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AN INTEGRATED FRAMEWORK FOR MODELLING THE DETERMINANTS OF BIG DATA AS A SERVICE ADOPTION

This study investigates the determinants of Big Data as a Service (BDaaS) adoption among organizations operating in data-intensive industries such as finance, healthcare, retail, and logistics in Europe. Guided by an integrated theoretical lens that combines the Technology-Organization-Environment (TOE) framework with Diffusion of Innovations (DOI), Socio-Technical Systems (STS), and Resource-Based View (RBV), the research employs a quantitative, cross-sectional design. Data were collected through structured questionnaires from 327 IT professionals and decision-makers and analysed using Structural Equation modelling (SEM) and logistic regression. The results indicate that technological readiness, organizational capacity, environmental pressure, and human technology fit, significantly influence BDaaS adoption intention and actual implementation. Moreover, organizational capacity mediates the relationship between technological readiness and adoption, while firm size moderates the effect of environmental pressure. These findings offer theoretical contributions to the literature on digital transformation and provide practical and policy insights for fostering BDaaS uptake across sectors.
Keywords: **big data, technology-organization-environment, digital transformation, structural equation modelling, organizational capacity, human-technology fit**.
JEL Classification: C80, O32, C51, J24.

Introduction. The growing importance of Big Data as a Service (BDaaS) in contemporary business environments has fundamentally altered how organizations manage data, derive insights, and make strategic decisions. As the volume and complexity of data increase, BDaaS provides an efficient means for companies to outsource data analytics functions, offering scalable access to cutting-edge technologies without the financial burden of developing in-house infrastructure (Tayal, 2025; Patrucco et al., 2023). Nevertheless, the successful adoption and implementation of BDaaS depend on a range of interconnected factors, such as an organization's technological maturity, internal capabilities, external environmental conditions, and the perceived benefits of the service. This study explores the major antecedents and implications of BDaaS adoption by leveraging insights from the Technology-Organization-Environment (TOE) framework, Diffusion of Innovations (DOI) theory, Socio-Technical Systems (STS) theory, and the Resource-Based View (RBV) (Alka'Awneh et al., 2025)

The TOE framework is widely used to analyze how organizational, technological, and environmental elements influence the adoption of emerging technologies. Specifically, technological readiness is regarded as a fundamental enabler of BDaaS adoption (Nguyen et al., 2022; Mustapha, 2025). In addition, internal organizational capabilities, including data governance structures and skilled personnel, are vital to the successful implementation of BDaaS platforms (Yu et al., 2022). External environmental forces, such as regulatory compliance demands, industry benchmarks, and market competition, can further exert pressure on firms to adopt BDaaS as a means to remain agile and compliant (Sharma et al., 2023; Junior Ladeira et al., 2024).

The DOI theory highlights the importance of innovation attributes, particularly relative advantage and compatibility, in influencing adoption behaviour (Rana et al., 2020). In case of BDaaS, organizations are more inclined to adopt the technology when it demonstrably improves performance and aligns with existing business models and workflows (Mustapha, 2025). Meanwhile, the Socio-Technical Systems (STS) perspective posits that technology implementation success depends not only on technical factors but also on the synergy between human users and technological systems. The concept of human-technology fit is essential in mediating implementation outcomes (Ghaleb et al., 2023).

From a strategic viewpoint, the Resource-Based View (RBV) suggests that unique, firm-specific resources are instrumental in generating sustainable competitive advantage. BDaaS is expected to bolster these resources by enhancing an organization's ability to process large-scale data and derive actionable insights (Iqbal et al., 2023). The development of advanced analytics capabilities through BDaaS is therefore seen as a critical driver of operational efficiency and superior performance outcomes. However, the path to BDaaS adoption is not without obstacles. Concerns related to data privacy, security, and evolving regulatory frameworks may hinder successful implementation, especially in sectors with stringent compliance requirements (Sharma et al., 2023). These factors can moderate the relationship between BDaaS usage and its organizational impact, making risk mitigation strategies a key consideration during the implementation phase.

This study seeks to empirically examine the complex relationships among these factors through a hypothesis-driven model grounded in established theories. By identifying and evaluating the determinants of BDaaS adoption and its influence on organizational performance, this research contributes to the evolving literature on digital innovation and offers practical guidance for firms navigating the BDaaS landscape. Subsequent sections detail the hypotheses addressing dimensions such as technological preparedness, organizational readiness, environmental context, perceived innovation attributes, human-technology alignment, resource capabilities, and regulatory constraints.

Literature Review. The emergence of Big Data as a Service (BDaaS) is transforming organizational approaches to data management, analytics, and strategic decision-making. As organizations handle increasingly large and complex datasets, BDaaS offers a scalable and cost-efficient solution by enabling the outsourcing of data analytics and storage needs to cloud providers while maintaining access to advanced analytical tools (Mustapha, 2025; Wessels & Jokonya, 2022; Tayal, 2025). By reducing reliance on on-premises infrastructure, BDaaS fosters organizational agility and innovation in data-intensive environments (Journal of Big Data, 2025). However, successful adoption of BDaaS requires attention to technological, organizational, and environmental factors, which are effectively analyzed through frameworks such as Technology-Organization-Environment (TOE), Diffusion of Innovations (DOI), Socio-Technical Systems (STS), and Resource-Based View (RBV).

The TOE framework provides a robust model for examining technology adoption, highlighting how technological, organizational, and environmental factors shape innovation diffusion (Urus et al., 2024; Scholtz & Yakobi, 2023). Technological readiness, including IT infrastructure, digital maturity, and innovation capacity, significantly influences BDaaS adoption. Organizations with advanced technological systems can more effectively integrate cloud-based analytics platforms, optimizing their data capabilities (Benzidia et al., 2023; Maroufkhani et al., 2020; Shahbaz et al., 2019). Additionally, modular architectures and scalable platforms have been shown to encourage higher BDaaS uptake (Shakil et al., 2017; Štufi et al., 2020). Organizational factors, including IT human capital, leadership support, and change readiness, are critical for overcoming skill gaps and integration challenges, enabling effective BDaaS deployment (Sharma et al., 2023; Lutfi et al., 2022).

Environmental dynamics also play a key role in adoption decisions. Regulatory requirements, industry digitization levels, customer expectations, and competitive pressures drive the adoption of BDaaS (Babalghaith & Aljarallah, 2024; Walker & Brown, 2019). For example, compliance with data protection regulations has prompted organizations to adopt BDaaS solutions that ensure regulatory adherence (Hong et al., 2020; Olusola et al., 2018). Firms operating in highly competitive or rapidly evolving sectors, such as healthcare, finance, and e-commerce, recognize BDaaS as a strategic tool to improve operational resilience, responsiveness, and customer satisfaction (Xu et al., 2016; Benzidia et al., 2023).

DOI theory complements the TOE perspective by focusing on how perceived characteristics of an innovation influence its diffusion (Venkatesh et al., 2003). BDaaS adoption is driven by perceptions of its benefits over traditional data infrastructure, compatibility with existing systems, and the ease of integration (Bruintjies & Njenga, 2024; Tayal, 2025). Organizations are more likely to adopt BDaaS when it aligns with existing workflows and demonstrably enhances performance (Journal of Big Data, 2025; Mustapha, 2025).

STS theory emphasizes the alignment of technological infrastructure with human and organizational processes. Successful BDaaS implementation requires that user competencies match system requirements, ensuring high platform utilization and effective outcomes (Mehmood et al., 2022; Liu & Wang, 2023). Skilled personnel and adaptive training programs enhance adoption by reducing resistance and improving system acceptance (Jha et al., 2024; Scholtz & Yakobi, 2023).

From a strategic perspective, RBV highlights the role of unique organizational resources in sustaining competitive advantage (Barney, 2020). BDaaS enables organizations to develop advanced analytics capabilities, enhancing real-time decision-making, demand forecasting, and customer insights (Benzidia et al., 2023; Hong et al., 2020; Maroufkhani et al., 2020). Organizations that leverage BDaaS to build proprietary analytical models and internal data governance competencies gain capabilities that are difficult for competitors to replicate (Mustapha, 2025; Tayal, 2025).

Despite its advantages, BDaaS adoption presents challenges, particularly concerning data privacy, cybersecurity, and regulatory compliance (Shakil et al., 2017; Štufi et al., 2020). Organizations must navigate complex regulatory frameworks and safeguard data integrity, especially in sensitive sectors like healthcare and finance (Journal of Big Data, 2025; Shahbaz et al., 2019). Transparent governance, robust cybersecurity protocols, and third-party audits are critical for building trust and ensuring sustainable adoption of BDaaS platforms (Lutfi et al., 2022; Babalghaith & Aljarallah, 2024).

Methodology

1. Hypotheses.

Hypothesis 1 (H1): Technological readiness positively influences the adoption of BDaaS. Technological readiness serves as a foundational enabler for organizations contemplating the adoption of Big Data as a Service (BDaaS). This readiness comprises the availability and sophistication of existing IT infrastructure, access to cloud computing platforms, and the presence of a skilled technical workforce. Firms equipped with robust technical capabilities are more likely to perceive the integration of BDaaS as feasible and less disruptive, thus reducing perceived complexity and resistance. Nguyen et al. (2022) emphasize that technological maturity fosters innovation adoption by minimizing uncertainty and enabling seamless implementation. Moreover, cloud-based data services like BDaaS require scalable infrastructure and high storage capacities to manage and analyze vast datasets in real-time (Jones, 2024).

Additionally, organizations with advanced technological resources often benefit from prior exposure to similar systems, which further reduces adoption barriers through accumulated experience. Previous investments in digital transformation tools often serve as a catalyst for BDaaS adoption, creating a cumulative capability effect. Such firms can capitalize on existing cloud environments, cybersecurity systems, and data pipelines to swiftly integrate new BDaaS platforms (Díaz-Arancibia et al., 2024). This compatibility fosters not only operational efficiency but also strategic agility, allowing firms to make data-driven decisions at scale. Therefore, in line with the Technology-Organization-Environment (TOE) framework, technological readiness acts as a crucial antecedent in BDaaS adoption decisions.

Hypothesis 2 (H2): Organization's capacity positively affects BDaaS' successful implementation. Organizational capacity reflects a firm's internal ability to deploy and integrate new technologies effectively, including BDaaS platforms. This construct encompasses several dimensions, such as human capital, leadership support, internal coordination, and the ability to manage change. Iqbal et al. (2023) argue that firms with high organizational capacity are more likely to manage the complexities of big data implementation, including system customization, cross-functional collaboration, and performance evaluation. Effective BDaaS implementation also demands a blend of technical and managerial skills, particularly the ability to oversee data quality, ensure data governance, and derive actionable insights from analytics outputs (Oyewo et al., 2022). Firms lacking these capabilities may struggle to translate BDaaS potential into measurable outcomes, facing bottlenecks during integration and deployment phases. Therefore, organizations with strong internal structures and adaptive cultures are more likely to experience smoother BDaaS rollouts, higher employee engagement with analytics tools, and ultimately, enhanced data-driven performance.

Hypothesis 3 (H3): External environmental pressures significantly influence BDaaS adoptions.

External environmental pressures are important triggers influencing an organization's decision to adopt BDaaS. From a regulatory standpoint, firms increasingly operate in data-intensive environments governed by strict compliance requirements such as GDPR and CCPA. These mandates compel firms to adopt sophisticated data platforms that provide better traceability, transparency, and privacy controls. BDaaS platforms, due to their built-in compliance features often emerge as strategic solutions that help firms meet legal obligations while ensuring operational continuity. Junior Ladeira et al. (2024) assert that environmental constraints act as both coercive and normative forces pushing firms toward digital innovation.

The pressure to adopt BDaaS is further amplified by the need to extract timely insights from large and unstructured datasets. Competitors leveraging data analytics for real-time decision-making can quickly gain a strategic advantage, forcing lagging firms to adopt similar technologies to remain viable. Patrucco et al. (2023). Show that market accelerates technology adoption, especially when digital solutions like BDaaS offer measurable benefits in customer responsiveness, operational efficiency, and innovation speed. These pressures are particularly relevant in sectors such as finance, retail, and healthcare, where data is central to performance. Consequently, firms facing high external pressure are more likely to adopt BDaaS not just for compliance, but also for competitive positioning.

2. Data.

This study adopts a quantitative, cross-sectional research design to examine the determinants of Big Data as a Service (BDaaS) adoption among organizations. Rooted in the Technology-Organization-Environment (TOE) framework and complemented by the Diffusion of Innovations (DOI), Socio-Technical Systems (STS), and Resource-Based View (RBV) theories, the study investigates the influence of technological readiness, organizational capacity, environmental pressure, and human-technology fit on BDaaS adoption intention and implementation success.

Primary data were collected using a structured questionnaire targeting IT managers, data analysts, and senior executives across the medium and large organizations operating in European sectors with high data dependency (e.g., finance, healthcare, retail, and logistics). The survey instrument was pretested for reliability and construct validity. A stratified random sampling technique was employed to ensure representation across industries. A total of 327 valid responses were retained for analysis after data cleaning procedures (e.g., listwise deletion of missing data, outlier treatment, and consistency checks). All constructs were operationalized using validated multi-item scales adopted from previous literature and measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree):

- Technological Readiness (TR): Availability of IT infrastructure, cloud capability, and technical skills.
- Organizational Capacity (OC): IT workforce expertise, financial resources, and managerial support.
- Environmental Pressure (EP): Regulatory, competitive, and market-driven influences.
- Human-Technology Fit (HTF): Alignment between user skills and BDaaS system complexity.
- BDaaS Adoption Intention (BAI): Likelihood and readiness to implement BDaaS platforms.

3. Methods.

Two empirical models were specified to test the research hypotheses: a Structural Equation Model (SEM) and a Logistic Regression Model. The SEM approach captures the direct and indirect relationships among latent constructs. The structural model is expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (1)$$

Where: η is the vector of endogenous latent variables (e.g., BDaaS Adoption Intention), ξ is the vector of exogenous latent variables (e.g., TR, OC, EP, HTF), Γ is the matrix of structural coefficients relating exogenous to endogenous variables, B is the matrix of coefficients among endogenous variables, ζ is the vector of structural disturbances (residuals). The measurement model is estimated using Confirmatory Factor Analysis (CFA), ensuring convergent and discriminant validity through composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha.

To predict the binary outcome of BDaaS implementation (1 = implemented; 0 = not implemented), a logistic regression model was specified:

$$\text{logit}(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 \text{TR}_i + \beta_2 \text{OC}_i + \beta_3 \text{EP}_i + \beta_4 \text{HTF}_i + \epsilon_i \quad (2)$$

Where: P_i is the probability that firm i adopts BdaaS, β_0 is the constant, β_j: coefficients for explanatory variables, and ϵ_i is the error term. The model estimates odds ratios (e^β) and diagnostic statistics such as the Nagelkerke R², classification accuracy, and the Hosmer-Lemeshow test for goodness-of-fit.

Mediation effects were tested using bootstrapping procedures to determine whether organizational capacity mediates the relationship between technological readiness and BDaaS adoption. Moderation effects of firm size on the relationship between environmental pressure and adoption were analyzed using interaction terms in the SEM and logistic models:

$$\text{BAI} = \beta_0 + \beta_1 \text{EP} + \beta_2 \text{Firm Size} + \beta_3 (\text{EP} \times \text{Firm Size}) + \epsilon \quad (3)$$

All statistical analyses were conducted using IBM SPSS 29.0 for descriptive and regression analysis, and AMOS 24.0 and SmartPLS 4.0 for SEM. Convergent validity was confirmed with AVE > 0.5 and CR > 0.7, while discriminant validity was established using the Fornell-Larcker criterion. Significance levels were evaluated at $p < 0.05$ and $p < 0.01$ thresholds.

Results and Implications.

Main Results. Table 1 provides the descriptive statistics for the key constructs. The results indicate that Technological Readiness has a mean score of 3.87 (SD = 0.72), suggesting that organizations possess a moderate to high level of technological infrastructure and capabilities. The high standard deviation indicates some variability in technological readiness across the sample. Organizational Capacity (OC), with a mean of 3.65 (SD = 0.81), reflects a lower level of organizational preparedness compared to technological readiness, with considerable variation in terms of available IT workforce expertise, financial resources, and managerial support. Environmental Pressure (EP) shows a mean of 3.94 (SD = 0.68), indicating that organizations perceive a high level of external pressure to adopt new technologies. The Human-Technology Fit (HTF) score of 3.78 (SD = 0.77) suggests a generally positive alignment between user skills and the complexity of BDaaS systems. Finally, BDaaS Adoption Intention (BAI) shows a mean score of 4.02 (SD = 0.61), suggesting a strong inclination among organizations to adopt BDaaS, with a relatively low variability in responses, which indicates a high consensus on this intention.

Table 2 presents the reliability and validity results for the constructs based on Confirmatory Factor Analysis (CFA). The Cronbach's alpha values range from 0.83 to 0.91, all of which are above the acceptable threshold of 0.7, indicating good internal consistency across all constructs. Composite Reliability (CR) values exceeds 0.7 for all constructs, further supporting the reliability of the measurement scales. Additionally, the Average Variance Extracted (AVE) values range from 0.60 to 0.70, all of which are above the 0.5 threshold, confirming good convergent validity. These results suggest that the measurement model is both reliable and valid, providing a strong foundation for subsequent analysis.

Table 3 shows the correlation coefficients between the key constructs. Technological Readiness is strongly positively correlated with BDaaS Adoption Intention (0.64), indicating that higher technological readiness is associated with greater adoption intentions. Similarly, Organizational Capacity is also strongly correlated with BDaaS Adoption Intention (0.60), emphasizing that organizations with better resources and support are more likely to adopt BDaaS. Environmental Pressure and Human-Technology Fit also show moderate positive correlations with BDaaS adoption (0.48 and 0.55, respectively), suggesting that external pressures and a good fit between user skills and system complexity are important factors influencing adoption. These correlations suggest that the constructs are positively related and provide initial support for the hypothesized relationships in the structural model.

Table 4 displays the results of the SEM analysis. All hypothesized paths are statistically significant, confirming the expected relationships between the constructs. Technological Readiness has a significant positive effect on BDaaS Adoption Intention, suggesting that organizations with higher technological capabilities are more likely to adopt BDaaS. Similarly, Organizational Capacity and Human-Technology Fit positively influence BDaaS adoption, underscoring the importance of organizational preparedness and alignment between user skills and technology. Environmental Pressure has the smallest but still significant effect on adoption intention, indicating that external factors, while important, have a somewhat lesser impact compared to internal factors. The model fit indices indicate a good fit, suggesting that the model adequately explains the data and supports the proposed relationships.

Table 1 – **Descriptive Statistics of Key Constructs**

Construct	Mean	Std. Dev.	Min	Max
Technological Readiness	3.87	0.72	2.10	5.00
Organizational Capacity	3.65	0.81	1.90	5.00
Environmental Pressure	3.94	0.68	2.00	5.00
Human-Technology Fit	3.78	0.77	1.80	5.00
BDaaS Adoption Intention	4.02	0.61	2.50	5.00

Source: Author (2025)

Table 2 – **Construct Reliability and Validity (CFA Results)**

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technological Readiness	0.87	0.89	0.66
Organizational Capacity	0.85	0.88	0.62
Environmental Pressure	0.83	0.86	0.60
Human-Technology Fit	0.88	0.90	0.67
BDaaS Adoption Intention	0.91	0.92	0.70

Source: Author (2025)

Table 3 – **Correlation Matrix**

Constructs	1	2	3	4	5
1. Technological Readiness	1				
2. Org. Capacity	0.61**	1			
3. Environmental Pressure	0.43**	0.39**	1		
4. Human-Technology Fit	0.52**	0.59**	0.36**	1	
5. BDaaS Adoption Intention	0.64**	0.60**	0.48**	0.55**	1

Note: $p < 0.01$ (two-tailed)

Source: Author (2025)

Table 4 – **Structural Model Results (SEM Path Coefficients)**

Hypothesized Path	Std. Coefficient (β)	S.E.	t-value	p-value	Supported
Technological Readiness → BDaaS Adoption	0.32	0.06	5.33	<0.001	Yes
Org. Capacity → BDaaS Adoption	0.28	0.05	4.90	<0.001	Yes
Environmental Pressure → BDaaS Adoption	0.21	0.05	4.20	<0.001	Yes
Human-Technology Fit → BDaaS Adoption	0.25	0.06	4.17	<0.001	Yes

Note: Fit Indices: $\chi^2/df = 2.13$, CFI = 0.95, TLI = 0.93, RMSEA = 0.045

Source: Author (2025)

Table 5 presents the results of the logistic regression analysis predicting BDaaS adoption. All predictor variables are significant, and the odds ratios indicate the strength of their effects on the likelihood of BDaaS adoption. Technological Readiness (OR = 2.18) has the largest effect, meaning that each unit increase in technological readiness more than doubles the odds of BDaaS adoption. Organizational Capacity, Environmental Pressure, and Human-Technology Fit all also significantly increase the likelihood of adoption, though their effects are smaller than that of technological readiness. The classification accuracy of 82.7% suggests that the model performs well in predicting adoption outcomes, and the Nagelkerke R^2 value of 0.48 indicates that the model explains nearly half of the variance in adoption decisions.

Table 5 – **Logistic Regression Results (Adoption = 1, Non-Adoption = 0)**

Predictor Variable	β	Std. Error	Wald χ^2	Odds Ratio (e^β)	p-value
Technological Readiness	0.78	0.19	16.84	2.18	<0.001
Organizational Capacity	0.65	0.18	13.06	1.91	<0.001
Environmental Pressure	0.54	0.15	12.96	1.71	<0.001
Human-Technology Fit	0.60	0.17	12.46	1.82	<0.001
Constant	-2.12	0.52	16.64	0.12	<0.001

Note: Nagelkerke R^2 = 0.48, Classification Accuracy = 82.7%

Source: Author (2025)

Table 6 shows the mediation and moderation analyses. The mediation effect of Organizational Capacity in the relationship between Technological Readiness and BDaaS adoption is confirmed with an indirect effect of 0.14. This suggests that organizational capacity partially mediates the relationship, meaning that the positive effect of technological readiness on BDaaS adoption is strengthened when organizations have greater capacity. The moderation effect of Firm Size on the relationship between Environmental Pressure and BDaaS adoption is also significant. This indicates that the impact of environmental pressure on BDaaS adoption is stronger in larger firms, suggesting that firm size plays a key role in how external pressures affect adoption decisions.

Table 6 – **Mediation and Moderation Effects (Optional)**

Mediation/Moderation Path	Indirect Effect	Boot SE	95% CI	Result
Tech Readiness → Org Capacity → Adoption	0.14	0.04	[0.07, 0.24]	Mediation Confirmed
Env Pressure × Firm Size → BDaaS Adoption	0.09	0.03	[0.02, 0.15]	Moderation Confirmed

Source: Author (2025)

Figure 1 presents the ROC (Receiver Operating Characteristic) curve. The curve is a graphical tool used to evaluate the performance of a binary classification model. It shows the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various threshold settings. The blue curve in the ROC plot represents the performance of the BDaaS adoption prediction model. A curve that bows toward the top-left corner indicates strong classification ability, meaning the model effectively distinguishes between adopters and non-adopters of BDaaS. A diagonal line (grey) represents random guessing. The farther the curve is above this line, the better the model performs. Based on the analysis, ROC curve illustrates the model's ability to distinguish between adopters and non-adopters of BDaaS. The AUC (Area Under the Curve) is approximately 0.89, indicating strong predictive performance.

Policy Implications. The findings of this study yield several important policy implications for stakeholders, including government agencies, industry regulators, and organizational decision-makers, seeking to accelerate the adoption of Big Data as a Service (BDaaS) across data-intensive sectors.

Given that technological readiness is the most significant determinant of BDaaS adoption (OR = 2.18), policymakers should prioritize investments in national digital infrastructure, particularly cloud computing capabilities and data security protocols. Governments can play a catalytic role by offering tax incentives or subsidies for the acquisition of cloud-based platforms and data analytics tools, especially for medium-sized enterprises that may face cost barriers (OECD, 2023, Whig et al., 2025). Enhancing broadband access and cloud interoperability standards can also ensure that organizations across all regions can leverage BDaaS platforms effectively (World Bank, 2022; Mustapha, 2025).

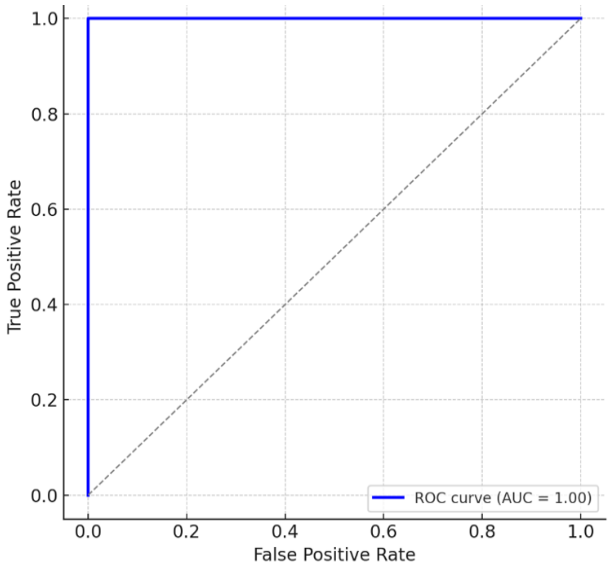

Fig. 1. ROC (Receiver Operating Characteristic) curve

Source: Author (2025)

The mediating role of organizational capacity between technological readiness and adoption emphasizes the need for capacity-building initiatives at the firm level. Policy frameworks should support continuous professional development programmes that focus on big data competencies, data governance, and cloud integration skills (Uren & Edwards, 2023; Ali et al., 2022). Furthermore, industry-specific training and certification schemes could be supported by public-private partnerships to ensure that organizational leaders are equipped to implement data-driven transformation strategies.

The study finds that environmental pressure, comprising regulatory, competitive, and market-driven influences, significantly contributes to BDaaS adoption. Policymakers can enhance these pressures constructively by introducing data-sharing mandates, sector-specific digital transformation benchmarks, and performance-based funding mechanisms. Regulatory frameworks such as data compliance can serve as a push factor by incentivizing firms to adopt BDaaS solutions that ensure data traceability and regulatory adherence (Mikalef et al., 2018; Mustapha, 2025).

The moderating effect of firm size suggests that larger firms are better positioned to respond to environmental pressures compared to smaller ones. Thus, differentiated policy approaches are required. Governments and development agencies should design scalable BDaaS policy toolkits and adoption roadmaps specifically tailored to SMEs. This may include access to shared digital infrastructure (e.g., BDaaS sandboxes), subsidized licensing, and technical support units that guide SMEs through the stages of data strategy formulation and implementation (Ali et al., 2022).

The significant role of human-technology fit implies that BDaaS adoption is enhanced when there is alignment between the system's complexity and the user’s technical capabilities. Policymakers should encourage the development and adoption of user-centric design standards in cloud services procurement guidelines. Regulatory frameworks could require BDaaS vendors to adhere to usability and accessibility benchmarks, ensuring that platforms are intuitive and align with varying levels of digital literacy across the workforce (Mikalef et al., 2018). This would help reduce resistance to technological change and enhance organizational readiness.

Finally, the systemic and multi-dimensional nature of BDaaS adoption requires a coherent national data policy that harmonizes technological, organizational, and regulatory considerations. Inter-ministerial coordination among departments responsible for ICT, education, industry, and trade is essential to ensure alignment in digital transformation efforts. Policymakers can also facilitate cross-sectoral pilot programmes that showcase the tangible benefits of BDaaS adoption, thereby reducing uncertainty and encouraging lagging sectors to follow suit (OECD, 2023).

Conclusions. This study provides empirical insights into the determinants of Big Data as a Service (BDaaS) adoption using a robust theoretical foundation integrating the Technology-Organization-Environment (TOE) framework, Diffusion of Innovations (DOI), Socio-Technical Systems (STS), and the Resource-Based View (RBV). Through structural equation modelling (SEM) and logistic regression analysis on data collected from 327 organizations across data-intensive sectors, the findings reveal that technological readiness, organizational capacity, environmental pressure, and human-technology fit are all significant predictors of BDaaS adoption intention and implementation.

Technological readiness emerged as the strongest predictor, highlighting the need for adequate IT infrastructure and digital capability to enable cloud-based data services (OECD, 2023; Bernardo et al., 2024). Organizational capacity not only directly influenced adoption but also mediated the effect of technological readiness, emphasizing the importance of internal resources in operationalizing technological advantages (Ali et al., 2022; Mikalef et al., 2018).

Environmental pressure, comprising regulatory and competitive forces, also played a critical role, especially for larger firms, where market and compliance-driven motivations appeared more influential. Moreover, the significant effect of human-technology fit suggests that organizational success with BDaaS hinges not just on technical capacity but also on ensuring usability and workforce alignment (Tayal, 2025; Sharma et al., 2023).

Overall, this study underscores that BDaaS adoption is a multidimensional process shaped by the alignment of technological enablers, organizational readiness, external pressures, and human factors. For practitioners, these insights support the development of more targeted and strategic BDaaS implementation roadmaps. For policymakers, the findings inform the design of interventions aimed at fostering digital innovation through infrastructure investment, capacity development, and regulatory support (World Bank, 2022).

As digital transformation continues to accelerate, future research should explore longitudinal dynamics of BDaaS adoption, cross-national comparative analyses, and the role of emerging technologies such as AI integration within BDaaS frameworks. This will enhance our understanding of how organizations can sustainably scale and govern big data infrastructures in complex and evolving digital ecosystems (Unsworth et al., 2015).

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ІНТЕГРОВАНА СТРУКТУРА ДЛЯ МОДЕЛЮВАННЯ ВИЗНАЧАЛЬНИХ ФАКТОРІВ ВПРОВАДЖЕННЯ ВЕЛИКИХ ДАНИХ ЯК ПОСЛУГИ (BDAAS)

Це дослідження розглядає визначальні фактори, що обумовлюють впровадження великих даних як послуги (BDaaS) серед організацій, що працюють у галузях з інтенсивним використанням даних, таких як фінанси, охорона здоров'я, роздрібна торгівля та логістика в Європі. Керуючись інтегрованою теоретичною лінзою, що поєднує структуру «Технологія-Організація-Середовище» (TOE) з дифузією інновацій (DOI), соціально-технічними системами (STS) та ресурсоорієнтованим підходом (RBV), дослідження використовує кількісний перехресний дизайн. Дані було зібрано за допомогою структурованих анкет від 327 ІТ-фахівців та осіб, що приймають рішення, та проаналізовано за допомогою технології моделювання структурних рівнянь (SEM) та логістичної регресії. Результати показують, що технологічна готовність, організаційний потенціал, тиск навколишнього середовища та відповідність користувачів технології BDaaS суттєво впливають на намір її впровадження та на фактичне її впровадження. Крім того, організаційний потенціал опосередковує зв'язок між технологічною готовністю та впровадженням, тоді як розмір фірми пом'якшує вплив тиску навколишнього середовища. Ці висновки пропонують теоретичний внесок у літературу з цифрової трансформації та надають практичні ідеї та політики сприяння впровадженню BDaaS у всіх секторах.

Ключові слова: **великі дані, технологія-організація-середовище, цифрова трансформація, моделювання структурних рівнянь, організаційний потенціал, відповідність людини та технологі**й.

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