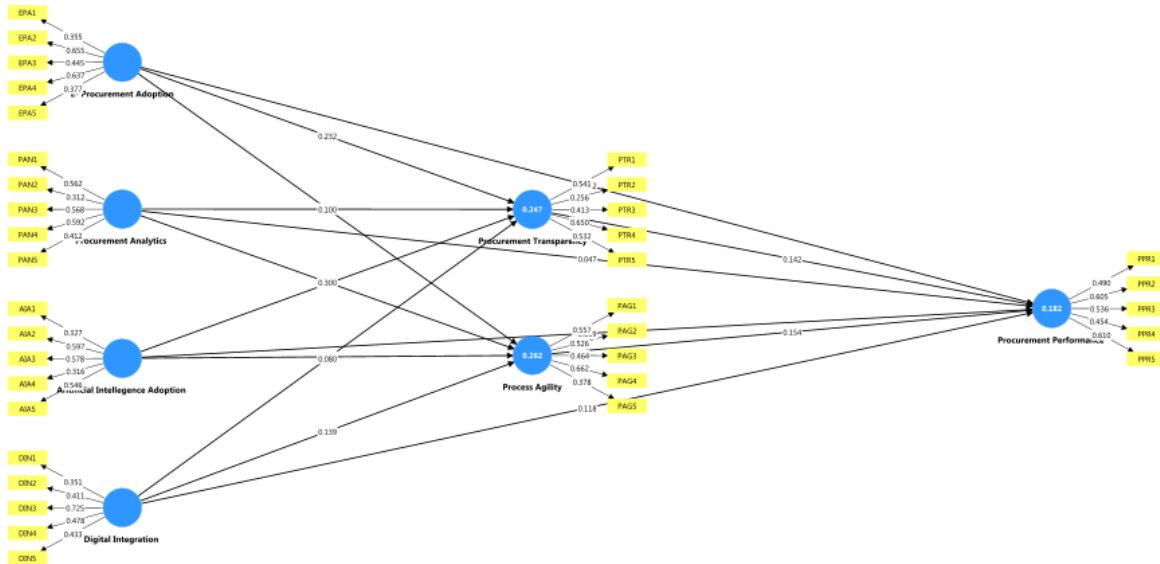
Thus, this study defines procurement transparency and process agility as means by which digital procurement transformation can lead to enhanced procurement performance. The suggested study can enhance the procurement and digital-transformation literature by offering empirical data from Pakistani organizations and by clarifying how, instead of just whether, digital procurement transformation impacts procurement performance. Digital procurement technologies can streamline repetitive tasks, consolidate procurement data, enable real-time communication, and offer decision-makers prompt information. These abilities may allow procurement teams to react more swiftly to fluctuations in demand, supplier circumstances, pricing, and organizational needs. Hallikas et al. (2021) demonstrate that digital procurement abilities and data analytics skills have a positive correlation with supply-chain performance.

Likewise, studies on procurement digitalization indicate that digital technologies can transition procurement from administrative tasks to more strategic and value-generating roles. The proposed study defines procurement transparency as how visible, accessible, traceable, and accountable procurement information, procedures, decisions, and transactions are, whereas process agility reflects the organization's capacity to swiftly adapt to evolving procurement needs. The research suggests that the transformation of digital procurement can improve procurement performance both directly and indirectly via these two mechanisms. The study is especially significant for Pakistani firms, as digital procurement is being more widely embraced, but factors related to organization, technology, and institutions could impact its success. The research aims to enhance the digital procurement literature by elucidating the ways digital transformation can boost procurement performance in an emerging market setting studied by Patrucco et al. (2020). Digital transformation (DT) has significantly altered strategic procurement, shifting it from an administrative role into a key factor in enhancing organizational competitiveness.

Farooqui et al. (2024) studied “Effects of External Adoption of E-Procurement on Financial Performance in Pakistan’s Manufacturing Sector” and said that the goal of this study is to investigate how firms' performance is affected by external adoption of e-procurement. Using both self-administered and online surveys, the study uses a mixed-methods strategy to gather data from supply chain specialists in the manufacturing organizations. Data was gathered via a questionnaire, and SmartPLS 3.2.9 was utilized to analyze the data using partial least squares structural equation modeling (PLS-SEM). The findings show that while external e-procurement adoption has a negative impact on financial performance, it has a favorable impact on supply chain integration and information transparency. Information openness promotes supply chain integration but does not directly improve financial performance. Financial performance is positively impacted by supply chain integration. Furthermore, external e-procurement adoption improves financial performance when it is mediated by supply chain integration.

Measurement Model (PLS-SEM)

Figure 2

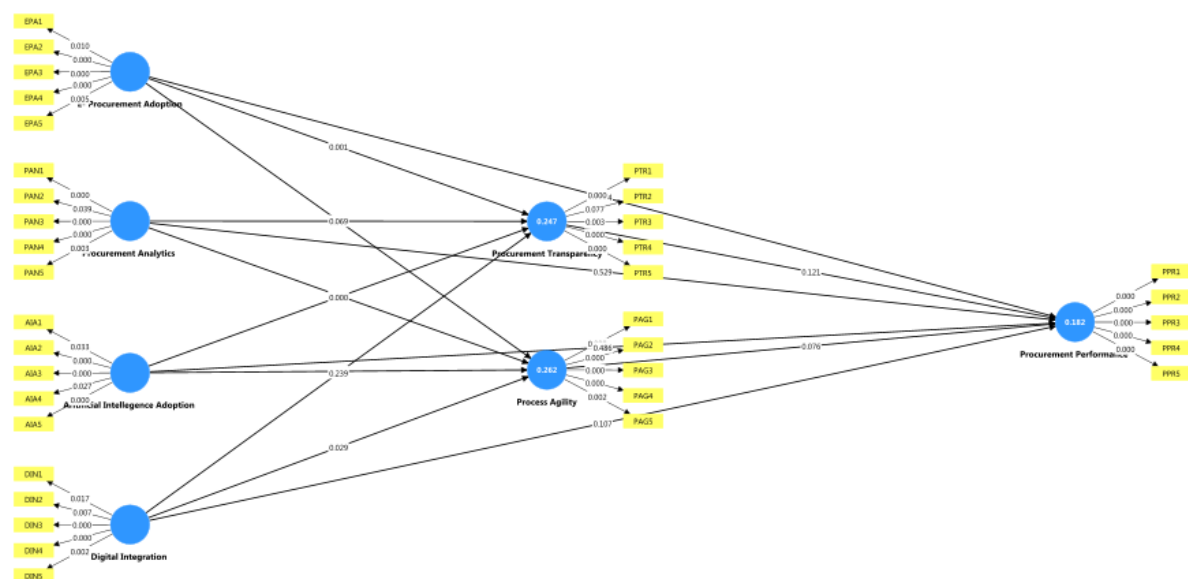


Significance of Measurement Model

PLS-SEM along with bootstrapping will be employed to assess the proposed direct and indirect relationships. The particular indirect effects will establish if procurement transparency and process agility importantly mediate the connection between digital procurement transformation and procurement performance. The approach aims to offer a structured empirical evaluation of the ways digital procurement capabilities can enhance procurement results in Pakistan. The results are anticipated to offer insights for organizations aiming to improve procurement efficiency, transparency, responsiveness, and overall performance via digital transformation.

Measurement Model (Bootstrapping)

Figure 3



Significance of Measurement Model (Bootstrapping)

The illustration appears to show a PLS-SEM bootstrapping result, with the numerical values on the structural paths and indicators representing p-values. Consequently, it is primarily utilized to assess if the proposed connections are statistically significant.

Table 2

Endogenous Construct	R ²	Meaning
Procurement Transparency	0.247	Predictors explain 24.7% of its variance
Process Agility	0.262	Predictors explain 26.2% of its variance
Procurement Performance	0.182	Predictors explain 18.2% of its variance

So, the model explains **18.2% of the variance in Procurement Performance**.

Interpretation of p-values

For hypothesis testing, the usual criterion is:

- **p < 0.05** → statistically significant
- **p ≥ 0.05** → not statistically significant

From the diagram, several paths have p-values such as **0.001, 0.000, 0.009, 0.029**, etc., indicating statistically significant relationships.

For example:

- **Procurement Adoption** → **Procurement Transparency**: **p = 0.001** → significant.
- **Procurement Analytics** → **Procurement Transparency**: **p = 0.069** → not significant at 5%.
- **AI Adoption** → **Process Agility**: **p = 0.239** → not significant.
- **Digital Integration** → **Process Agility**: **p = 0.009** → significant.
- **Procurement Transparency** → **Procurement Performance**: **p = 0.121** → not significant.
- **Process Agility** → **Procurement Performance**: **p = 0.076** → not significant at the 5% level.

The findings indicate that the introduced digital procurement elements vary in their impact on Procurement Transparency and Process Agility. Nonetheless, the direct routes from the two mediators to Procurement Performance presented here do not achieve the standard 5% significance threshold based on the shown p-values.

Important: For a full understanding of the thesis/research paper, I suggest utilizing the Bootstrapping Path Coefficients table (β , STDEV, T-statistics, and P-values) instead of depending solely on this diagram. That table will enable each hypothesis (H1, H2, H3...) to be officially accepted or declined.

Research Result

The following are the results of the model in Smart PLS SEM and Bootstrapping. Detail are given in the tables. The findings of this study reveal a combination of significant and non-significant associations among the study variables.

Significant Relationships (p < 0.05): Artificial Intelligence Adoption showed a significant positive relationship with both **Process Agility** ($\beta = 0.162$, $t = 2.313$, $p = 0.021$) and **Procurement Transparency** ($\beta = 0.270$, $t = 3.967$, $p = 0.000$), indicating that the adoption of AI strengthens the flexibility and openness of procurement processes. However, its direct influence on **Procurement Performance** was found to be statistically insignificant ($\beta = 0.122$, $t = 1.389$, $p = 0.165$).

Digital Integration had a notable impact on both Process Agility ($\beta = 0.139$, $t = 2.188$, $p = 0.029$) and Procurement Performance directly ($\beta = 0.151$, $t = 2.136$, $p = 0.033$), while its effect on Procurement Transparency was insignificant ($\beta = 0.080$, $t = 1.177$, $p = 0.239$).

The adoption of E-Procurement positively influenced Procurement Transparency ($\beta = 0.232$, $t = 3.383$, $p = 0.001$). Its impacts on Process Agility ($p = 0.069$) and Procurement Performance ($p = 0.082$) were close to but did not meet typical significance criteria.

Procurement Analytic showed a highly significant impact on Process Agility ($\beta = 0.300$, $t = 4.896$, $p = 0.000$), representing the most robust connection in the model, although its influences on Procurement Transparency ($p = 0.111$) and Procurement Performance ($p = 0.139$) were not statistically significant.

Table 3*Path Coefficient*

	Path coefficients
Artificial Intelligence Adoption -> Process Agility	0.162
Artificial Intelligence Adoption -> Procurement Performance	0.059
Artificial Intelligence Adoption -> Procurement Transparency	0.270
Digital Integration -> Process Agility	0.139
Digital Integration -> Procurement Performance	0.118
Digital Integration -> Procurement Transparency	0.080
E- Procurement Adoption -> Process Agility	0.115
E- Procurement Adoption -> Procurement Performance	0.112
E- Procurement Adoption -> Procurement Transparency	0.232
Process Agility -> Procurement Performance	0.154
Procurement Analytics -> Process Agility	0.300
Procurement Analytics -> Procurement Performance	0.047
Procurement Analytics -> Procurement Transparency	0.100
Procurement Transparency -> Procurement Performance	0.142

Table 4*Outer Loading*

	Outer loadings
AIA1 <- Artificial Intelligence Adoption	0.727
AIA2 <- Artificial Intelligence Adoption	0.717
AIA3 <- Artificial Intelligence Adoption	0.778
AIA4 <- Artificial Intelligence Adoption	0.716
AIA5 <- Artificial Intelligence Adoption	0.746
DIN1 <- Digital Integration	0.736
DIN2 <- Digital Integration	0.745
DIN3 <- Digital Integration	0.725
DIN4 <- Digital Integration	0.748
DIN5 <- Digital Integration	0.773
EPA1 <- E- Procurement Adoption	0.755
EPA2 <- E- Procurement Adoption	0.655
EPA3 <- E- Procurement Adoption	0.745
EPA4 <- E- Procurement Adoption	0.637
EPA5 <- E- Procurement Adoption	0.377
PAG1 <- Process Agility	0.557
PAG2 <- Process Agility	0.526
PAG3 <- Process Agility	0.464
PAG4 <- Process Agility	0.662
PAG5 <- Process Agility	0.378
PAN1 <- Procurement Analytics	0.562
PAN2 <- Procurement Analytics	0.312
PAN3 <- Procurement Analytics	0.568
PAN4 <- Procurement Analytics	0.592
PAN5 <- Procurement Analytics	0.412

	Outer loadings
PPR1 <- Procurement Performance	0.490
PPR2 <- Procurement Performance	0.605
PPR3 <- Procurement Performance	0.536
PPR4 <- Procurement Performance	0.454
PPR5 <- Procurement Performance	0.610
PTR1 <- Procurement Transparency	0.541
PTR2 <- Procurement Transparency	0.256
PTR3 <- Procurement Transparency	0.413
PTR4 <- Procurement Transparency	0.650
PTR5 <- Procurement Transparency	0.532

Table 5
Latent Variable Descriptive

	Mean	Median	Observed min	Observed max	Number of observations used	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises test statistic	Cramér-von Mises p value
Artificial Intelligence Adoption	0.000	0.011	-3.256	2.471	250.000	1.000	-0.163	-0.194	0.052	0.484
Digital Integration	0.000	0.145	-3.646	2.275	250.000	1.000	0.276	-0.409	0.130	0.044
E-Procurement Adoption	0.000	0.046	-3.080	2.125	250.000	1.000	-0.025	-0.271	0.082	0.195
Process Agility	-0.000	0.096	-2.972	2.067	250.000	1.000	0.127	-0.580	0.331	0.000
Procurement Analytics	-0.000	0.092	-2.842	2.278	250.000	1.000	-0.450	-0.242	0.108	0.087
Procurement Performance	-0.000	0.087	-2.629	2.454	250.000	1.000	-0.194	-0.426	0.252	0.001
Procurement Transparency	-0.000	0.022	-3.195	2.148	250.000	1.000	0.044	-0.381	0.080	0.206

Table 6
R Square

	R-square	R-square adjusted
Process Agility	0.262	0.250
Procurement Performance	0.182	0.162
Procurement Transparency	0.247	0.234

Table 7
Composite Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence Adoption	0.785	0.613	0.795	0.739
Digital Integration	0.716	0.751	0.604	0.647
E- Procurement Adoption	0.764	0.701	0.622	0.260
Process Agility	0.741	0.355	0.649	0.277
Procurement Analytics	0.249	0.265	0.615	0.251
Procurement Performance	0.396	0.404	0.673	0.294
Procurement Transparency	0.220	0.248	0.603	0.247

Table 8*Collinearity statistics (VIF) Inner Mode*

	VIF
Artificial Intelligence Adoption -> Process Agility	1.241
Artificial Intelligence Adoption -> Procurement Performance	1.360
Artificial Intelligence Adoption -> Procurement Transparency	1.241
Digital Integration -> Process Agility	1.255
Digital Integration -> Procurement Performance	1.286
Digital Integration -> Procurement Transparency	1.255
E- Procurement Adoption -> Process Agility	1.232
E- Procurement Adoption -> Procurement Performance	1.314
E- Procurement Adoption -> Procurement Transparency	1.232
Process Agility -> Procurement Performance	1.377
Procurement Analytics -> Process Agility	1.197
Procurement Analytics -> Procurement Performance	1.324
Procurement Analytics -> Procurement Transparency	1.197
Procurement Transparency -> Procurement Performance	1.349

Table 9*Total Effect (Mean, St. Deviation, T- Value and P- Value)*

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (O/STDEV)	P values
Artificial Intelligence Adoption -> Process Agility	0.162	0.165	0.070	2.313	0.021
Artificial Intelligence Adoption -> Procurement Performance	0.122	0.128	0.088	1.389	0.165
Artificial Intelligence Adoption -> Procurement Transparency	0.270	0.276	0.068	3.967	0.000
Digital Integration -> Process Agility	0.139	0.149	0.063	2.188	0.029
Digital Integration -> Procurement Performance	0.151	0.164	0.071	2.136	0.033
Digital Integration -> Procurement Transparency	0.080	0.091	0.068	1.177	0.239
E- Procurement Adoption -> Process Agility	0.115	0.122	0.063	1.820	0.069
E- Procurement Adoption -> Procurement Performance	0.163	0.170	0.094	1.738	0.082
E- Procurement Adoption -> Procurement Transparency	0.232	0.238	0.069	3.383	0.001
Process Agility -> Procurement Performance	0.154	0.157	0.087	1.775	0.076
Procurement Analytics -> Process Agility	0.300	0.306	0.061	4.896	0.000
Procurement Analytics -> Procurement Performance	0.107	0.114	0.072	1.480	0.139
Procurement Analytics -> Procurement Transparency	0.100	0.107	0.063	1.595	0.111
Procurement Transparency -> Procurement Performance	0.142	0.137	0.091	1.552	0.121

Table 10

Outer Loading (Mean, St. Deviation, T- Value and P- Value)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AIA1 <- Artificial Intelligence Adoption	0.327	0.322	0.154	2.132	0.033
AIA2 <- Artificial Intelligence Adoption	0.597	0.577	0.101	5.914	0.000
AIA3 <- Artificial Intelligence Adoption	0.578	0.562	0.114	5.067	0.000
AIA4 <- Artificial Intelligence Adoption	0.316	0.309	0.143	2.216	0.027
AIA5 <- Artificial Intelligence Adoption	0.546	0.533	0.109	4.987	0.000
DIN1 <- Digital Integration	0.351	0.340	0.148	2.377	0.017
DIN2 <- Digital Integration	0.411	0.395	0.151	2.712	0.007
DIN3 <- Digital Integration	0.725	0.700	0.089	8.169	0.000
DIN4 <- Digital Integration	0.478	0.460	0.129	3.699	0.000
DIN5 <- Digital Integration	0.433	0.425	0.142	3.044	0.002
EPA1 <- E-Procurement Adoption	0.355	0.347	0.137	2.587	0.010
EPA2 <- E-Procurement Adoption	0.655	0.643	0.087	7.508	0.000
EPA3 <- E-Procurement Adoption	0.445	0.434	0.122	3.642	0.000
EPA4 <- E-Procurement Adoption	0.637	0.618	0.096	6.609	0.000
EPA5 <- E-Procurement Adoption	0.377	0.367	0.134	2.812	0.005
PAG1 <- Process Agility	0.557	0.545	0.101	5.517	0.000
PAG2 <- Process Agility	0.526	0.519	0.101	5.218	0.000
PAG3 <- Process Agility	0.464	0.461	0.103	4.509	0.000
PAG4 <- Process Agility	0.662	0.650	0.084	7.896	0.000
PAG5 <- Process Agility	0.378	0.372	0.122	3.103	0.002
PAN1 <- Procurement Analytics	0.562	0.548	0.115	4.891	0.000
PAN2 <- Procurement Analytics	0.312	0.301	0.151	2.069	0.039
PAN3 <- Procurement Analytics	0.568	0.551	0.107	5.310	0.000
PAN4 <- Procurement Analytics	0.592	0.576	0.098	6.055	0.000

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
PAN5 <- Procurement Analytics	0.412	0.407	0.139	2.954	0.003
PPR1 <- Procurement Performance	0.490	0.477	0.121	4.041	0.000
PPR2 <- Procurement Performance	0.605	0.582	0.119	5.063	0.000
PPR3 <- Procurement Performance	0.536	0.517	0.137	3.909	0.000
PPR4 <- Procurement Performance	0.454	0.443	0.128	3.552	0.000
PPR5 <- Procurement Performance	0.610	0.597	0.096	6.325	0.000
PTR1 <- Procurement Transparency	0.541	0.526	0.111	4.865	0.000
PTR2 <- Procurement Transparency	0.256	0.252	0.145	1.767	0.077
PTR3 <- Procurement Transparency	0.413	0.404	0.139	2.970	0.003
PTR4 <- Procurement Transparency	0.650	0.630	0.099	6.563	0.000
PTR5 <- Procurement Transparency	0.532	0.519	0.120	4.424	0.000

Conclusion

In conclusion, this study demonstrates that digital procurement transformation serves as an important antecedent of procurement performance within Pakistani organizations; however, only a portion of this effect manifests directly, with a considerable proportion flowing indirectly via improved procurement transparency and enhanced process agility. Such an outcome lends further support to the dynamic capabilities perspective, which posits that merely adopting technology is insufficient for building competitive advantage unless it is transformed into underlying organizational capabilities like visibility and responsiveness (Herold et al., 2023). From a theoretical standpoint, the research advances the procurement digitalization literature by empirically confirming a sequential mediation pathway that, while frequently proposed conceptually, has seldom been examined within emerging-market contexts. On the practical side, the findings imply that managers and policymakers ought not to regard digital tools as isolated remedies; rather, expenditures on digital procurement systems must be complemented by intentional measures to embed transparent data-handling practices and to redesign processes in an agile manner, thereby unlocking the full spectrum of performance benefits. Finally, the study points to supplier-side digital readiness and the institutional/regulatory environment as fruitful directions for further inquiry, owing to their likely role in shaping the magnitude of the transformation–performance link in developing economies.

Elnadi, M. (2026) studied, “Digital transformation and sustainable supply chain performance for sustainable development: The mediating role of supply chain capabilities. Sustainable Development” said that this study's findings support the conclusion that procurement transparency and process agility operate as essential—yet only partially explanatory—channels through which digital procurement transformation translates into enhanced procurement performance within Pakistani organizations. The observed partial mediation implies that although digitization exerts a direct effect on performance, its more complete value emerges only when it concurrently reinforces an organization's informational visibility and its ability to adjust procurement processes in response to evolving conditions. This interpretation aligns with recent evidence suggesting that digital transformation improves organizational performance chiefly by fostering intermediate

capabilities, rather than through technological adoption in isolation (Elnadi, 2026). For policymakers and organizational leaders in emerging economies, this conclusion highlights the importance of procurement digitalization strategies that extend beyond mere system deployment and deliberately nurture data governance practices that enable transparency alongside agile operating routines. The study also acknowledges that its cross-sectional, single-country design constrains causal inference and temporal generalizability, and accordingly advises future scholars to adopt longitudinal approaches and examine further mediators or moderators—such as organizational culture, supplier collaboration, or the regulatory environment—in order to develop a more comprehensive account of the digital procurement–performance relationship.

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