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Agentic AI Readiness and Sustainable Service Performance in Digital Retailers

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ABSTRACT

Purpose: This study explore how digital and artificial intelligence (AI)based organisational capabilities relate to sustainable service performance in digital retail companies, via operational agility mechanisms.
Method: This paper adopted a quantitative research methodology with survey data collected from digital retailers' managers and with the help of partial least squares approach to structural modeling.
Findings: The results demonstrate that the use of customer analytics, data quality capability, and process digitization are directly as well as positively associated with sustainable service performance through operational agility. This is a key factor in the successful translation of digital strengths into better service results, which requires agility for operational and processes change and to make quick decisions. By contrast, the influence of agentic artificial intelligence capability on service performance is not statistically significant, suggesting that high-level AI technologies are not enough to create value unless well-integrated into the organization. Additionally, data governance maturity does not enhance the relationship between operational agility and service performance, indicating that governance is mostly an enabler infrastructure rather than a performance enhancer.
Novelty: Our contribution to the literature is therefore three-fold in unpacking artificial intelligence capability, analytics use and process digitization from a single resource-based dynamic capabilities perspective, while providing nuanced evidence within the digital retail context.
Implications: Findings empirically contribute to strategic managerial recommendation that managers need to prioritize agility based digital investments, and theoretically how service performance sustainability develops line of the orchestration of data, technology, and operational capabilities in dynamic markets.

1. Introduction

The future of digital retail is undergoing a sea change, with AI evolving in depth. It is no longer merely about task automation; AI systems are

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becoming progressively more agent-like, designed to make decisions independently as they receive inputs and acquire knowledge from feedback, and initiate cross-functional workflows within one organisation or several. Online retailers and direct-to-consumer (D2C) companies are widely adopting AI agents to improve customer service, demand forecasting, personalisation, and real-time operational coordination. Recent research suggests that integrating AI into core service operations and managerial decision-making can lead to improved organisational performance and business resilience (Mariani et al., 2023; Mikalef et al., 2019, 2020; Wamba et al., 2020). In the face of mounting customer expectations for enhanced service speed, reliability and personalisation, numerous digital retailers are prioritising the strategic implementation of advanced AI to gain a competitive edge in delivering exceptional service.

The impact of AI in digital retail is not uniform, despite the growing use of the technology. Most organisations struggle to make the most of their AI investments, with poor data quality, faulty digital processes and a failure to integrate customer analytics into operational decision-making hindering their ability to deliver consistent and effective services. AI-enabled value creation is, according to the findings of numerous studies, dependent on complementary organisational capabilities. These include data quality management, process digitisation and the use of effective analytics (Bhatt et al., 2024; Leeflang et al., 2014; Verhoef et al., 2021). What's more, the digital retail business model operates in a volatile environment. Moreover, digital retail operates in a highly volatile environment characterised by fluctuating demand, omnichannel complexity, and frequent service disruptions, amplifying the need for organisations to be agile to sustain service performance over time.

The previous literature mainly utilises the resource-based view (RBV) as a framework to explain the functioning aspect of digital capabilities in performance or dynamic capability theory to highlight agility in their fast-paced environment. Nevertheless, the tendency towards synthesis between these two views has not been as popular to publications within research field at large and more rarely studied in digital retail contexts and agentic AI. In doing so, various researches treat AI or analytics capabilities as simple antecedents of performance and do not detail the dynamic process through which such capabilities directly influence service outcomes (Barney, 1991; Gupta et al., 2018; Teece, 2007) or performance (Mikalef et al., 2019, 2020). In addition, the moderating role of data governance in capability-based models has not been empirically examined.

Empirical evidence highlights the diversity of outcomes from AI, analytics and digitalisation for performance. Strong and positive effects are reported in some studies, yet they also have weak or situational effects (Cvitić et al., 2021; Leeflang et al., 2014; Mikalef et al., 2019; Papagiannidis et al., 2023; Verhoef et al., 2021). These contrasts suggest the presence of counter mechanisms and moderating factors that are not yet comprehended. More specifically, the neglect of operational agility as mediator and data governance maturity as moderator represents a crucial theoretical void. Thus, it has become increasingly more pertinent to study how digital capability bundles determine service performance through agility, and how the latter are underpinned by governance.

Departing from these postulations, this study intends to examine the effects of Agentic AI Capability, Data Quality Capability, Process Digitization and Customer Analytics Use on Sustainable Service Performance directly and indirectly via Operational Agility and investigate the moderating role of Data Governance Maturity. Chain-wise, this research serves theoretically as a basis for the enhancement of integration between RBV and DC in AI-based digital retail. On a practical level, the study results can help retail and D2C managers in shaping AI, data, and digitization strategies which focus on long-term sustainable service performance.

The rest of the paper is structured as follows. Literature review and hypotheses development This study is introduced by Section 2 that reviews the literature and develops theoretical framework and research hypotheses. The research methodology, tools and procedures (including the data collection) are discussed in section 3. Section 4 presents the

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empirical findings and explains their interpretation. 5 Conclusions This section concludes with a summary of the primary findings and discussions on theoretical and managerial implications, study limitations, and future research directions.

2. Literature Review

2.1 Digital capability bundle and sustainable service performance

RBV point of view, when the organisational capabilities are developed as a blend or mix of valuable... unique resources that can be managed and deployed within operations (service processes), they contribute to superior performance. The service of sustainable and stable ones in digital retail refers to the bundle of AIC, DQC, PD and CAU capabilities. Recent research suggests that AI capabilities are linked to enhanced organisational performance and sustainability, notably when AI is integrated in decision making processes and service operations, for instance (Latan et al., 2018; Wamba et al., 2020). Furthermore, technology-based retail research highlights that the combination of data, process and technology (incuding GenAI) enhances retail success by enabling effective cxustomer experience, efficiency and operational stability (Vhatkar et al., 2024). It has also been evidenced recently in business analytics literature that analytical capability and its deployment are associated with customer satisfaction and company performance, particularly in dynamic contexts where it is necessary to be agile (Alfadhel, 2025). Hence, the digital capability bundle is seen as the key antecedent of Sustainable Service Performance (SSP) represented by retention, revenue stability, cost effectiveness, complaint settlement and long-term reputation.

Hypothesis 1. AI Agency capabilities improve Sustainable Service Performance.
Hypothesis 2. Data Quality capabilities improve Sustainable Service Performance.
Hypothesis 3. Process Digitalization improves Sustainable Service Performance.
Hypothesis 4. Use of Customer Analytics improves Sustainable Service Performance.

2.2 Digital capability bundle and operational agility

Under the Dynamic Capabilities view, great organizations do not merely have resources at their disposal, but can instead sense–seize–reconfigure to adapt rapidly in response to changes in competitive conditions. Operational Agility (OA) is the operational dimension of the dynamic capability and encompasses quick change, process piggybacking, fast decision making, readiness to disruption and shorter time-to-market. Recent research validates this connection between below the competition level AI and agility: if we "infuse" AI into our operations, agility will be enhanced through quicker coordination or execution or response in operations (Atienza-Barba et al., 2024). Additional evidence displays that business analytics capabilities (encompassing data, tools, talent and the way they are used) have an impact through mechanisms of dynamic capabilities and agility in firm-level longitudinal data (Alfadhel, 2025). In the retail industry, (Vhatkar et al., 2024) note that digital technology, processes and data create operational transformation in which companies become more agile regarding the variability of channels, demand and during customer services. Thus, AIC (DQC, PD and CAU should enhance OA are of an intermediate nature that is, between digital capabilities to service outputs .

Hypothesis 5. The agency's artificial intelligence (AI) capabilities improve operational agility.
Hypothesis 6. Data quality capabilities improve operational agility.
Hypothesis 7. Process digitalisation improves operational agility.
Hypothesis 8. The use of customer analytics improves operational agility.

2.3 Operational agility and sustainable service performance

Understanding operational agility is particularly relevant for grasping how digital retail organisations can sustain service performance in the face of fluctuating demand, pressures on omnichannel strategies, and growing customer expectations. Competitiveness in a fast-paced environment depends on an organisation's ability to reconfigure its processes, resources and decision-making structures, according to the concept of dynamic

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capabilities. Research indicates that digital and AI capabilities are linked to firm performance, with agility being a key mechanism through which this link is established. This is because agility enhances responsiveness, efficiency and quality of service (Masialeti et al., 2024). Recent research in business analytics has shown that a company's use of analytics for performance and customer experience is dependent on its ability to be agile. This means being able to make decisions or changes to operations based on market conditions (Alfadhel, 2025). Being more agile in the retail sector would also mean that companies can get back to normal more quickly when things go wrong (e.g. when products are out of stock, deliveries are late, or there are a lot of complaints). It would also help them to keep their customers happy and make sure their revenue is steady, while avoiding costs related to uncertainty and risk of damage to their reputation in the long term (Vhatkar et al., 2024).

Hypothesis 9. Operational Agility meningkatkan Sustainable Service Performance.

2.4 The mediating role of operational agility

RBV emphasises capabilities as strategic resources, and dynamic capabilities explain how these capabilities are realised in performance when operating in a fast-paced environment. The internal driver that converts AIC, DQC, PD and CN into enduring service performance outputs is now treated as a mediating dimension, otherwise known as operational agility. AI capability portfolios, particularly the ability to maintain and refresh AI applications, are suggested to be transmitted via agility and performance. This lends support to the mechanistic path from digital capabilities to agility (Masialeti et al., 2024). Longitudinal studies of business analytics also demonstrate that the impact of analytics on firm performance and customer satisfaction frequently operates through the mechanism of dynamic capabilities, agility, and contingent upon environmental factors (Alfadhel, 2025). In digital retail, PD and DQC, when applied, will minimise operational friction (e.g. slow approvals and out-of-sync data), whereas CAU, with its shortened insight-to-action cycle, will increase agility. Together, they contribute to increased agility, which should enhance SSP support by means of more sustainable, effective, responsive services (Vhatkar et al., 2024).

Hypothesis 10. Operational Agility mediates the influence of Agentic AI Capability on Sustainable Service Performance.
Hypothesis 11. Operational Agility mediates the influence of Data Quality Capability on Sustainable Service Performance.
Hypothesis 12. Operational Agility mediates the influence of Process Digitization on Sustainable Service Performance.
Hypothesis 13. Operational Agility mediates the influence of Customer Analytics Use on Sustainable Service Performance.

2.5 The moderating role of data governance maturity

The growing use of agentic AI and analytics requires strong data governance to ensure the robustness of value derivation in various decision contexts, where AI decisions depend on clean data, access control, audit trails and consideration of ethical and privacy implications. This 'institutional backbone', known as Data Governance Maturity (DGM), ensures that AI and analytics run consistently and safely using policies, ownership, access control, auditing, and ethical and privacy principles. The importance of data governance frameworks, maturity models and quality management practices has been increasingly highlighted in the literature (Bernardo et al., 2024). These practices are intended to leverage value from data and minimise errant decisions. In practice, mature governance enhances the reliability of agile decision-making because data is standardised and other conditions are built in, as well as being accessible for compliance management. The impact of operational agility on sustainable service performance is more pronounced when DGM is high. This is because agility is fast and minimises waste, which is also quick to deliver accuracy, security and dependability. In a similar way, studies of AI capability and performance also show how the results of AI are very dependent on how ready an organisation is with regard to governance and decision-making electronics (Neiroukh et al., 2024).

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Hypothesis 14. Data Governance Maturity strengthens the influence of Operational Agility on Sustainable Service Performance.

2.7

2.6 Conceptual framework

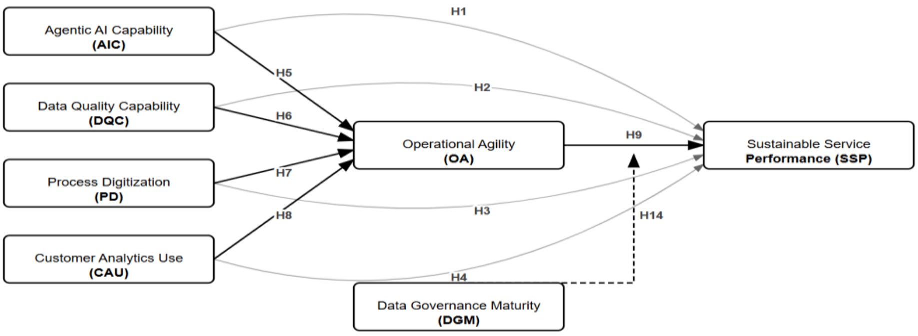

Fig. 1: Conceptual model framework.

3. Methods Innovation

3.1 Design research

The research uses a method of explanation that is quantitative in nature to establish how AI readiness in terms of agentic capability affects sustainable service performance through operational agility in the context of differing data governance maturity. As the study aims to test theoretically based associations rather than changes over time, a cross-sectional survey method is most suitable. This design is consistent with earlier research on identifying AI capability using digital analytics and service innovation, which rely on managers' views of company-level abilities and results (Barney, 1991; Teece et al., 1997). According to the RBV, digital and AI capabilities can be viewed as strategic resources that have value when used properly. Dynamic CapabilitiesTheory delves more deeply into how these resources are converted into performance through adaptive processes, such as agility. Recent empirical applications in the context of digital retail and AI-enabled services demonstrate something. They demonstrate that cross-sectional PLS-SEM designs are still suitable for assessing complex models. This is the case in emerging markets where there are few objective secondary sources of data. These designs incorporate effects of mediation and moderation.

3.2 Research population and data collection

The population was digital retail companies in Indonesia, which include modern retail chains, direct to customer (D2C) brands, omnichannel retailers (retailers that have both offline and online channels), e-commerce entity pure players, and marketplace-based entities. Indonesia serves as an applicable empirical setting because of a boom in digital commerce and varying AI adoption readiness among organizations. The organization is the unit of analysis with senior managers and founders who have direct responsibilities related to digital operations, analytics or service performance being the respondents. This is a purposive sampling technique (Mohajan, 2017), as the authors wanted respondents who had knowledge of AI use, data quality and governance. Following a web-based survey, 253 valid firm-level responses were obtained, well above required minimum sample size for PLS-SEM. Earlier research on AI capability and analytics-based performance validates the measure of manager informants as a proxy for organizational capabilities and strategic results.

3.3 Variables and measurement instruments

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All constructs were operationalized with reflective multi-item scales borrowed from prominent top-tier articles in the AI capability, data quality, digital processes, analytics use and organizational agility literature. On the other hand, each of Agentic AI Capability, Data Quality Capability, Process Digitization, Customer Analytics Use, Operational Agility and Sustainable Service Performance was also operationalized by five indicators to preserve sufficient construct coverage and content validity. Responses were collected in a five-point Likert type-scale, commonly used to measure organizational and service behaviour. Theoretical constructs and empirical items were conceptually aligned with the backbone of RBV and combination of DC in the process of instrumentalization development. Previous empirical work confirms that perceptual measures provide reliable proxies for hidden types of organisational capabilities and performance results, as organisations differ greatly in terms of size, stage of being digitalised and extent of information disclosure.

3.4 Data analysis

SmartPLS 4 was employed to analyze data following the most widely accepted practices for PLS-SEM. The analysis thereupon took place in two steps. The model of measurement was tested by examining indicator reliability, internal consistency reliability, convergent validity and discriminant validity firstly. Second, the structural model was evaluated by examining path coefficients together with coefficient of determination (R^2), effect sizes (f^2) and predictive relevance (Q^2) through a bootstrapping method based on 5,000 resamples. Specify indirect effects were used to test mediation, and interaction terms between data governance maturity and our operational agility key predictors as they pertain to moderation. This methodological approach is consistent with recent recommendations to test moderated mediation models in AI-related organizational research, and it strengthened the reliability and predictive validity of our results.

4. Results of Innovation and Discussion

4.1 Measurement model assessment

Table 1., indicator reliability the results of Outer Loadings for All Constructs in Measurement Model table 2 Structural Model: Direct Effects The direct effect are estimated to be significant. The results of the assessment indicate moderate to high loadings on both constructs for all indicators, the outer loadings higher than their threshold values, demonstrating sufficient indicator reliability. Factors of Agentic Artificial Intelligence Capability, Customer Analytics Use, Data Governance Maturity, Data Quality Capability, Operational Agility, Process Digitization and Sustainable Service Performance have all high loads that are powerful indicators of convergent validity as alignment between these measures and their latent factors is obviously good. The findings validate that each item meaningfully affects its construct, indicating the strength of the measurement items. This measurement model meets the indicator reliability requirements, and indicates to confirm the internal consistency, convergent validity and structural relationships for further analysis.

Tables 2-4 present the internal consistency, convergent validity and discriminant validity of the measurement model. As illustrated in Table 2, all the constructs demonstrate strong internal consistency, as evidenced by Cronbach's alpha and composite reliability values that surpass generally acceptable standards. This is indicative of reliable measurement scales. Convergent validity is supported by the fact that the average variance extracted values of all constructs are greater than the minimum threshold value. This indicates that the manifest variables adequately measure their respective latent variables. As illustrated in Table 3, the square roots of the average variance extracted for each construct exceed the between-construct correlations, thereby validating the Fornell–Larcker criterion. Furthermore, as illustrated in Table 4, all heterotrait-monotrait ratio coefficients are below the established conservative threshold. This indicates

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that discriminant validity was supported. The findings indicate the presence of a reliable and valid measurement model, which can be used for further structural analysis.

Table 1. Indicator reliability (outer loadings)

Construct	Indicator	Outer loading
AIC	AIC1	0.786
	AIC2	0.84
	AIC3	0.828
	AIC4	0.819
	AIC5	0.843
CAU	CAU1	0.816
	CAU2	0.833
	CAU3	0.838
	CAU4	0.843
	CAU5	0.856
DGM	DGM1	0.813
	DGM2	0.799
	DGM3	0.842
	DGM4	0.803
	DGM5	0.849
DQC	DQC1	0.82
	DQC2	0.843
	DQC3	0.823
	DQC4	0.784
	DQC5	0.802
OA	OA1	0.848
	OA2	0.862
	OA3	0.816
	OA4	0.825
	OA5	0.83
PD	PD1	0.794
	PD2	0.837
	PD3	0.824
	PD4	0.82
	PD5	0.809
SSP	SSP1	0.851
	SSP2	0.856
	SSP3	0.86
	SSP4	0.839
	SSP5	0.86

Table 2. Internal consistency and convergent validity

Construct	Cronbach's alpha	(ρA)	(ρC)	AVE
AIC	0.881	0.884	0.913	0.678
CAU	0.893	0.894	0.921	0.701
DGM	0.879	0.882	0.912	0.675
DQC	0.873	0.877	0.908	0.664
OA	0.893	0.894	0.921	0.7
PD	0.875	0.878	0.909	0.667
SSP	0.907	0.909	0.931	0.728

Table 3. Fornell–Larcker criterion

	AIC	CAU	DGM	DQC	OA	PD	SSP
AIC	0.823						
CAU	0.662	0.837					
DGM	0.58	0.491	0.821				
DQC	0.542	0.488	0.695	0.815			

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	AIC	CAU	DGM	DQC	OA	PD	SSP
OA	0.486	0.562	0.453	0.461	0.836		
PD	0.573	0.492	0.48	0.538	0.445	0.817	
SSP	0.487	0.57	0.475	0.509	0.689	0.499	0.853

Table 4. HTMT ratio

	AIC	CAU	DGM	DQC	OA	PD	SSP
AIC							
CAU	0.745						
DGM	0.657	0.551					
DQC	0.618	0.551	0.793				
OA	0.548	0.629	0.512	0.518			
PD	0.653	0.554	0.543	0.615	0.502		
SSP	0.541	0.631	0.529	0.57	0.761	0.557	

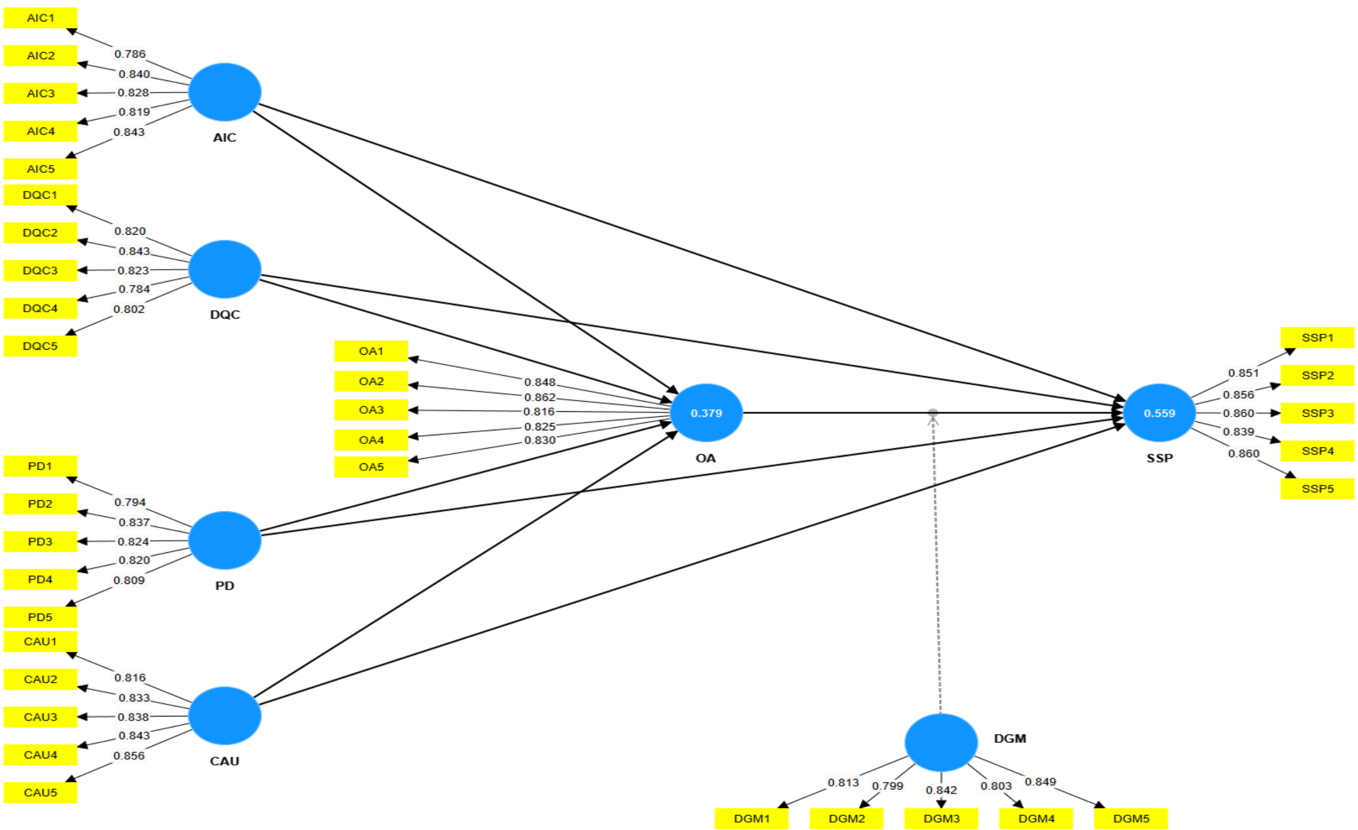

Figure 2. Outer loadings

4.2 Structural model assessment

Collinearity diagnostics show that multicollinearity is not a problem in the structural model. All VIF values of the inner-model are 1.090 to 2.317, still far below a commonly used limit (e.g., 3.3 or F5). This implies that predictors of OA (AIC, CAU, DQC, PD) and predictors of SSP (the AIC, CAU, the DQC, PD, OA, DGM and the interaction term between AO and DGM) are contributing uniquely for explanation rather than same variance. As a result, the path coefficients based on these estimates are

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less affected by inflation of standard errors caused by multicollinearity and we can interpret the estimated path coefficients with more certainty that such over-estimation are not as likely to have bias statistical inference in our bootstrapping results.

The model exhibits good explanatory and predictive ability of the endogenous constructs. The predictors account for 37.9% variance in OA (R^2 = 0,379), and thus it can be concluded that digital capability bundle explains a part of the cultural agency in digital retailors. In addition, the model accounts for 55.9 per cent of the variance in SSP intentions (R^2 = 0.559), indicating a large explanatory capacity with respect to sustainable service outcomes. Predictive validity is further evidenced by positive Q^2 values for both constructs (OA = 0.260; SSP = 0.398), which means the model possesses predictive relevance and performs better than naive criterion. In general, these findings suggest that the proposed RBV resources and dynamic capability mechanism are strong in predicting service performance sustainability in digitally intensive retail settings.

Among the predictors, OA > SSP is found to be the major contributor to the model with significant and large effect size (f^2=0.302), which confirms agile strength as driver of performance- converting mechanism and supportive of Dynamic Capabilities Theory. CAU > OA presents the highest significance in its contribution to the agility antecedents (f^2 = 0.112, small–>moderate), followed by DQC > OA (0.029) and PD > OA (0.016) that offer lower additional explanatory power. Diagnostic effects on SSP are typically small, as CAU > SSP (0.036) and PD > SSP (0.023) outweigh AIC's near-zero prediction (0.001). The moderator path DGM × OA > SSP is non-significant (0.001), providing weak evidence for its incremental effect in this model.

The structural findings suggest that OA is a powerful predictor for SSP (β = 0.465, p <.001), which supports the dynamic capabilities perspective. Of the direct capability effects on SSP, CAU (β = 0.182; p = 0.002) and PD (β = 0.133; p= 0.021) are significant, with AIC being non-significant and negligibly negative (p= 0.677), indicating that AI readiness alone may not be sufficient to realize sustainable service outcomes without adequate implementation. CAU, DQC, and PD positively influence OA as agility antecedents, whereas AIC>OA is not found. Finally, the moderation DGM × OA > SSP is not significant, which indicates governance maturity does not enhance the OA–SSP relationship in this population.

Table 5. Collinearity assessment (VIF values)

Endogenous construct	Predictor	VIF
OA	AIC	2.182
	CAU	1.888
	DQC	1.629
	PD	1.698
SSP	AIC	2.317
	CAU	2.118
	DQC	2.302
	PD	1.728
	DGM	2.218
	DGM × OA	1.09
SSP	OA	1.628

Table 6. Coefficient of determination (R^2) and predictive relevance (Q^2)

Endogenous construct	R^2	Adjusted R^2	Q^2 (redundancy)
OA	0.379	0.369	0.26
SSP	0.559	0.547	0.398

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Table 7. Effect size (f²) of structural relationships

Relationship	f^2
AIC > OA	0.005
CAU > OA	0.112
DQC > OA	0.029
PD > OA	0.016
AIC > SSP	0.001
CAU > SSP	0.036
DQC > SSP	0.013
PD > SSP	0.023
OA > SSP	0.302
DGM > SSP	0.002
DGM × OA > SSP	0.001

Table 8. Direct effects and hypothesis testing results

Hypothesis	Path	β (O)	t-value	p-value	Decision
H1	AIC > SSP	-0.025	0.416	0.677	Not supported
H2	DQC > SSP	0.114	1.828	0.068	Not supported
H3	PD > SSP	0.133	2.303	0.021	Supported
H4	CAU > SSP	0.182	3.137	0.002	Supported
H5	AIC > OA	0.079	1.157	0.247	Not supported
H6	DQC > OA	0.172	2.864	0.004	Supported
H7	PD > OA	0.128	1.982	0.048	Supported
H8	CAU > OA	0.363	5.981	0.000	Supported
H9	OA > SSP	0.465	9.207	0.000	Supported
H14	DGM × OA > SSP	0.018	0.435	0.664	Not supported

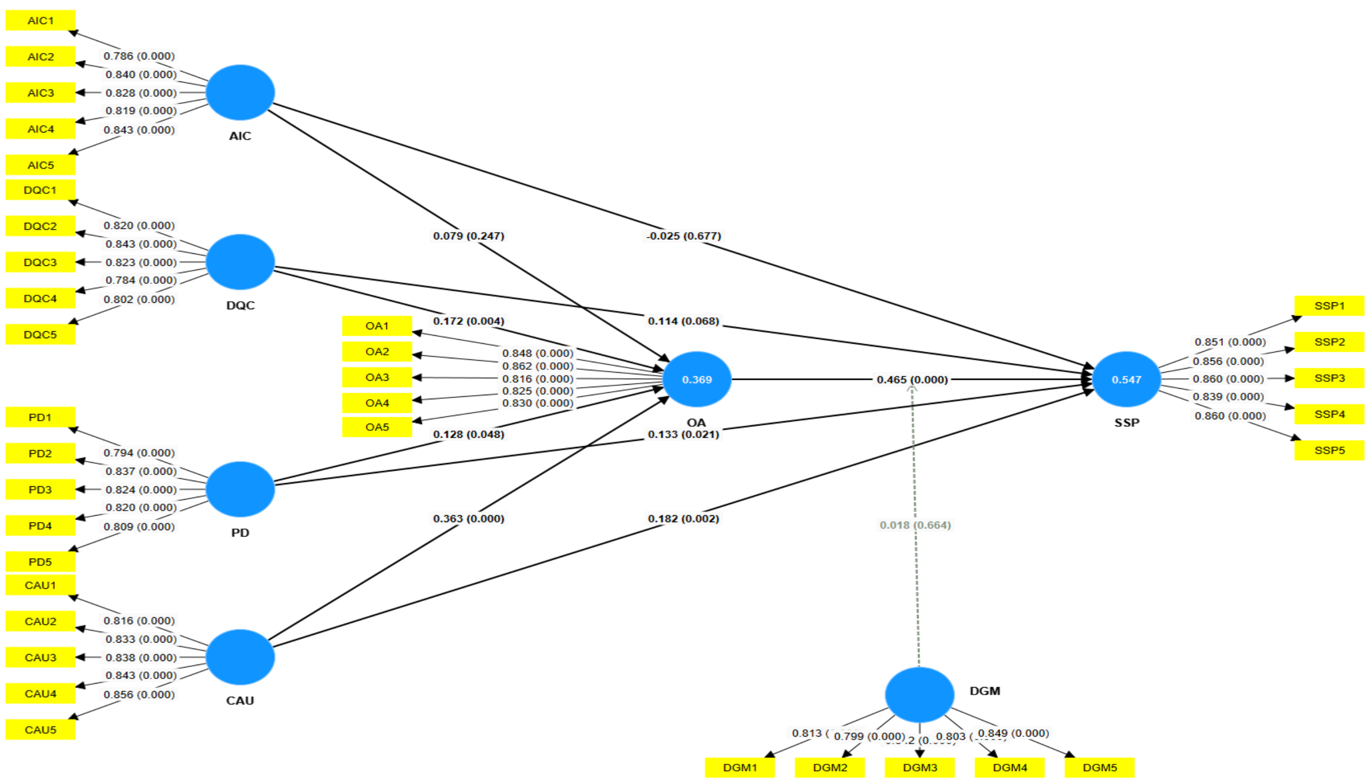

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Figure 3. Structural model results with standardized path coefficients

4.3 Mediation effect assessment

The mediation analysis results show that OA effectively mediates digital capabilities influence on SSP. Of all the indirect effects, Customer Analytics Use has by far the strongest (β = 0.169; p < 0.001), suggesting that data-driven insights improve service performance mainly by promoting organizational agility. Data Quality Capability also demonstrates a direct impact (β = 0.080; p = 0.008), emphasizing the role of reliable data plays in facilitation to be an agile operations. While the indirect effect of Process Digitization is negative (p = 0.059), Agentic AI Capability does not demonstrate a significant mediating influence. This study indicates that agility is a mechanism driving the persistent service performance effects of data and analytics capability.

Total effects reveal the key importance of Operational Agility which has the highest weight on SSP (β = 0.465; p < 0.001). Regarding exogenous capabilities, Customer Analytics Use is the variable which exhibits the highest total effect on SSP (β = 0.351), followed by Data Quality Capability (β = 0.194) and Process Digitization (β = 0.192), pointing to their strategic relevance. On the other hand, Agentic AI Capability does not have an important total effect deposit of.130; the result would be indicating that it is unsustainable to implement AI readiness in service level without ensuring secure data, analytics and process integration. SSP is not influenced by Data Governance Maturity nor does it interact with OA. Overall, the findings highlight that performance improvements derive mainly from agility mediated use of analytics and high-value data, not by AI capabilities percent.

The mediating type testing suggests that OA is a partial mediator in most capability–performance relationships. For Customer Analytics Use, direct and indirect paths are significant, indicating that analytics improve performance of service directly and indirectly through agility. Data Quality Capability also shows partial mediation, since its indirect effect through OA is significant and the direct one loses power. The partial and somewhat weaker mediation pattern of Process Digitization implies that digitized processes support SSP partly through agility. On the other hand, Agentic AI Capability is no longer significant both directly and indirectly (no mediation). Our findings provide further support to Dynamic Capabilities Theory, suggesting that agility is a central tool (but not the only) for mobilizing digital capabilities into sustainable service outcomes.

Table 9. Specific indirect effects via Operational Agility

Indirect relationship	Indirect effect (β)	t-value	p-value	Decision
AIC > OA > SSP	0.037	1.147	0.252	Not supported
CAU > OA > SSP	0.169	5.313	0.000	Supported
DQC > OA > SSP	0.08	2.649	0.008	Supported
PD > OA > SSP	0.06	1.891	0.059	Marginally supported

Table 10. Total effects of the research model

Relationship	Total effect (β)	t-value	p-value	Decision
AIC > OA	0.079	1.157	0.247	Not supported
AIC > SSP	0.012	0.166	0.868	Not supported
CAU > OA	0.363	5.981	0.000	Supported
CAU > SSP	0.351	5.795	0.000	Supported
DQC > OA	0.172	2.864	0.004	Supported
DQC > SSP	0.194	3.002	0.003	Supported
PD > OA	0.128	1.982	0.048	Supported
PD > SSP	0.192	3.071	0.002	Supported

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OA > SSP	0.465	9.207	0.000	Supported
DGM > SSP	0.043	0.655	0.512	Not supported
DGM × OA > SSP	0.018	0.435	0.664	Not supported

Table 11. Mediation type assessment

Path	Direct effect (X > Y)	Indirect effect (X > OA > Y)	Mediation type
AIC > SSP	Not significant	Not significant	No mediation
CAU > SSP	Significant	Significant	Partial mediation
DQC > SSP	Marginal / Significant	Significant	Partial mediation
PD > SSP	Significant	Marginal	Partial mediation

4.4 Moderation effect assessment

In the test of moderation, Data Governance Maturity (DGM) is also not found to significantly moderate the relationship between Operational Agility (OA) and Sustainable Service Performance (SSP). The interaction term is small (β = 0.018) and non-significant (t = 0.435, p = 0.664), including zero in the confidence interval (95% CI: −0.063 to 0.098). This implies that for this set of digital retailers and d2c brands, the performance payoffs to agility are fairly similar across varying levels of governance maturity. This finding suggests that governance might work as a fundamental condition (e.g. achieving data quality and compliance) rather than enhance the impact directly on the OA>SSP path, in this particular model specification.

Simple slope analysis is conducted as reported to supplement the interaction test. The corresponding differences in slopes across low versus high values of DGM are not meaningfully different since the interaction term DGM × OA is not statistically significant (p = 0.664). In substantive terms, this means that while the relative OA>SSP association stays consistent and does not exhibit a clear upward or downward trend over maturity levels of governance in our current dataset. Thus, post-hoc probing (e.g., Johnson–Neyman intervals or testing slope differences at ±1 SD) would be unlikely to uncover qualitatively different conditional effects. The evidence therefore means that we should interpret OA as a strong driver of SSP not contingent on governance in maturation but rather as potentially effective in stronger governing settings.

Table 12. Moderation effects of Data Governance Maturity

Moderation path	β (O)	t-value	p-value	95% CI (2.5%, 97.5%)	Decision
DGM × OA > SSP	0.018	0.435	0.664	[-0.063, 0.098]	Not supported

Table 13. Simple slope analysis for moderation effects

Interaction term	Moderation target	Result
DGM × OA	OA > SSP	Not significant (p = 0.664)

4.5 Model fit and predictive assessment

Overall model fit assessment reports that PLS-SEM is acceptable in practical use. The SRMR (0.042–0.043) values are small enough to be regarded as implying a good approximate fit for variance-based SEM. The NFI of 0.874 indicates a moderate fit improvement against a completely null model, but does not satisfies the more stringent "close-to-0 or greater" meta-criteria cut-off. 90" analyses commonly conducted in covariance-based SEM. The comparability of saturated and estimated model indices reflect that the proposed structural models inflict only minor distortion on the implied correlation structure. Fit statistics in general provide support for the empirical coherence and admissibility to inference of the model, placing great emphasis—again consistent with the main objective of PLS-SEM as a tool for prediction and theory

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development–the predictive assessment and variance explanation.

Predictive validity indicates significant out-of-sample predictive validity for the endogenous constructs. The Q² redundancy values are high and positive for OA (0.260) but higher in the case of SSP (0.398), this means that the model is able to predict better these outcome than a naïve benchmark. Consistent with this, endogenous constructs have Q² redundancy of 0.000 for exogenous constructs due to having no structural model predictions. The Q² communality is high (~ 0.49-0.58) indicating the measurement model has a good predictive quality of constraining indicator variance. Overall, these findings speak to the robustness of both empirical specification and predictive goodness-of-fi t of the model towards achieving operational agility and sustainable service performance outcomes in line with the predictive focus of PLS-SEM.

Table 14. Model fit indices

Fit index	Saturated model	Estimated model
SRMR	0.042	0.043
d_ULS	1.131	1.16
d_G	0.516	0.517
Chi-square	749.354	749.127
NFI	0.874	0.874

Table 15. PLS-Predict assessment results

Construct	Q² (redundancy)	Q² (communality)
OA	0.26	0.544
SSP	0.398	0.584
AIC	0.000	0.512
CAU	0.000	0.543
DGM	0.000	0.506
DQC	0.000	0.491
PD	0.000	0.496

4.6 Hypotheses test

Our findings prove that the Operational Agility (OA) is the critical channel of transmission mechanism for digital capabilities to Sustainable Service Performance (SSP). There is a direct effect where CAU and PD are positively related to SSP, but AIC and DQC do not exert direct effects. The test of the indirect effect proves that OA indeed mediates the effects of DQC and CAU on SSP, partially (marginally) also for PD: This supports a dynamic capabilities view. Agility is an important performance driver for digital retail Two of the relationships between agility and the four service sections (OA>SFD, OA>SSP) hold, evidence with clear practical implications. Nevertheless, DGM does not moderate the OA–SSP relationship strongly, which indicates that governance maturity might not enhance agility-related performance effects so much in this setting.

Table 16. Summary of hypothesis testing results

Structural relationship	β (O)	t-value	p-value	Decision
AIC > SSP	−0.025	0.416	0.677	Not supported
DQC > SSP	0.114	1.828	0.068	Not supported
PD > SSP	0.133	2.303	0.021	Supported

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Structural relationship	β (O)	t-value	p-value	Decision
CAU > SSP	0.182	3.137	0.002	Supported
AIC > OA	0.079	1.157	0.247	Not supported
DQC > OA	0.172	2.864	0.004	Supported
PD > OA	0.128	1.982	0.048	Supported
CAU > OA	0.363	5.981	0.000	Supported
OA > SSP	0.465	9.207	0.000	Supported
AIC > OA > SSP	0.037	1.147	0.252	Not supported
DQC > OA > SSP	0.08	2.649	0.008	Supported
PD > OA > SSP	0.06	1.891	0.059	Marginal
CAU > OA > SSP	0.169	5.313	0.000	Supported
DGM × OA > SSP	0.018	0.435	0.664	Not supported

4.7 Discussion

This research offers strong empirical evidence on how digital and AI-enabled organisational capabilities, when combined, contribute to sustainable service performance in digital retail firms. The dominant mediating mechanism here is operational agility. The findings demonstrate that CAU, DQC and PDC have a positive and significant association with SSP, whereas agentic AI capability does not have a statistically significant direct impact on SSP. Looking at what is available, this result shows that advanced technologies are not useful on their own unless they are used as part of the way a company does things, the way decisions are made and the way services are delivered (Teece et al., 1997; Teece, 2019). Previous research in retail and service markets has also emphasised that improved performance outcomes are more likely to result from the effective application of analytics and digitalised processes than from the mere adoption of AI innovations (Setia et al., 2013; Verhoef et al., 2021; Vhatkar et al., 2024).

The large positive impact of customer analytics use on both operational agility and sustainable service performance highlights the importance of analytics-enabled insight discovery and usage in contemporary digital retailing. This is also consistent with previous studies that have demonstrated the ability of customer analytics to enhance service quality, customer retention, and revenue generation by enabling firms to identify changes in consumer behaviour and respond swiftly to such insights (Wedel & Kannan, 2016; Setia et al., 2013; Alfadhel, 2025). From a dynamic capabilities perspective, customer analytics helps firms to sense and seize opportunities, enabling them to forecast changes in demand, customise their services and proactively react to new service problems in a highly dynamic setting (Sambamurthy et al., 2003; Hansen et al., 2024).

The results also indicate that operational agility has the greatest impact on sustainable service performance, as it has the largest effect size in all structural relationships. This supports the theoretical argument that agility is the end result of operationalising dynamic capabilities, since it enables fast decision-making, process reconfiguration and effective disruption response (Tallon & Pinsonneault, 2011; Teece, 2010). Recent research findings support this viewpoint, demonstrating that agility plays a crucial role in converting digital and analytics competencies into enhanced service quality and organisational effectiveness, particularly in omnichannel and service-oriented industries (Masialeti et al., 2024; Neiroukh et al., 2024; Atienza-Barba et al., 2024).

Mediation analysis provides further pointers on these mechanisms. Operational Agility broadly mediates the relationships of Customer Analytics Use and Data Quality Capability to Sustainable Service Performance. It seems that a superior standard of data and analytics has value mostly in what it enables the organisation to do (commit or adapt operations), not how by itself it improves performance. This is consistent with previous research where data quality and governance adds to performance only when it mitigates decision latency and operational friction (Wang & Strong, 1996; Batini

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& Scannapieco, 2016; Bernardo et al., 2024). On the other hand, no significant mediated or direct impacts of Agentic Artificial Intelligence Capability on Service Performance is indicative of still relatively nascent organizational acceptance and assimilation of semi-autonomous AI systems where the performance-enhancing attributes associated with dependable system learning maturity and managerial trust have yet to translate into robust service performance improvements (Davenport et al., 2020; Fosso Wamba et al., 2024; Hansen et al., 2024).

Third, the lack of strong moderating effect by Data Governance Maturity on the Operational Agility-Sustainable Service Performance link indicates that governance mechanisms could play more of a basic facilitator role and less towards performance leverage in digital retail contexts. Although data governance is a necessity for controlling risks, ensuring compliance and promoting integrity (Vial, 2023; Bernardo et al., 2024), its incremental impact on enhancing agility-induced service performance is likely to be modest in high-speed retail settings where responsiveness and speed take precedence as competitive priorities (Overby, 2008; Lu & Ramamurthy, 2011; Teece, 2019).

5. Conclusions

Contributions This paper contributes to the digital retail transformation literature by showing that Sustainable Service Performance is supported by effectively employing digital- and data-designed capabilities rather than simply having in place sophisticated artificial intelligence technologies. Empirical findings suggest that both Customer Analytics Use, and Data Quality Capability and Process Digitization influence service performance directly and indirectly, whereas Operational Agility acts as the core mediation mechanism for those two capabilities to turn into better performance. In contrast, we find that Agentic Artificial Intelligence Capability has no direct effect, indicating that autonomous artificial intelligence systems are valuable only when they are deeply incorporated into organizational routines and supported by agile structures for decision-making. Our findings strengthen the dynamic capabilities view that competitive advantage in dynamical environments is more about the orchestrating ability of reconfiguring operational processes than merely having individual technological resources.

Managerial and Practical Implications From a management and practical point of view, the findings suggest that digital retailers need to focus on investments in customer analytics capabilities, data quality management, and end to end process digitization as these could support them to achieve higher levels of agility and longterm service performance. Managers should opt for an acceptance of artificial intelligence as an adjunct rather than a panacea, and formulate governance, integration and learning approaches that enable the quick operational adaptation. Even if Data Governance Maturity is not a conditioning factor for the agility performance relationship, it will continue to be an essential hygiene factor in guaranteeing data quality, accountability and ethical use that becomes increasingly vital as adoption of analytics/artificial intelligence escalates. In sum, our findings offer implementable executive advice for achieving sustainable service excellence and inform theory by specifying the contingencies under which digitally enabled artificial intelligence capabilities deliver discernible value in contemporary retail organizations.

CRediT Author Statement

Amelia Syifa Isfahan: Conceptualization, Writing original draftwriting – review & editingLiterature reviewInstrument developmentData collectionData curationFormal analysis. **Diana Puspitasari:** Supervision, Methodology, Validation, Writing – review & editing; Theoretical guidance and Interpretation of results

Declaration of Competing Interest

The authors confirm that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request. The data are provided in full in the article as they cannot be made publicly available because of confidentiality agreements with organizational respondents.

Appendix/Appendices

Appendix A. Sample Profile of Digital Retail Firms and Respondents

Variable	Category / Range	Frequency (n)	Percentage (%)
Company Type	Modern Retail Chain	68	26.9
	Direct-to-Consumer (D2C) Brand	67	26.5
	Omnichannel Retailer	46	18.2
	E-commerce Pure Play	43	17
	Marketplace Seller Enterprise	29	11.5
Respondent Position	Founder / Owner	54	21.3
	Operations Manager	70	27.7
	Digital / E-commerce Manager	53	20.9
	Data / Analytics / CRM Manager	55	21.7
	Other Managers	21	8.3
Firm Age (Years)	2–5 years	–	64.8
	6–10 years	–	26.1
	11–15 years	–	9.1
Firm Size (Employees)	10–50	173	68.4
	51–200	68	26.9
	201–500	12	4.7
Geographical Location	Jabodetabek	–	–
	Other major cities in Java & Indonesia	–	–

Appendix B. Measurement Instruments and Sources

No	Abbrev.	Code	Measurement Item	Source
	Agentic AI Capability (AIC)			
1	AIC	AIC1	Our AI systems autonomously automate routine service and operational tasks.	(Prakruthi R Rai, Preethi Nanjundan, 2024; Teece, 2010)
2		AIC2	AI applications provide real-time recommendations to support managerial decisions.	(T. Davenport et al., 2020; T. H. Davenport & Mittal, 2022; Fosso Wamba et al., 2024)
3		AIC3	AI is integrated across workflows and digital service processes.	(Hansen et al., 2024)
4		AIC4	AI systems continuously learn from feedback and performance outcomes.	(Dwivedi, 2025)
5		AIC5	AI-driven decisions are reliable and consistently improve service execution.	(Prakruthi R Rai, Preethi Nanjundan, 2024)
	Data Quality Capability (DQC)			

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No	Abbrev.	Code	Measurement Item	Source
6	DQC	DQC1	Our operational data are accurate and free from significant errors.	(C. Batini & Scannapieco, 2016; Wang & Strong, 1996)
7		DQC2	Data used for decision-making are complete and sufficiently detailed.	(N. Batini & Durand, 2024)
8		DQC3	Data definitions and formats are consistent across systems.	(Khatri, 2016)
9		DQC4	Data are available in a timely manner for operational decisions.	(L. C. Günther et al., 2019; R. Günther & Schmitt, 2024; W. A. Günther et al., 2017)
10		DQC5	Metadata and data governance standards are clearly defined and applied.	Otto et al. (2023)
	Process Digitization (PD)			
11	PD	PD1	Standard operating procedures are fully digitized.	(Verhoef et al., 2021; Vial, 2023)
12		PD2	Approval and coordination processes are conducted electronically.	(Leeflang et al., 2014)
13		PD3	Digital dashboards are used to monitor service and operational performance.	Susanti et al. (2023)
14		PD4	Digital systems are integrated across functions and departments.	(Nambisan et al., 2019)
15		PD5	Digital records enable traceability and accountability in operations.	(Scholta et al., 2020; Vial, 2023)
	Customer Analytics Use (CAU)			
16	CAU	CAU1	Customer data are used to segment customers effectively.	Wedel & Kannan (2016); Mikalef et al. (2020)
17		CAU2	Analytics support personalized offers and service interactions.	Verhoef et al. (2021)
18		CAU3	Predictive analytics are used to anticipate customer churn.	Erevelles et al. (2016)
19		CAU4	A/B testing is used to evaluate service and marketing initiatives.	Kohavi et al. (2020)
20		CAU5	Analytical insights are rapidly translated into operational actions.	(Setia et al., 2013) Mikalef et al. (2023)
	Operational Agility (OA)			
21		OA1	Our operations adapt quickly to changes in customer demand.	(Overby, 2008; Teece, 2010, 2019; Teece et al., 1997)
22		OA2	Operational processes are flexible and can be rapidly reconfigured when needed.	(Lu & Ramamurthy, 2011; Sambamurthy et al., 2003)
23		OA3	Decisions can be made rapidly when unexpected operational issues arise.	(Tallon & Pinsonneault, 2011)
24		OA4	Our organization responds effectively to operational disruptions or service failures.	(Chakravarty, 2013; Overby, 2008)
25		OA5	New service or process changes can be implemented quickly ahead of competitors.	(Setia et al., 2013; Teece, 2010; Teece et al., 1997)

References

Alfadhel, M. (2025). Unpacking when and how business analytics affect firm performance and customer satisfaction: A longitudinal examination. *Journal of Retailing and Consumer Services*, *84*, 104219. https://doi.org/https://doi.org/10.1016/j.jretconser.2024.104219

Atienza-Barba, M., Río-Rama, M. de la C. del, Meseguer-Martínez, Á., & Barba-Sánchez, V. (2024). Artificial intelligence and organizational agility: An analysis of scientific production and future trends. *European Research on Management and Business Economics*, *30*(2), 100253. https://doi.org/https://doi.org/10.1016/j.iedeen.2024.100253

Barney, Jay. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 499-518
DOI: https://doi.org/10.69725/jebi.v2i4.320

Batini, C., & Scannapieco, M. (2016). *Introduction to Information Quality BT - Data and Information Quality: Dimensions, Principles and Techniques* (C. Batini & M. Scannapieco (eds.); pp. 1–19). Springer International Publishing. https://doi.org/10.1007/978-3-319-24106-7_1

Batini, N., & Durand, L. (2024). *Accounting for Nature in Economic Models*.

Bernardo, B. M. V., Mamede, H. S., Barroso, J. M. P., & dos Santos, V. M. P. D. (2024). Data governance & quality management—Innovation and breakthroughs across different fields. *Journal of Innovation & Knowledge*, *9*(4), 100598. https://doi.org/https://doi.org/10.1016/j.jik.2024.100598

Bhatt, H., Bahuguna, R., Swami, S., Singh, R., Gehlot, A., Akram, S. V., Gupta, L. R., Thakur, A. K., Priyadarshi, N., & Twala, B. (2024). Integrating industry 4.0 technologies for the administration of courts and justice dispensation—a systematic review. *Humanities and Social Sciences Communications*, *11*(1), 1076. https://doi.org/10.1057/s41599-024-03587-0

Chakravarty, V. (2013). Managing a supply chain's web of risk. *Strategy & Leadership*, *41*(2), 39–45. https://doi.org/10.1108/10878571311318231

Cvitić, I., Peraković, D., Periša, M., & Gupta, B. (2021). Ensemble machine learning approach for classification of IoT devices in smart home. *International Journal of Machine Learning and Cybernetics*, *12*(11), 3179–3202. https://doi.org/10.1007/s13042-020-01241-0

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Davenport, T. H., & Mittal, N. (2022). How companies can prepare for the coming "AI-first" world. *Strategy & Leadership*, *51*(1), 26–30. https://doi.org/10.1108/SL-11-2022-0107

Dwivedi, M. (2025). Opportunities and Challenges of AI Implementation in Human Resource Management: A Systematic Review. *International Journal of Multidisciplinary Research and Growth Evaluation*, *6*(4), 1160–1168. https://doi.org/10.54660/.ijmrge.2025.6.4.1160-1168

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676–5696. https://doi.org/10.1080/00207543.2023.2294116

Günther, L. C., Colangelo, E., Wiendahl, H.-H., & Bauer, C. (2019). Data quality assessment for improved decision-making: a methodology for small and medium-sized enterprises. *Procedia Manufacturing*, *29*, 583–591. https://doi.org/https://doi.org/10.1016/j.promfg.2019.02.114

Günther, R., & Schmitt, R. H. (2024). Maturity Assessment for the Introduction of Predictive Quality Approaches in Production Environments. *Procedia CIRP*, *122*, 1053–1058. https://doi.org/https://doi.org/10.1016/j.procir.2024.02.036

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, *26*(3), 191–209. https://doi.org/https://doi.org/10.1016/j.jsis.2017.07.003

Gupta, S., Kumar, S., Singh, S. K., Foropon, C., & Chandra, C. (2018). Role of cloud ERP on the performance of an organization. *The International Journal of Logistics Management*, *29*(2), 659–675. https://doi.org/10.1108/IJLM-07-2017-0192

Hansen, H. F., Lillesund, E., Mikalef, P., & Altwaijry, N. (2024). Understanding Artificial Intelligence Diffusion through an AI Capability Maturity Model. *Information Systems Frontiers*, *26*(6), 2147–2163.

OPEN ACCESS
ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 499-518
DOI: https://doi.org/10.69725/jebi.v2i4.320

https://doi.org/10.1007/s10796-024-10528-4

Khatri, V. (2016). Managerial work in the realm of the digital universe: The role of the data triad. *Business Horizons*, *59*(6), 673–688. https://doi.org/https://doi.org/10.1016/j.bushor.2016.06.001

Latan, H., Chiappetta Jabbour, C. J., Lopes de Sousa Jabbour, A. B., Renwick, D. W. S., Wamba, S. F., & Shahbaz, M. (2018). 'Too-much-of-a-good-thing'? The role of advanced eco-learning and contingency factors on the relationship between corporate environmental and financial performance. *Journal of Environmental Management*, *220*, 163–172. https://doi.org/https://doi.org/10.1016/j.jenvman.2018.05.012

Leeflang, P. S. H., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European Management Journal*, *32*(1), 1–12. https://doi.org/https://doi.org/10.1016/j.emj.2013.12.001

Lu, Y., & Ramamurthy, K. (Ram). (2011). Understanding the Link Between Information Technology Capability and Organizational Agility: An Empirical Examination. *MIS Quarterly*, *35*(4), 931–954. https://doi.org/10.2307/41409967

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*, 102623. https://doi.org/https://doi.org/10.1016/j.technovation.2022.102623

Masialeti, M., Talaei-Khoei, A., & Yang, A. T. (2024). Revealing the role of explainable AI: How does updating AI applications generate agility-driven performance? *International Journal of Information Management*, *77*, 102779. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2024.102779

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, *30*(2), 272–298. https://doi.org/https://doi.org/10.1111/1467-8551.12343

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/https://doi.org/10.1016/j.im.2019.05.004

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), 103773. https://doi.org/https://doi.org/10.1016/j.respol.2019.03.018

Neiroukh, S., Emeagwali, O. L., & Aljuhmani, H. Y. (2024). Artificial intelligence capability and organizational performance: unraveling the mediating mechanisms of decision-making processes. *Management Decision*, *63*(10), 3501–3532. https://doi.org/10.1108/MD-10-2023-1946

Overby, E. (2008). Process Virtualization Theory and the Impact of Information Technology. *Organization Science*, *19*(2), 277–291. https://doi.org/10.1287/orsc.1070.0316

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI Governance: Identifying Best Practices and Potential Barriers and Outcomes. *Information Systems Frontiers*, *25*(1), 123–141. https://doi.org/10.1007/s10796-022-10251-y

Prakruthi R Rai, Preethi Nanjundan, J. P. G. (2024). Enhancing Industrial Operations through AI-Driven Decision-Making in the Era of Industry 4.0. In *AI-Driven IoT Systems for Industry 4.0* (1st Editio).

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping Agility through Digital Options: Reconceptualizing the Role of Information Technology in Contemporary Firms. *MIS Quarterly*, *27*(2), 237–263. https://doi.org/10.2307/30036530

Scholta, H., Halsbenning, S., Distel, B., & Becker, J. (2020). *Walking a Mile in Their Shoes–A Citizen Journey to*

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 499-518
DOI: https://doi.org/10.69725/jebi.v2i4.320

Explore Public Service Delivery from the Citizen Perspective BT - Electronic Government (G. Viale Pereira, M. Janssen, H. Lee, I. Lindgren, M. P. Rodríguez Bolívar, H. J. Scholl, & A. Zuiderwijk (eds.); pp. 164–178). Springer International Publishing.

Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging Digital Technologies: How Information Quality Leads to Localized Capabilities and Customer Service Performance1. *Management Information Systems Quarterly*, *37*(2), 565–590. https://doi.org/10.25300/MISQ/2013/37.2.11

Tallon, P. P., & Pinsonneault, A. (2011). Competing Perspectives on the Link Between Strategic Information Technology Alignment and Organizational Agility: Insights from a Mediation Model. *MIS Quarterly*, *35*(2), 463–486. https://doi.org/10.2307/23044052

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/https://doi.org/10.1002/smj.640

Teece, D. J. (2010). Chapter 16 - Technological Innovation and the Theory of the Firm: The Role of Enterprise-Level Knowledge, Complementarities, and (Dynamic) Capabilities. In B. H. Hall & N. B. T.-H. of the E. of I. Rosenberg (Eds.), *Handbook of The Economics of Innovation, Vol. 1* (Vol. 1, pp. 679–730). North-Holland. https://doi.org/https://doi.org/10.1016/S0169-7218(10)01016-6

Teece, D. J. (2019). A capability theory of the firm: an economics and (Strategic) management perspective. *New Zealand Economic Papers*, *53*(1), 1–43. https://doi.org/10.1080/00779954.2017.1371208

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/https://doi.org/10.1016/j.jbusres.2019.09.022

Vhatkar, M. S., Raut, R. D., Gokhale, R., Kumar, M., Akarte, M., & Ghoshal, S. (2024). Leveraging digital technology in retailing business: Unboxing synergy between omnichannel retail adoption and sustainable retail performance. *Journal of Retailing and Consumer Services*, *81*, 104047. https://doi.org/https://doi.org/10.1016/j.jretconser.2024.104047

Vial, G. (2023). Data governance and digital innovation: A translational account of practitioner issues for IS research. *Information and Organization*, *33*(1), 100450. https://doi.org/https://doi.org/10.1016/j.infoandorg.2023.100450

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*, 107498. https://doi.org/https://doi.org/10.1016/j.ijpe.2019.09.019

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, *12*(4), 5–33. https://doi.org/10.1080/07421222.1996.11518099