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Effect of Evidence-Based Policymaking on Public Service Delivery Efficiency: Evidence from the Indian Technology Industry Policy

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Abstract: This study examines the relationships among Evidence-Based Policymaking (EBPM), Data Analytics Capability (DAC), Policy Implementation Quality (PIQ), and Public Service Delivery Efficiency (PSDE) in the context of the Indian technology industry. Drawing on a quantitative, cross-sectional survey of 380 policy stakeholders, including government officials, industry professionals, and consultants, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed conceptual model. Results indicate that both EBPM and DAC have significant positive effects on PSDE, with PIQ partially mediating these relationships. The findings highlight the critical role of effective policy implementation in translating evidence-based and data-driven practices into enhanced service delivery outcomes. The study contributes theoretically by integrating EBPM, DAC, and implementation quality into a unified model and empirically validating their interrelationships. Practically, it underscores the importance of investing in evidence-based practices, analytical capabilities, and high-quality implementation mechanisms to improve governance performance, transparency, and citizen satisfaction. Limitations include the cross-sectional design and sector-specific focus, suggesting future research could explore longitudinal approaches and multi-sector comparisons.

Keywords: Evidence-Based Policymaking; Data Analytics Capability; Policy Implementation Quality; Public Service Delivery Efficiency

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1. Introduction

Public sector governance is undergoing a profound transformation as governments increasingly rely on data, digital technologies, and analytical tools to design and implement effective policies. In this evolving landscape, evidence-based policymaking (EBPM) has emerged as a central paradigm aimed at improving the quality, transparency, and accountability of public decisions. EBPM promotes the systematic use of empirical data, research findings, and evaluation outcomes to guide policy processes, thereby enhancing policy effectiveness and service delivery performance (Mulgan, 2005; Sanderson, 2002, 2003). The relevance of this approach is particularly evident in technology-driven sectors, where rapid innovation and complex service demands require adaptive and informed policy responses. Recent advancements in artificial intelligence and big data analytics have further strengthened the potential of EBPM by enabling real-time insights and more precise decision-making (Anshari et al., 2025; Hossin et al., 2023). From a theoretical perspective, EBPM is grounded in the broader traditions of rational decision-making and New Public Management, which emphasise efficiency, performance measurement, and results-oriented governance. However, contemporary scholarship suggests a shift towards "evidence-informed" policymaking, acknowledging that evidence is only one of several factors influencing policy decisions (Head, 2016). For instance, Paul Cairney (2022) argues that policymaking occurs within a complex and decentralised environment where multiple actors, interests, and institutional constraints shape outcomes. Similarly, Head (2010, 2024) and Demir (2022) highlight the challenges associated with interpreting and applying evidence in diverse policy contexts. The emergence of policy analytics further extends this theoretical framework by incorporating computational methods and data-driven approaches into policy processes (De Marchi et al., 2016). In addition, growing attention to policy capacity underscores the importance of institutional and analytical capabilities in enabling effective evidence use (Newman et al., 2017; Newman & Mintrom, 2023).

Despite the increasing emphasis on EBPM and data-driven governance, significant gaps remain in understanding how these elements translate into improved public service delivery outcomes. While prior studies have explored the role of evidence in policy design, relatively limited attention has been given to the mechanisms through which evidence influences implementation and performance (Heinrich, 2007; Martin et al., 2010). In particular, the quality of policy implementation has often been overlooked as a critical intermediary factor linking policy design and service delivery efficiency. Moreover, although emerging research highlights the role of digital technologies and analytics in policymaking, there is a lack of integrated empirical models that simultaneously examine evidence-based approaches, data analytics capability, and implementation processes (Hossin et al., 2023; Anshari et al., 2025). Additionally, the complexities and contestations surrounding evidence use, as noted by Cairney (2022) and Head (2010), suggest that the effectiveness of EBPM cannot be assumed without examining contextual and operational dynamics.

In response to these gaps, this study aims to develop and empirically test a comprehensive framework linking evidence-based policymaking and data analytics capability to public service delivery efficiency through the mediating role of policy implementation quality. Specifically, the study seeks to: (i) examine the effect of EBPM on policy implementation quality, (ii) analyse the influence of data analytics capability on implementation processes, (iii) investigate the impact of implementation quality on service delivery efficiency, and (iv) assess the mediating role of implementation quality in these relationships. This study makes several important contributions to the literature and practice of public policy and governance. Theoretically, it extends the EBPM framework by integrating data analytics capability and policy implementation quality into a unified model, thereby bridging the gap between policy design and service delivery outcomes. It also responds to calls for more nuanced and context-sensitive analyses of evidence use in policymaking (Head, 2016; Newman & Mintrom, 2023). Empirically, the study provides evidence from a technology-driven policy environment, contributing to the limited body of research on EBPM in digital governance contexts. Practically, the findings offer actionable insights for policymakers and administrators by highlighting the importance of combining evidence-based approaches with strong analytical capabilities and effective implementation systems. Furthermore, by emphasising efficiency outcomes, the study aligns with broader public sector reform agendas aimed at improving service delivery, enhancing citizen satisfaction, and achieving sustainable development goals (Anshari et al., 2025; Chhetri & Zacarias, 2021).

2. Literature Review

The concept of evidence-based policymaking (EBPM) has gained increasing prominence in public administration as governments seek to enhance the effectiveness and legitimacy of policy decisions. Early contributions emphasised the systematic use of empirical evidence, evaluation findings, and expert knowledge to guide policy formulation and implementation (Mulgan, 2005; Sanderson, 2002, 2003). However, the literature also recognises that EBPM is not a purely technical or linear process; rather, it is embedded within complex political and institutional environments (Head, 2010, 2016). For instance, Paul Cairney (2022) challenges the assumption of fully rational, evidence-driven policymaking by highlighting the fragmented and multi-actor nature of modern governance systems. Similarly, Demir (2022) and Head (2024) argue that while evidence can improve policy quality, its interpretation and utilisation are often contested, shaped by institutional contexts, expertise, and competing policy narratives.

Recent studies have expanded the EBPM framework by incorporating advances in data analytics, artificial intelligence, and digital governance. The transition from traditional EBPM to policy analytics reflects the growing importance of big data, computational tools, and real-time monitoring systems in policymaking (De Marchi et al., 2016). Empirical evidence suggests that data-driven approaches enhance the precision, responsiveness, and adaptability of public policies (Hossin et al., 2023). In this context, Muneer Anshari et al. (2025) demonstrate that the integration of artificial intelligence into public service delivery can significantly improve efficiency and alignment with sustainable development goals, although it introduces governance and ethical complexities. Furthermore, Newman and Mintrom (2023) highlight that the intersection of AI and policymaking requires new analytical competencies and ethical considerations, reinforcing the importance of strong data analytics capability within public institutions.

Despite the increasing emphasis on evidence and data, the translation of policy design into effective implementation remains a critical challenge. Studies on performance management and policy capacity indicate that the success of EBPM depends largely on the quality of implementation processes, including coordination, monitoring, and institutional learning (Heinrich, 2007; Newman et al., 2017). Research by Martin et al. (2010) and Chhetri and Zacarias (2021) further suggests that evidence utilisation is most effective when embedded within organisational routines and supported by stakeholder engagement mechanisms. In addition, experiential and simulation-based learning approaches, as highlighted by David F. Andersen et al. (2025), provide policymakers with opportunities to better understand complex systems and improve implementation outcomes through iterative learning.

In terms of outcomes, a growing body of literature links EBPM and data-driven governance to improvements in public service delivery efficiency. Evidence-informed policies are associated with reduced service delivery costs, enhanced accessibility, and improved citizen satisfaction, particularly in digitally enabled governance contexts (Anshari et al., 2025; Hossin et al., 2023). However, challenges remain in ensuring the validity, utilisation, and contextual relevance of evidence, especially in diverse and rapidly evolving policy environments (Head, 2010; Martin et al., 2010). Moreover, the effectiveness of EBPM is contingent upon the alignment between evidence generation, analytical capacity, and implementation quality. Despite the growing body of literature on evidence-based policymaking (EBPM), several critical gaps remain inadequately addressed. First, existing studies predominantly focus on the role of evidence in policy formulation, with comparatively limited attention given to how such evidence translates into effective implementation and tangible service delivery outcomes (Heinrich, 2007; Martin et al., 2010). Second, while recent research highlights the importance of digital technologies, big data, and artificial intelligence in policymaking, these elements are often examined in isolation rather than as part of an integrated framework linking evidence use, analytical capability, and implementation processes (Hossin et al., 2023; Anshari et al., 2025). Third, the mediating role of policy implementation quality remains underexplored, despite its central importance in bridging the gap between policy design and performance outcomes. Furthermore, the contested and context-dependent nature of evidence utilisation, as emphasised by Paul Cairney (2022) and Head (2010), suggests the need for empirical models that capture the complexity of real-world policymaking environments. Finally, there is a scarcity of empirical studies focusing on technology-driven policy contexts, such as the Indian technology industry, where data-driven governance is rapidly evolving. Addressing these gaps, this study proposes a comprehensive framework that integrates EBPM, data analytics capability, and policy implementation quality to better understand their combined effect on public service delivery efficiency.

H1: Evidence-based policymaking has a positive and significant effect on policy implementation quality.

H2: Data analytics capability has a positive and significant effect on policy implementation quality.
H3: Policy implementation quality has a positive and significant effect on public service delivery efficiency.
H4: Evidence-based policymaking has a positive and significant indirect effect on public service delivery efficiency through policy implementation quality.
H5: Data analytics capability has a positive and significant indirect effect on public service delivery efficiency through policy implementation quality.

3. Methodology

This study employed a quantitative, cross-sectional research design to examine the relationships among evidence-based policymaking (EBPM), data analytics capability (DAC), policy implementation quality (PIQ), and public service delivery efficiency (PSDE) within the Indian technology industry policy context. A quantitative approach was chosen because it allowed for empirical testing of theory-based hypotheses using structured data and provided the ability to generalize findings to a larger population (Hair et al., 2019). The cross-sectional design enabled the capture of stakeholders' perceptions at a single point in time, which is common in public policy and governance research, particularly when evaluating institutional processes and service delivery outcomes (Newman et al., 2017). The study followed a deductive approach, building upon established theories of EBPM, policy analytics, and governance performance to develop a conceptual model and test relationships between constructs (De Marchi et al., 2016; Head, 2016).

The target population consisted of professionals actively involved in the formulation, implementation, and evaluation of technology-related policies in India. This included government officials from ministries and regulatory agencies, industry professionals from IT firms and start-ups, policy analysts, and consultants with direct involvement in policy design and execution. Considering the specialised nature of the population, purposive sampling was employed to ensure that respondents possessed the requisite knowledge and experience (Etikan et al., 2016). To ensure adequate representation across stakeholder groups, stratification was applied by role (government, industry, consultancy) and sectoral involvement (IT services, software development, digital platforms). Following the "10-times rule" recommended for Partial Least Squares Structural Equation Modelling (PLS-SEM), a minimum sample size of 150–200 respondents was required given the number of structural paths in the conceptual model. However, the study collected data from 380 respondents to enhance statistical power and robustness.

Data were collected using a structured questionnaire, a widely used instrument in governance and policy research to capture perceptions, attitudes, and experiences (Martin et al., 2010; Chhetri & Zacarias, 2021). The questionnaire consisted of five sections: respondent profile, EBPM, DAC, PIQ, and PSDE. All constructs were measured using reflective multi-item scales, with items adapted from prior studies. Evidence-Based Policymaking (EBPM) was operationalized using indicators such as the integration of empirical research, pilot testing, expert consultation, and impact evaluations (Head, 2010; Demir, 2022; Andersen et al., 2025). Data Analytics Capability (DAC) captured the availability of digital infrastructure, analytical tools, real-time data access, and staff competencies in data processing and analytics (Hossin et al., 2023; Newman & Mintrom, 2023). Policy Implementation Quality (PIQ) was measured using indicators assessing clarity of policy guidelines, inter-agency coordination, monitoring and evaluation mechanisms, and adaptability of policies (Heinrich, 2007; Newman et al., 2017). Public Service Delivery Efficiency (PSDE) was assessed using cost-effectiveness, timeliness, accessibility, and citizen satisfaction (Anshari et al., 2025; Martin et al., 2010). All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), following standard practice in social science and governance research (Hair et al., 2019).

Before full-scale data collection, a pilot study was conducted with approximately 30 respondents to assess the clarity, validity, and reliability of the measurement items. Feedback from the pilot study was used to refine the questionnaire, enhancing content validity and reducing potential measurement errors (Hair et al., 2019). The survey was administered online using platforms such as Google Forms and Qualtrics, facilitating access to geographically dispersed respondents. Respondents were provided with a clear explanation of the study purpose and assurances regarding anonymity, confidentiality, and voluntary participation.

The study applied Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine relationships among the constructs, a method suitable for complex models with multiple constructs and mediation effects (Hair et al., 2019). PLS-SEM enabled simultaneous assessment of measurement and structural models, providing robust estimates even with moderate sample sizes. The analysis proceeded in two stages. First, the measurement model was assessed for reliability and validity. Internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR), with thresholds above 0.70. Convergent validity was assessed using the Average Variance Extracted (AVE > 0.50), and discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio (< 0.85) (Hair et al., 2019). Second, the structural model was tested to assess hypothesized relationships. Path coefficients (β values) were examined for significance, and the coefficient of determination (R^2) assessed the explanatory power of endogenous constructs. Effect sizes (f^2) and predictive relevance (Q^2) were also calculated to assess the impact and predictive quality of the model. Mediation effects of PIQ were evaluated using bootstrapping with 5,000 resamples, providing robust estimates of indirect effects (Hair et al., 2019).

Since data were collected from a single source, common method bias (CMB) was addressed using procedural and statistical remedies. Procedural measures included ensuring respondent anonymity, reducing item ambiguity, and separating the measurement of independent and dependent variables. Statistically, Harman's single-factor test and Variance Inflation Factor (VIF) analysis were conducted to detect potential CMB.

4. Results

Table 1 presents the demographic profile of the 380 respondents who participated in the study. The sample included a majority of male respondents (60.5%), with female participants comprising 36.8%, and a small proportion (2.7%) identifying as other or preferring not to state. Age distribution was fairly balanced, with the largest group aged 30–39 years (39.5%), followed by 20–29 years (25%), 40–49 years (23.7%), and 50 years or older (11.8%). Respondents were drawn from various professional roles, including government officials (31.6%), industry professionals (47.4%), and policy analysts or consultants (21%). Years of experience ranged from 0–5 years (19.7%) to over 16 years (23.7%), ensuring representation from both early-career and experienced professionals. In terms of organizational affiliation, half of the respondents (50%) were from IT firms or start-ups, 31.6% from government ministries or agencies, and 18.4% from consultancy firms. Sectoral involvement spanned software/IT services (42.1%), digital platforms (34.2%), and emerging technology projects (23.7%).

Table 1: Respondent Demographics and Profile (n = 380)

Demographic Variable	Category/Group	Frequency (n)	Percentage (%)
Gender	Male	230	60.5
	Female	140	36.8
	Other/Prefer not to say	10	2.7
Age	20–29	95	25.0
	30–39	150	39.5
	40–49	90	23.7
	50+	45	11.8
Role/Position	Government Official	120	31.6
	Industry Professional	180	47.4
	Policy Analyst/Consultant	80	21.0

Years of Experience	0–5	75	19.7
	6–10	120	31.6
	11–15	95	25.0
	16+	90	23.7
Organisation Type	Government Ministry/Agency	120	31.6
	IT Firm/Start-up	190	50.0
	Consultancy	70	18.4
Sectoral Involvement	Software/IT Services	160	42.1
	Digital Platforms	130	34.2
	Emerging Technology Projects	90	23.7

Table 2 provides descriptive statistics for the study constructs: EBPM, DAC, PIQ, and PSDE. The means indicate that respondents generally perceived a high level of evidence-based policymaking (M = 4.12), data analytics capability (M = 3.98), policy implementation quality (M = 4.05), and public service delivery efficiency (M = 4.08). Standard deviations ranged from 0.61 to 0.68, suggesting moderate variability in responses. Skewness values were slightly negative across constructs (-0.30 to -0.45), indicating a modest leftward skew, while kurtosis values (2.05–2.18) suggested distributions were approximately normal.

Table 2: Descriptive Statistics of Constructs (n = 380)

Construct	Mean	Standard Deviation (SD)	Skewness	Kurtosis
EBPM	4.12	0.61	-0.45	2.18
DAC	3.98	0.68	-0.30	2.05
PIQ	4.05	0.64	-0.38	2.10
PSDE	4.08	0.62	-0.42	2.12

Note: EBPM = Evidence-Based Policymaking; DAC = Data Analytics Capability; PIQ = Policy Implementation Quality; PSDE = Public Service Delivery Efficiency.

Table 3 reports the measurement model's reliability and convergent validity. All constructs exhibited high internal consistency, with Cronbach's Alpha ranging from 0.85 to 0.88 and Composite Reliability (CR) exceeding 0.89, confirming the reliability of multi-item scales. Factor loadings for all items were above the recommended threshold of 0.70, indicating that individual items adequately reflected their respective constructs. Convergent validity was supported by Average Variance Extracted (AVE) values ranging from 0.68 to 0.72, exceeding the 0.50 benchmark.

Table 3: Measurement Model – Reliability and Validity (n = 380)

Construct	Item	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
EBPM	EBPM1	0.82	0.87	0.91	0.72
	EBPM2	0.84			
	EBPM3	0.81			
DAC	DAC1	0.79	0.85	0.89	0.68
	DAC2	0.83			
	DAC3	0.80			
PIQ	PIQ1	0.85	0.88	0.91	0.71
	PIQ2	0.83			
	PIQ3	0.82			
PSDE	PSDE1	0.84	0.86	0.90	0.69
	PSDE2	0.81			
	PSDE3	0.82			

Note: Factor loadings >0.70, Cronbach's Alpha >0.70, CR >0.70, and AVE >0.50 indicate adequate reliability and convergent validity (Hair et al., 2019).

Table 4 assesses discriminant validity using the Heterotrait-Monotrait (HTMT) ratio. All HTMT values were below 0.85, ranging from 0.61 to 0.75, indicating that each construct was empirically distinct from the others. This finding confirms that EBPM, DAC, PIQ, and PSDE are conceptually and statistically separate constructs, which is critical for the validity of subsequent structural model analysis.

Table 4: Discriminant Validity – HTMT Ratios

Construct	EBPM	DAC	PIQ	PSDE
EBPM				
DAC	0.68			
PIQ	0.72	0.65		
PSDE	0.69	0.63	0.75	

Note: All HTMT ratios <0.85 indicate adequate discriminant validity (Hair et al., 2019).

Table 5 presents the correlation matrix among the four study constructs: EBPM, DAC, PIQ, and PSDE. All constructs were positively and significantly correlated with each other at $p < 0.01$. Evidence-Based Policymaking (EBPM) demonstrated strong correlations with Policy Implementation Quality (PIQ, $r = 0.70$) and Public Service Delivery Efficiency (PSDE, $r = 0.68$), indicating that higher adoption of evidence-based practices is associated with more effective policy implementation and improved service delivery. Data Analytics Capability (DAC) was moderately correlated with EBPM ($r = 0.62$) and PIQ ($r = 0.64$), suggesting that the availability and use of data-driven tools and competencies support both policy formulation and implementation outcomes.

Table 5: Correlation Matrix of Constructs (n = 380)

Construct	EBPM	DAC	PIQ	PSDE
EBPM	1	0.62	0.70	0.68
DAC	0.62	1	0.64	0.61
PIQ	0.70	0.64	1	0.73
PSDE	0.68	0.61	0.73	1

Note: All correlations are significant at $p < 0.01$.

Table 6 shows the structural model results, including path coefficients, t-values, p-values, and hypothesis testing outcomes. All hypothesized direct effects were supported. EBPM had a significant positive effect on PSDE ($\beta = 0.35$, $p < 0.001$) and on PIQ ($\beta = 0.42$, $p < 0.001$), while DAC significantly influenced PSDE ($\beta = 0.28$, $p < 0.001$) and PIQ ($\beta = 0.30$, $p < 0.001$). In turn, PIQ exerted a strong positive effect on PSDE ($\beta = 0.39$, $p < 0.001$). These results indicate that both EBPM and DAC directly contribute to public service efficiency and indirectly through policy implementation quality, confirming the theoretical model that links evidence-based practices and data analytics to improved governance outcomes.

Table 6: Structural Model – Path Coefficients and Hypothesis Testing (n = 380)

Hypothesis	Path	β Value	t-value	p-value	Result
H1	EBPM → PSDE	0.35	6.12	<0.001	Supported
H2	DAC → PSDE	0.28	4.87	<0.001	Supported
H3	EBPM → PIQ	0.42	7.05	<0.001	Supported
H4	DAC → PIQ	0.30	5.10	<0.001	Supported
H5	PIQ → PSDE	0.39	6.88	<0.001	Supported

Note: β = path coefficient; t-value and p-value obtained via bootstrapping with 5,000 resamples.

Table 7 reports the coefficient of determination (R^2) and effect sizes (f^2) for the endogenous constructs. The R^2 values indicate that 52% of the variance in PIQ and 61% of the variance in PSDE were explained by the independent variables. Effect sizes (f^2) were large for PIQ (0.33) and medium-to-large for PSDE (0.28), suggesting that EBPM, DAC, and PIQ have substantive impacts on public service delivery efficiency. These results demonstrate that the proposed model has strong explanatory power and that both evidence-based policymaking and data analytics capability, along with effective policy implementation, are significant drivers of service delivery performance in the Indian technology policy context.

Table 7: Coefficient of Determination (R^2) and Effect Sizes (f^2)

Endogenous Construct	R^2	Predictor(s)	f^2	Effect Interpretation
PIQ	0.52	EBPM, DAC	0.33	Large
PSDE	0.61	EBPM, DAC, PIQ	0.28	Medium-Large

Note: R^2 indicates variance explained by predictors; f^2 effect sizes interpreted as small (0.02), medium (0.15), and large (0.35).

Table 8 presents the mediation analysis results, examining Policy Implementation Quality (PIQ) as a mediator between Evidence-Based Policymaking (EBPM) and Data Analytics Capability (DAC) on Public Service Delivery Efficiency (PSDE). The results indicate that PIQ partially mediates the relationships for both predictors. Specifically, the indirect effect of EBPM on PSDE through PIQ was $\beta = 0.16$ ($t = 5.88$, $p < 0.001$), while DAC's indirect effect through PIQ was $\beta = 0.12$ ($t = 4.96$, $p < 0.001$). The total effects were higher than the direct effects alone, confirming that part of the influence of EBPM and DAC on PSDE operates through the enhancement of policy implementation quality.

Table 8: Mediation Analysis – PIQ as Mediator (n = 380)

Path	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)	t-value (Indirect)	p-value	Mediation Result
EBPM → PIQ → PSDE	0.35	0.16	0.51	5.88	<0.001	Partial Mediation
DAC → PIQ → PSDE	0.28	0.12	0.40	4.96	<0.001	Partial Mediation

Note: Bootstrapping with 5,000 resamples was used to assess indirect effects (Hair et al., 2019).

Table 9 reports the predictive relevance (Q^2) of the endogenous constructs PIQ and PSDE. Both constructs demonstrated Q^2 values greater than zero (PIQ = 0.38; PSDE = 0.42), indicating that the model possesses medium predictive relevance. This suggests that the independent variables, EBPM and DAC, along with the mediator PIQ, can meaningfully predict the values of PSDE and PIQ for respondents in similar policy contexts. The positive Q^2 values also confirm that the proposed PLS-SEM model is not only statistically significant but also practically useful for anticipating outcomes in public service delivery and policy implementation efficiency.

Table 9: Predictive Relevance (Q^2) of Endogenous Constructs (n = 380)

Endogenous Construct	Q^2	Interpretation
PIQ	0.38	Medium Predictive Relevance
PSDE	0.42	Medium Predictive Relevance

Note: Q^2 values > 0 indicate predictive relevance per Hair et al. (2019).

Table 10 presents the robustness checks through subgroup analyses across stakeholder types, including government officials, industry professionals, and consultants/analysts. Path coefficients for EBPM → PSDE, DAC → PSDE, and PIQ → PSDE remained consistent across all three subgroups. For instance, the EBPM → PSDE path ranged from 0.33 to 0.36, while DAC → PSDE varied from 0.27 to 0.29, and PIQ → PSDE from 0.37 to 0.40.

Table 10: Robustness Checks – Subgroup Analysis (n = 380)

Subgroup	EBPM → PSDE (β)	DAC → PSDE (β)	PIQ → PSDE (β)	Observation
Government Officials	0.33	0.27	0.38	Path coefficients consistent with full sample
Industry Professionals	0.36	0.29	0.40	Slightly higher effects for EBPM

Consultants/Analysts	0.34	0.28	0.37	Consistent across roles

Note: Robustness assessed by comparing path coefficients across stakeholder groups.

5. Discussions

The findings of this study demonstrate that Evidence-Based Policymaking (EBPM) has a significant positive impact on public service delivery efficiency (PSDE) in the context of the Indian technology industry. This supports the theoretical assertion that incorporating empirical evidence, pilot studies, expert consultations, and rigorous impact evaluations strengthens the effectiveness of policy implementation (Andersen et al., 2025; Head, 2010). The results align with prior studies highlighting the importance of EBPM in improving governance outcomes and institutional performance (Demir, 2022; Cairney, 2022). Specifically, the direct influence of EBPM on policy implementation quality (PIQ) and PSDE observed in this study corroborates the argument that policies grounded in solid evidence are more likely to achieve intended outcomes and enhance organizational efficiency (Heinrich, 2007; Martin et al., 2010).

Data Analytics Capability (DAC) was also found to positively influence both PIQ and PSDE, reinforcing the role of technological and analytical resources in contemporary policy environments. These findings echo previous work on the transformative potential of big data and advanced analytics in public service decision-making (Hossin et al., 2023; Newman & Mintrom, 2023). The observed relationship underscores that access to digital infrastructure, real-time data, and skilled analytical personnel can enhance monitoring, evaluation, and overall responsiveness of government and industry initiatives (Anshari et al., 2025). This highlights that DAC is not only a technical capability but a strategic enabler that supports evidence-based approaches in achieving more efficient service delivery outcomes.

Policy Implementation Quality (PIQ) was identified as a significant mediator between EBPM, DAC, and PSDE, indicating that both evidence-based practices and analytical capabilities exert their full effect on service efficiency through effective implementation mechanisms. This finding resonates with Heinrich's (2007) work, which emphasizes that policy impact depends not solely on the quality of policy design but also on its execution, coordination, and adaptability. Similarly, Newman et al. (2017) and Chhetri and Zacarias (2021) argue that high-quality implementation processes enhance the translation of policy intentions into measurable outcomes, suggesting that strengthening institutional processes is essential for maximizing the benefits of EBPM and DAC.

The study's results also provide empirical support for the interrelatedness of EBPM and DAC, reflecting the increasing convergence between knowledge-based policymaking and technology-driven decision support systems. De Marchi et al. (2016) and Mulgan (2005) contend that integrating evidence with analytical tools allows policymakers to move beyond intuition-driven decisions, creating a more systematic approach to governance. The strong correlations between EBPM, DAC, and PIQ found in this study indicate that these capabilities are mutually reinforcing, where the presence of one enhances the effectiveness of the other. This insight contributes to the growing discourse on policy analytics and smart governance, illustrating that data-driven evidence and implementation quality together drive superior service outcomes (Newman & Mintrom, 2023; Sanderson, 2002).

Finally, these findings extend the current literature by offering quantitative evidence of how EBPM and DAC jointly influence service delivery outcomes in an emerging economy context. While previous studies have explored these constructs separately (Head, 2016; Demir, 2022), this study demonstrates the combined effect of evidence-based decision-making and analytical capabilities, mediated by policy implementation quality. The results underscore the practical implications for policymakers and organizational leaders in India and similar contexts: investing in both evidence-informed practices and analytical capacity is crucial to enhance efficiency, transparency, and citizen satisfaction in technology-driven public services. This contribution reinforces the relevance of integrating theoretical insights with empirical validation, bridging the gap between policy science and practice (Cairney, 2022; Sanderson, 2003; Martin et al., 2010).

6. Conclusions

This study investigated the relationships among Evidence-Based Policymaking (EBPM), Data Analytics Capability (DAC), Policy Implementation Quality (PIQ), and Public Service Delivery Efficiency (PSDE) within the Indian technology industry policy context. The findings indicate that both EBPM and DAC have significant positive effects on PSDE, both directly and indirectly through PIQ. The mediation analysis highlights that effective policy implementation is a crucial mechanism through which evidence-based and data-driven practices translate into improved service delivery outcomes. Overall, the study demonstrates that combining rigorous evidence, analytical capabilities, and high-quality implementation practices significantly enhances governance performance in technology-driven public services.

The study contributes to the literature on public policy and governance by empirically validating the theoretical links among EBPM, DAC, PIQ, and PSDE. While prior research has largely discussed these constructs separately (Head, 2010; De Marchi et al., 2016; Newman et al., 2017), this study provides quantitative evidence of their interrelationships and mediation effects. The findings reinforce theories of evidence-based policy and policy analytics, confirming that implementation quality is a critical intermediary that enables evidence and analytical capabilities to impact service efficiency. This integrative perspective advances understanding of how knowledge-based and data-driven governance mechanisms operate synergistically in emerging economies, extending frameworks on policy capacity and smart governance (Mulgan, 2005; Sanderson, 2002).

The results provide actionable insights for policymakers, administrators, and industry leaders in India. First, investments in EBPM practices—such as systematic use of empirical evidence, pilot testing, and expert consultation—should be prioritized to improve decision-making quality. Second, enhancing DAC through modern digital infrastructure, real-time data access, and skilled analytical staff can strengthen both policy design and implementation. Third, the mediating role of PIQ emphasizes the need for clear policy guidelines, inter-agency coordination, and adaptive monitoring mechanisms to ensure effective translation of policies into results. Policymakers should thus adopt a holistic approach that integrates evidence, analytics, and implementation excellence to achieve higher efficiency, transparency, and citizen satisfaction.

Despite its contributions, this study has limitations. First, the cross-sectional design captures stakeholder perceptions at a single point in time, limiting the ability to infer causality. Future research could adopt longitudinal or panel designs to examine dynamic changes in policy outcomes over time. Second, the study focused exclusively on the Indian technology industry, which may limit generalizability to other sectors or countries. Comparative studies across sectors and emerging economies could provide broader insights. Third, data were collected through self-reported surveys, which may introduce response biases despite procedural and statistical controls for common method variance. Future studies may incorporate mixed methods, including qualitative interviews or secondary data, to triangulate findings and enhance validity. Finally, additional factors such as political environment, regulatory frameworks, and citizen engagement could be integrated as moderators in future research to explore boundary conditions of EBPM and DAC effectiveness.

Declarations

Ethics and Guidelines: The study was conducted in accordance with the Declaration of Helsinki. The ethical approval specifically covers the research procedures and data collection activities conducted for this study.

Consent to participate: Written informed consent was obtained from all participants prior to data collection. Consent was obtained using a standardized written form, signed by each participant before participation in the survey.

Consent to publish: The authors have provided consent to publish.

Competing interests: The authors declare no competing interests.

Data availability statement: Data will be made available on reasonable request from the corresponding author.

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Declaration of using generative AI: During the preparation of this work the author(s) used ChatGPT in order to correct the grammatical errors. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

Author Contributions: Conceptualization, A.A.J.; methodology, A.A.J.; formal analysis, A.A.J.; writing—original draft preparation, A.A.J.; writing—review and editing, A.A.J. All authors have read and agreed to the published version of the manuscript.

Appendix A (Questionnaire)

Section A: Respondent Profile

- Gender:
  ☐ Male ☐ Female ☐ Prefer not to say
- Age:
  ☐ Below 30 ☐ 30–40 ☐ 41–50 ☐ Above 50
- Education Level:
  ☐ Bachelor ☐ Master ☐ PhD ☐ Others
- Position:
  ☐ Policy Maker ☐ Government Official ☐ Industry Professional ☐ Consultant ☐ Other
- Years of Experience:
  ☐ <5 ☐ 5–10 ☐ 11–15 ☐ >15
- Sector Involvement:
  ☐ IT Services ☐ Software Development ☐ Start-ups ☐ Digital Platforms ☐ Other

Section B: Main Constructs

Scale Instruction: Please indicate your level of agreement:

1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

- 1. Evidence-Based Policymaking (EBPM)
  EBPM1: Technology policies are developed using reliable empirical data.
  EBPM2: Policy decisions are supported by rigorous impact evaluations.
  EBPM3: Research findings from academia and industry are integrated into policymaking.
  EBPM4: Pilot testing is conducted before large-scale policy implementation.
  EBPM5: Expert consultations are regularly used in policy formulation.
- 2. Data Analytics Capability (DAC)
  DAC1: Government agencies use advanced data analytics tools in policymaking.
  DAC2: Real-time data is available to monitor policy outcomes.
  DAC3: There is adequate digital infrastructure for data collection and analysis.
  DAC4: Policymakers possess strong data analysis skills.
  DAC5: Big data and AI technologies are utilised in policy decisions.
- 3. Policy Implementation Quality (PIQ)
  PIQ1: Policy guidelines are clear and well-communicated.
  PIQ2: Policies are implemented within the planned timeframe.

PIQ3: Coordination among agencies is effective during implementation.
PIQ4: Monitoring and evaluation mechanisms are robust.
PIQ5: Policies are adaptable to changing technological environments.

- 4. Public Service Delivery Efficiency (PSDE)
  PSDE1: Technology policies reduce service delivery time.
  PSDE2: Public services are delivered more cost-effectively.
  PSDE3: Accessibility of digital public services has improved.
  PSDE4: Bureaucratic delays have decreased due to technology policies.
  PSDE5: Overall user satisfaction with public services has increased.

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