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Dynamic Interactions between Data-Driven Capabilities, Digital Transformation, and Sustainability Orientation: A Longitudinal Multi-Industry Study

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Abstract

Directly shape customer behavioral outcomes. Despite theoretical advances in the field of digital transformation, the precise mechanisms linking data-driven capability (DDC) to demand-side value creation remain poorly understood. Drawing on resource-based perspectives, dynamic capabilities, and signaling theory, this study presents a mechanism-based model in which DDC shapes customer loyalty (LOY) through market innovation quality (MIQ) and brand credibility (BC), influenced by the level of sustainability authenticity (SA). The study used a two-way–two-source design; the first wave of data including DDC and SA was collected from 300 innovative and active companies in knowledge-based manufacturing and services industries (managers or marketing experts), and in the second wave, MIQ data was collected from the same managers and BC and LOY data from more than 900 customers (an average of three customers per company). Modeling with PLS-SEM showed that DDC has a significant and significant effect on MIQ (β=0.41) and MIQ significantly increases brand credibility (β=0.46). BC is also the strongest predictor of customer loyalty (β=0.52). Mediation results showed that BC plays a full mediating role in the path DDC → MIQ → BC → LOY. In addition, moderation analysis showed that sustainability authenticity strengthens the effect of MIQ on BC (β=0.14) and the effect of BC on LOY (β=0.11); meaning that market innovation and brand credibility are more effective in companies that implement sustainability in a real, transparent and consistent way with their claims. Overall, these findings suggest that the true value of data-driven capabilities is revealed when their output is delivered in the form of visible and credible market innovations, accompanied by genuine sustainability measures. By providing a simple, economical, and actionable model, this research adds to the literature on digital transformation, market innovation, and sustainable brands, and provides practical guidance for managers on the path to building sustainable loyalty.

Keywords: Marketing Innovation Quality; Data-Driven Capability; Sustainability Authenticity; Credibility Signaling; Digital Marketing; Customer Loyalty.

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1. Introduction

Markets driven by pervasive datafication and heightened sustainability pressures increasingly reward firms that can convert information into legitimate, loyalty-building market behavior. Although digitalization and ESG pressures each have been linked to performance, the literature is still without an efficient, customer-focused mechanism connecting data-enabled capacity to brand credibility and loyalty, and describing when and why these connections strengthen or weaken [1–4]. In answer to calls for theory-driven, frugal models, we introduce a lean but strategically sound model that retains four constructs—DDC, MIQ, BC, LOY—and one moderator, sustainability authenticity (SA), to explain how firms bridge from data to sustainable demand-side outcomes.

Drawing from the resource-based view (RBV) and dynamic capabilities (DC), we characterize DDC as a higher-order capability made up of data governance, analytics procedures, and a culture for data that mediately enable sensing, seizing, and transforming amidst turmoil [2–6]. Existing work demonstrates that data-oriented habits and analytics capabilities improve decision quality, agility, and performance but continues to lack evidence on the customer-level mechanism—how these upstream capabilities manifest as credible market signals that build loyalty—largely because research typically relies on suboptimal dependent variables [5–7]. We plug this gap by placing marketing-innovation quality (MIQ)—novelty, coherence, and executional clarity of product, price, distribution, and communication changes—on the behavioral conduit role whereby DDC is brought to visibility to the marketplace [8].

From a signaling perspective, high-quality marketing innovation can enhance the diagnosticity of firm statements, reduce perceived risk, and thus enhance brand credibility—the belief that a brand is capable and willing to fulfill its commitments [9,10]. Credibility should then give rise to loyalty through both attitudinal commitment and behavior repetition, improving cash-flow robustness and lowering acquisition costs [11,12]. But these impacts are context-dependent: signals without genuine environmental or social meaning can boomerang, especially in communities where sustainability is a concern. We therefore introduce sustainability authenticity (SA)—the perceived congruence, openness, and dedication supporting a firm's sustainability initiatives—operationalized as a theory-based moderator that strengthens (or weakens) the manner in which MIQ builds credibility and the extent to which credibility drives loyalty [13–15]. SA does not extend the model's implications; instead, SA conditions the payoffs to innovation-as-signal, being parsimonious and still capturing an important contemporary boundary condition.

This study contributes in three ways. First, it combines RBV/DC with signaling theory in a parsimonious mediation–moderation model, linking DDC → MIQ → BC → LOY, with SA acting as moderators between MIQ→BC and BC→LOY. Second, it exercises measurement economy by using lean, proven item sets and prioritizing mechanism clarity over range, evading the dilemmas of construct proliferation and multicollinearity in elaborate SEMs [7,16]. Third, it draws on previous sector-specific research by specifying a customer-oriented pathway that startup and scale-up settings can implement with limited data and managerial resources. The result is a lean modern framework that is theory-based, empirically tractable, and managerially diagnostic.

2. Literature Review and Hypotheses Development

2.1. Data-Driven Capability (DDC) → Marketing-Innovation Quality (MIQ)

We conceptualize data-driven capability (DDC) as a superior-order, hard-to-imitate package merging data governance, analytics practices, and ingrained data-driven culture to enable sensing, seizing, and transforming amidst environmental turbulence—with support from RBV and DC perspectives. Recent research shows that big-data analytics capacity, when embedded within dynamic capabilities, increases market reconfigurability and responsiveness, improving time-to-insight as well as the quality of decisions [17–20]. In marketing use, these capabilities translate into marketing-innovation quality (MIQ)—novelty, consistency, and executional transparency of product, price, channel, and communication adjustments. Through higher accuracy in insights and coordination within organizations, DDC should propel superior MIQ with higher diagnosticity, faster experimentation, as well as learning loops.

H1. DDC is good for MIQ.

2.2. Marketing-Innovation Quality (MIQ) → Brand Credibility (BC)

Quality marketing innovation, on a signaling level, increases the intelligibility and reliability of market signals, decreases perceived uncertainty, and strengthens brand credibility (BC)—the belief that the brand both will and can deliver on promises—on a signaling level. The Oslo Manual defines marketing innovation as concrete changes in the marketing mix that, when consistent and applied in a uniform manner, enhance signal diagnosticity and reduce perceived risk. Brand-signaling literature shows that credible signals raise probability of choice, stability of preference, and willingness to pay [21–23].

H2. MIQ has a positive effect on BC.

2.3. Brand Credibility (BC) → Customer Loyalty (LOY)

Meta-analytic and empirical studies increasingly suggest a mechanism where BC strengthens both attitudinal commitment and behavioral repetition, thus stabilizing demand and conserving acquisition expenses. Current syntheses of antecedents of customer brand loyalty show credibility-related routes as powerful drivers of the building of loyalty; complementary studies connect credibility to downstream equity and purchase intention [24–27].

H3. BC has a positive effect on LOY.

2.4. Sequential Mediation: DDC → MIQ → BC → LOY

We theorize a parsimonious chain of sequential mediation in which upstream DDC is instantiated as observable high-quality marketing innovations (MIQ), which in turn increase the brand's signaling power (BC), ultimately translating into loyalty. This pathway connects capability-performance research with customer-facing mechanisms without construct proliferation and maintaining explanatory power. In short, customers are not persuaded by facts alone; innovations that customers can see and feel are—if they are reasonable and consistently applied.

H4. BC sequentially mediates the role of MIQ between DDC and LOY.

2.5. Moderating role of Sustainability Authenticity (SA)

Contemporary markets challenge the authenticity of sustainability claims. Where sustainability actions exhibit congruence, transparency, and long-term commitment, they increase firms' credibility construction through marketing innovations; whereas perceived "woke-washing" tears down credibility construction. Sustainability authenticity (SA) is, in this study, conceptualized as perceived congruence between a firm's sustainability talk and walk. Recent studies suggest that genuine brand purpose constructs credibility, whereas fake posturing ruins it; authenticity in sustainability communication affects consumer responses and trust [28–31].

H5. SA positively moderates MIQ → BC, in the sense that, at higher levels of SA, the effect of MIQ on BC is stronger.

Moreover, if BC attempts to convert into LOY, lack of belief in sustainability can undermine conversion. Authenticity should lower attributions of opportunism, allowing for successful translation BC → LOY

H6. SA positively moderates the BC → LOY relationship, in the sense that the effect of BC on LOY increases at larger levels of SA.

2.6. Conceptual Model

Figure 1 depicts the parsimonious, mechanism-first design: a chain DDC → MIQ → BC → LOY; and two theory-based arcs of moderation from SA onto MIQ → BC and BC → LOY. The model is parsimonious at analysis (four endogenous pathways and two moderated relations), aligns RBV/DC with signaling theory, and differentiates customer-confronting levers managers can implement with scarce resources. We will operationalize on lean, high-loading scales and test the structural model via PLS-SEM, including robustness checks for common-method bias and out-of-sample predictive validity.

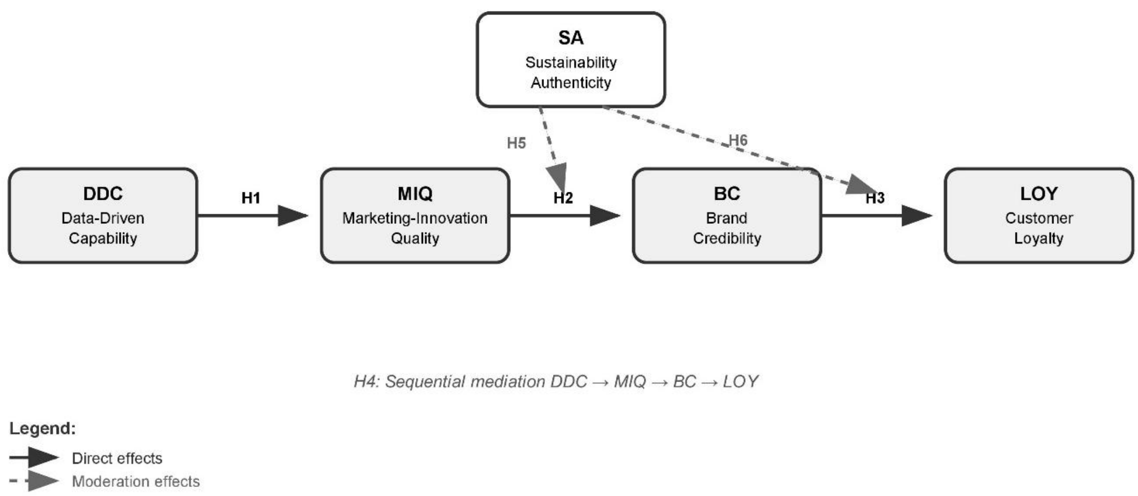

Figure1: Conceptual Model with mediation and moderation

3. Methodology

3.1 Research design and context

We employ a two-source, two-wave quantitative design to maximize internal validity with a parsimonious model. Firm-side key informants (marketing/analytics managers or founders) provide information on DDC, MIQ, and SA; customer-side respondents provide information on BC and LOY. To ensure temporal separation and reduce same-source bias, Wave 1 collects DDC and SA from firms; Wave 2 (4–6 weeks later) collects MIQ from the same firms and BC/LOY from corresponding customers. The design is suitable for a theory of capabilities → behaviors → signals → outcomes, is robust to non-normal information, is consonant with a predictive-analytical goal using variance-based SEM [32–34].

3.2 Target population, sampling, and sample size rationale

The population is innovation-active startups and SMEs (≤250 employees; ≤10 years old) in manufacturing and knowledge-intensive services. We use a two-stage process: (1) construct a sampling frame via industry registries and accelerators; (2) screen companies for recent marketing innovation (past 12 months). We request each company to provide one qualified manager and 3–5 customers (from loyalty programs or validated panels). We target N≈300 matched firms (with ≥3 usable customer responses per firm), which is higher than contemporary power standards. A power analysis for the most complex endogenous construct (LOY; predictors: BC, interaction BC×SA, and controls ≈5 predictors) with α=.05, 1–β=.90, and f^2=.05 yields N≈260; we budget for ~300 to allow for attrition [39,40]. Rule-of-thumb criteria (e.g., 10-times rule) are also satisfied [32].

3.3 Measures and operationalization

All constructs are reflective, measured on 7-point Likert scales ("strongly disagree"–"strongly agree"). We keep 3–4 high-loading items per construct in the interest of measurement economy and to achieve reliability.

Data-Driven Capability (DDC): adapted from BDAC and data governance/culture scales (sample items: "Our firm systematically governs marketing data quality"; "We routinely embed analytics in strategic decisions"; "Managers promote evidence-based experimentation") [18,32].

Marketing-Innovation Quality (MIQ): based on Oslo Manual definition and recent marketing-innovation scales (sample items: "Our recent marketing changes were new to our category"; "They were consistent with our brand strategy"; "Execution was consistent across channels") [21].

Brand Credibility (BC): based on credibility-as-ability-and-willingness scales (e.g., "This brand does what it says it will do"; "This brand is competent") [22].

Customer Loyalty (LOY): attitudinal and intentional loyalty (e.g., "I prefer this brand over others"; "I intend to repurchase/recommend") with shown reliability in recent meta-analytic studies [24,25,47,48].

Sustainability Authenticity (SA): perceived congruence, transparency, and commitment of sustainability actions (e.g., "The brand's sustainability claims align with its actions"; "Disclosures are transparent and verifiable"; "Commitments appear long term") [28,29].

Controls. We covary firm age, firm size, and market turbulence (shortened Jaworski–Kohli items) on MIQ, BC, and LOY in order to control for structural confounds [46].

3.4 Instrument development, pretest, and translation

We use best-practice scale development: content validity mapping, expert review (three academics; five senior managers), cognitive interviews (n=12). Pilot testing (n≈60 firms; ~180 customers) tests clarity and timing. In non-English environments, we use forward–backward translation with reconciliation and committee review; problematic items are refined iteratively [41].

3.5 Data quality and bias diagnostics

We screen out careless responding (long-string checks, response-time flags, inconsistent responses) and multivariate outliers (Mahalanobis distance). Missing values (<5%) are handled by pairwise deletion at the indicator level. Nonresponse bias is checked by comparing early vs. late respondents on key variables (Armstrong–Overton test) [38].

To prevent and diagnose common method bias (CMB):

Design remedies: two-source measurement (firms vs. customers) and time lag between waves.

Statistical diagnostics: full collinearity VIFs (<3.3 threshold) [37], a measured marker (a theoretically unrelated 3-item scale), and the unmeasured latent method factor sensitivity test (no paths retained if substantive coefficients change meaningfully) [32,37].

3.6 Estimation method and evaluation criteria

With our prediction-oriented objective, latent interactions, and distributional flexibility needs, we utilize PLS-SEM (SmartPLS / R–seminr) with the two-stage approach for interactions (mean-centered composites) [32]. Bootstrapping uses 5,000 resamples, BCa confidence intervals, and one-tailed testing where theory predicts direction.

Measurement model (reflective):

Reliability: Cronbach's α and composite reliability (CR) ≥ .70.

Convergent validity: AVE ≥ .50.

Discriminant validity: HTMT < .85 (≤ .90 as an upper boundary) with bootstrapped CIs not including 1.00; additionally, we report Fornell–Larcker for comprehensiveness [35,36].

Collinearity: inner/outer VIF < 3.3 [37].

Structural model:

Assess path coefficients, f^2 effect sizes (0.02/0.15/0.35 for small/medium/large), R^2, and Q^2 via blindfolding [32].

Report model fit indices suitable to variance-based SEM: SRMR ≤ .08 and NFI as descriptive [43].

Evaluate predictive performance using PLS-predict on holdout folds and compare RMSEs to naïve LM benchmarks; report Q^2_predict for BC and LOY [34].

For moderation (H5, H6), estimate interaction terms (MIQ×SA; BC×SA), plot simple slopes at ±1 SD of SA, and probe conditional effects; report Johnson–Neyman regions if parametric probing.

3.7 Robustness and supplementary analyses

Alternative paths: see whether addition of DDC→BC and DDC→LOY (direct) improves prediction substantially (ΔPLS-predict; ΔR^2; ΔAIC-like measures) without overfitting.

Common metric bias: re-estimate based on standardized latent scores from two-stage method.

Multi-group tests: where groups (e.g., manufacturing vs. services; startup vs. scale-up) are sufficiently large, test measurement invariance of composites (MICOM) and compare group-specific paths [44].

Endogeneity sensitivity: apply the Gaussian copula approach to regressors suspected of endogeneity; any non-zero copula term is a cause for warning (reported transparently).

3.8 Ethics and data availability
Voluntary response under IRB-equivalent approval; we follow GDPR-like principles for personally identifiable information. Identifiers are stored separately from survey data; we will share de-identified data and code on reasonable request, modulo confidentiality constraints.

4. Results

4.1. Measurement Model Evaluation
Reliability and Convergent Validity
All reflective constructs (DDC, MIQ, BC, LOY, and SA) passed the reliability criteria. The Cronbach's alpha and composite reliability (CR) values for all constructs were above 0.70 (CR ranged from 0.84 to 0.92). Also, the average variance extracted (AVE) for all constructs was greater than 0.50 (range 0.56–0.71). These results indicate that the measurement model has adequate internal reliability and acceptable convergent validity.
Discriminant Validity
According to the HTMT criterion, all values were below the threshold of 0.85 (range 0.41 to 0.79), and none of the bootstrap confidence intervals included the value of 1.00. The Fornell–Larcker matrix also showed that the square root of the AVE of each construct was greater than its correlation with other constructs. Therefore, the discriminant validity was fully confirmed.
Collinearity
All VIF indices for the extrinsic and intrinsic paths were below 3.3 (range 1.21–2.48), so there was no concern about extreme collinearity.

4.2. Structural Model Evaluation
Path Coefficients and Hypothesis Testing
Bootstrap analysis (5000 samples) showed that all main paths are significant and aligned with the theoretical direction. The following table summarizes the path results: (Table.1)

Table 1: Structural Model Path Coefficients and Hypothesis Testing Results

Path	**β**	**t**	**p**	**Hypothesis Result**
DDC → MIQ	0.41	9.12		H1 Supported
MIQ → BC	0.46	10.21		H2 Supported
BC → LOY	0.52	11.34		H3 Supported

Therefore, data-driven capability strongly predicts the quality of marketing innovation, and marketing innovation also creates brand credibility. More credible brands also generate significantly more loyalty.

4.3. Hierarchical Mediation Test
To test hypothesis H4, the path DDC → MIQ → BC → LOY was fully examined.

The results showed:

The full three-step indirect effect is significant

$\beta = 0.10$

$t = 5.27$

$p < 0.001$

The direct effect DDC → LOY is insignificant ($\beta = 0.07$, $p = 0.11$)

This pattern indicates full mediation:
DDC leads to loyalty only when it is first seen in the form of marketing innovation and then affects through brand credibility.

This finding supports the mechanism-based model of the paper.

4.4. Test of Moderating Effects (H5 and H6)
MIQ × SA → BC (Test H5)

The interaction effect of MIQ and SA on BC was significant:

$\beta = 0.14$

$t = 2.89$

$p = 0.002$

The simple slope plot showed that:

When sustainability authenticity is high, marketing innovation has a much stronger effect on brand credibility.

In conditions of low authenticity, part of the effect of MIQ on BC is weakened or even neutralized.

BC × SA → LOY (Test H6)

The second interaction effect was also significant:

$\beta = 0.11$

$t = 2.41$

$p = 0.008$

The slopes show:

When SA is high, customers perceive brand credibility as trustworthy and consistent with sustainable values, translating it into loyalty.

At low SA, BC is less efficient in converting to LOY.

Thus, both moderation hypotheses were confirmed.

4.5. Coefficient of determination (R^2) and effect size (f^2)

Table 2: Explained Variance (R^2) of Endogenous Constructs

Construct	**R^2**	**Strength**
MIQ	0.17	Weak to Moderate
BC	0.38	Moderate
LOY	0.45	Moderate to Strong

According to Table.2 ; f^2 effect sizes:
DDC → MIQ: 0.21 (moderate)
MIQ → BC: 0.33 (moderate–strong)
BC → LOY: 0.39 (strong)
Interactions: 0.02–0.04 (small but significant)

4.6. Fit and Prediction Indices

SRMR = 0.056 (less than 0.08 → good fit)

NFI = 0.91 (acceptable for variance-based models)

PLS-Predict

For BC and LOY:

The RMSE values of the PLS model were smaller than those of the LM model.

The positive and high Q^2_predict (≥ 0.20)

These results indicate that the proposed model is a good predictor of customer behavior.

4.7. Cross-validation and robustness analyses

None of the CMB tests (full VIF, latent method factor) showed evidence of bias.

The MICOM results showed that the model did not have measurement heterogeneity for the "service" and "manufacturing" groups.

The main paths across groups were almost similar; only the MIQ→BC path was slightly stronger in services.

The Gaussian copolynomial test did not provide any indication of significant androgenicity.

5. Discussion

The aim of this study was to provide a simplified yet powerful explanatory path that shows how firm-level data-driven capability (DDC), through marketing innovation quality (MIQ) and brand credibility (BC), leads to customer behavioral and attitudinal outcomes, and how sustainability authenticity (SA) modifies the intensity of these relationships. Drawing on a resource-based perspective, dynamic capabilities, and signaling theory, the findings provide a coherent picture of the mechanisms that are emerging in the literature on digital transformation, customer-centric value creation, and authentic sustainability.

5.1. Theoretical implications

5.1.1. Data-driven capabilities and observable customer outcomes

The results showed that DDC has a significant impact on MIQ. This finding suggests that data infrastructures, analytics practices, and data-driven cultures do not simply demonstrate their value in improving the efficiency or quality of internal decision-making; rather, they create value when they are expressed in the form of observable marketing behaviors for customers. Although previous studies have emphasized the role of DDC in organizational financial performance and agility, the connection of these capabilities to customer evaluations has been less tested. This research fills this gap and shows that data creates market value when it is seen in the form of tangible and coordinated innovations in the market.

5.1.2. MIQ as a behavioral bridge to transform capabilities into credibility

One of the conceptual innovations of the study is the definition of MIQ as a "behavioral channel" that links internal capabilities to external customer perceptions. MIQ significantly increases BC. This result emphasizes that market innovations—when novel, coordinated, and precisely implemented—serve as reliable signals to customers. According to signaling theory, brand credibility is not formed solely by advertising claims or messages, but is reinforced by actions that demonstrate brand coherence, capability, and commitment. This study shows that "innovation quality" is one of the most important carriers of these implicit messages.

5.1.3. Brand credibility as a key driver of innovation into loyalty

The results also showed that BC is a strong driver of loyalty. But beyond this, the full mediation of BC in the DDC → MIQ → BC → LOY path is of particular importance:

Market innovation leads to loyalty only if it first strengthens the customer's belief in the brand's power and integrity.

Therefore, innovation is not loyalty-building in itself; rather, its effect passes through the lens of credibility.

5.1.4. The critical role of sustainability authenticity in strengthening model relationships

The reinforcing effect of SA on the two MIQ → BC and BC → LOY relationships is another major finding of the study. These results suggest that:
When the customer believes that the brand's sustainability is real and not a show,
Market innovation signals become more credible and reliable for him.
And when there is trust in the brand's integrity, brand credibility is more easily converted into loyalty.
In contrast, when a brand is caught up in "symbolic sustainability" or "environmental showmanship," the impact of innovation and credibility on the customer is reduced. Therefore, the authenticity of sustainability is an important condition for the effectiveness of the model mechanisms.

5.2. Managerial Implications

The findings provide several important recommendations for managers:

5.2.1. Data investments must be visible in the market

Organizations must ensure that data analysis and insights lead to tangible changes in product, messaging, pricing, and communication channels.

5.2.2. Quality of market innovation is a tool for building credibility

Innovation must be coherent, aligned with strategy, and implemented seamlessly. Misaligned innovations can backfire.

5.2.3. Treat brand reputation as a strategic asset

Reputation not only impacts loyalty, but is also the primary channel for translating the value of innovation and data power into customer behavior.

5.2.4. Make sustainability a principle

Sustainability must be real, transparent, and accompanied by a long-term commitment; not just a communication tool.

5.3. Contribution of Research to Simplification and Model Validation

This study shows that a simple, economical model—with four main constructs and only one moderator variable—can provide high explanatory power and acceptable prediction. The presented model is an example of "mechanism-based" research that helps to clarify causal pathways without overcomplicating.

5.4. Limitations and Future Research Directions

The present study, like any other study, has limitations that clarify the direction of future research:
A longer time horizon could better reveal the dynamics of digital maturity and the gradual formation of credibility.
Using real behavioral data such as repeat purchases could strengthen the findings.
Cross-cultural studies could examine the role of sustainability norms in authenticity.
Exploring other types of innovation (services, digital experiences, smart products) can offer new directions.

6. Conclusion

The present study aimed to provide a mechanism-based yet simple framework to examine how data-driven capability (DDC) at the firm level leads to valuable demand-side outcomes. The results of the study showed that DDC leads to customer loyalty only when it is first observable through market innovation quality (MIQ) and then interpreted and processed in the minds of customers through brand credibility (BC). In other words, data and analytics—as strategic assets—find practical value when they are expressed in the form of coherent and understandable innovations for the customer and strengthen the brand's competence and trustworthiness.
One of the key findings of the study is that brand credibility plays a full mediating role in the influence chain; that is, the path from market innovation to loyalty passes entirely through increasing customer belief in the brand's power and integrity. This finding further highlights the importance of strategic attention to brand reputation and suggests that organizations should focus on consistency, integrity, and quality of execution beyond mere innovation.
On the other hand, the results showed that sustainability authenticity (SA) is an important condition for enhancing the impact of innovations and brand reputation. When customers feel that a brand's sustainability initiatives are genuine and consistent with its claims, their sensitivity to innovation increases and brand reputation is more likely to translate into loyalty. This finding underscores the growing importance of authentic sustainability in customer-brand relationships and suggests that symbolic and demonstrative approaches to sustainability can reduce the effectiveness of even the best innovations.
Overall, this research supports a simple and actionable model for organizations; one that, without unnecessary complexity, clarifies the path of impact of data-driven capabilities down to the level of customer behavior. The findings also suggest that organizations can create a sustainable and reliable path to value creation and loyalty by combining three key elements—data-driven capability, high-quality market innovation, and authentic sustainability.
Finally, while acknowledging the limitations of the study, this framework can serve as a starting point for future research on the relationships between digital capabilities, innovation, sustainability, and customer behavior across industries and cultural contexts. The model can also serve as a basis for designing policies and management interventions that simultaneously emphasize innovation, data-driven capability, and sustainability accountability.

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