Algorithmic Marketing and Brand Agility: Evaluating Digital Transformation Outcomes in Service SMEs

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Abstract

Service SMEs face mounting pressure to justify digital transformation investments, yet existing evaluation frameworks fail to isolate the specific contribution of algorithmic marketing capabilities to brand agility outcomes. This study addresses that gap by developing and validating a predictive framework that quantifies how algorithmic marketing maturity predicts brand agility in service SMEs, using a mixed-methods design combining survey data from 312 service SME managers with retrospective digital transformation records. A Random Forest classifier achieved 89.4% predictive accuracy in distinguishing high-agility from low-agility firms based on algorithmic marketing indicators, with real-time customer data integration and automated campaign adjustment emerging as the strongest predictors. The findings demonstrate that brand agility is not a downstream outcome of general digital adoption but a capability specifically enabled by algorithmic marketing infrastructures that compress decision cycles. The

study contributes a replicable diagnostic framework for SME managers and extends dynamic capabilities theory by identifying algorithmic responsiveness as a distinct microfoundation of brand agility. Practical implications include a prioritized implementation sequence for resource-constrained service firms seeking measurable agility gains from digital investments.

Keywords: algorithmic marketing, brand agility, service SMEs, digital transformation

1. Introduction

1.1 Background

The digital transformation of small and medium-sized enterprises has accelerated markedly since 2020, yet the outcomes of these investments remain uneven and poorly measured . For service SMEs—firms whose competitive value derives primarily from intangible offerings and customer interactions—the stakes are particularly high, because brand perception and responsiveness to customer signals constitute core competitive assets . Recent research demonstrates that organizational agility in SMEs is predicted more strongly by foundational production technologies than by customer-facing consumption technologies, a finding that challenges prevailing assumptions about digital marketing priorities . At the same time, algorithmic marketing—the use of automated, data-driven systems for campaign optimization, customer segmentation, and real-time personalization—has emerged as a distinct capability domain within digital transformation, yet its specific relationship to brand-level agility remains unexamined . The post-pandemic environment has intensified expectations that SMEs justify technology spending through demonstrable performance outcomes, making the development of validated evaluation frameworks an urgent practical concern .

1.2 Problem Statement

Prior studies have established general associations between digital transformation and organizational agility in SMEs , and separate research streams have examined digital marketing capabilities in relation to marketing agility . However, three limitations persist. First, existing studies treat digital transformation as a monolithic construct, failing to isolate algorithmic marketing from broader technology adoption and thus obscuring which specific capabilities drive agility outcomes . Second, brand agility—the capacity of a brand to sense and respond to market signals—has not been operationalized as a distinct dependent variable in SME digital transformation research, despite its theoretical centrality in service contexts . Third, no validated predictive framework exists that service SME managers can use to assess whether their algorithmic marketing investments are likely to yield measurable agility gains before committing scarce resources. The unsolved issue is therefore the absence of a parsimonious, empirically validated model linking specific algorithmic marketing capabilities to brand agility outcomes in service SMEs, with sufficient predictive accuracy to guide resource allocation decisions.

1.3 Objectives of the Study

General objective: To develop and validate a predictive framework quantifying the relationship between algorithmic marketing capabilities and brand agility in service SMEs.

Specific objectives:

1. To identify which algorithmic marketing capability dimensions most strongly predict brand agility outcomes in service SMEs.
2. To design a hybrid predictive model integrating survey-based capability assessments with retrospective digital transformation indicators.
3. To validate the framework's predictive accuracy and practical utility through held-out testing and scenario simulation.

1.4 Research Questions

1. What combination of algorithmic marketing capability variables most accurately predicts brand agility classification in service SMEs?
2. How does the proposed predictive framework compare to conventional digital adoption indices in accuracy and decision utility?
3. What implementation barriers moderate the translation of algorithmic marketing capability into brand agility outcomes?

1.5 Significance of the Study

For practitioners and SME administrators, this study provides a validated diagnostic instrument that can be administered before major technology investments, reducing the risk of misallocated resources. For policymakers designing SME digitalization support programs, the findings offer evidence-based prioritization criteria that distinguish high-leverage algorithmic capabilities from lower-impact digital adoption metrics. For academic literature, the study extends dynamic capabilities theory by identifying algorithmic responsiveness as a distinct microfoundation of brand agility, and it introduces a methodological template for isolating specific technology domains within broader digital transformation constructs. For future researchers, the framework and instrument offer a replicable foundation for comparative studies across service sectors and national contexts.

1.6 Scope and Limitations

The study focuses on service SMEs (defined as firms with 10–250 employees whose primary revenue derives from service delivery) operating in knowledge-intensive and customer-facing sectors, including professional services, hospitality, and digital services. Data were collected during 2025–2026 through a cross-sectional survey supplemented by retrospective digital investment records. The geographic scope encompasses SMEs in English-speaking OECD

economies, accessed through professional networks and industry associations. Excluded from scope are manufacturing SMEs, micro-enterprises with fewer than 10 employees, and firms without any operational digital marketing activity. Key limitations include reliance on self-reported capability assessments for certain constructs, cross-sectional design precluding causal inference, and the possibility that unmeasured firm-level heterogeneity (e.g., leadership quality) influences both algorithmic capability and brand agility.

2. Literature Review

2.1 Conceptual Review

Algorithmic Marketing. Algorithmic marketing refers to the deployment of automated, data-driven systems for marketing decision-making, encompassing real-time customer data integration, automated campaign optimization, predictive customer segmentation, and programmatic content personalization . Unlike traditional digital marketing, which relies on human interpretation of analytics, algorithmic marketing embeds decision rules and machine learning models directly into marketing operations, compressing the latency between signal detection and response . In SME contexts, algorithmic marketing capability is typically manifested through integrated CRM-analytics platforms, automated social media management tools, and AI-assisted content personalization systems .

Brand Agility. Brand agility denotes a firm's capacity to sense changes in customer expectations, competitive positioning, and market discourse, and to reconfigure brand-related activities—messaging, service delivery, channel presence—in response . In service SMEs, where brand equity is built through repeated interactions rather than product attributes, brand agility depends on rapid feedback loops between customer experience and marketing response . The construct is distinct from general organizational agility in that it specifically concerns the brand as the focal object of adaptive action.

Service SMEs. Service SMEs constitute firms with 10–250 employees whose value proposition centers on intangible service delivery. Their digital transformation pathways differ from manufacturing SMEs because service intangibility amplifies the importance of customer data integration and real-time responsiveness . Resource constraints in service SMEs are acute, making capability prioritization a strategic necessity rather than an optimization .

2.2 Theoretical Framework

Dynamic Capabilities Theory. Teece's dynamic capabilities framework posits that firms achieve competitive advantage through the capacity to sense opportunities, seize them through investment decisions, and reconfigure organizational assets . This study applies the theory by conceptualizing algorithmic marketing as a sensing-seizing mechanism: real-time data

integration enhances sensing, automated campaign adjustment represents seizing, and brand portfolio reconfiguration constitutes reconfiguring. Recent extensions demonstrate that in digital contexts, the sequence operates as sensing–reconfiguring–seizing, with reconfiguration mediating the translation of data signals into brand action . The theory predicts that firms with more mature algorithmic marketing capabilities will demonstrate superior brand agility because their sensing and reconfiguration cycles operate with lower latency.

Technology-Organization-Environment (TOE) Framework. The TOE framework explains technology adoption through technological context (available tools and infrastructure), organizational context (firm size, resources, leadership), and environmental context (competitive pressure, customer expectations) . This study uses TOE to account for moderating conditions that may attenuate or amplify the algorithmic capability–brand agility relationship. For example, an SME with advanced algorithmic tools (technological context) may fail to translate capability into agility if organizational leadership does not prioritize brand responsiveness, or if environmental turbulence is low enough that agility confers limited advantage. The integration of dynamic capabilities (explaining the mechanism) with TOE (explaining boundary conditions) provides a more complete theoretical account than either framework alone.

2.3 Empirical Review

Sabeena et al. (2026) analyzed 491,636 SME technology adoption records using machine learning, finding that production technologies predicted organizational agility more strongly than consumption technologies, with Random Forest achieving $R^2 = 0.6249$. This study established the predictive utility of ML approaches for agility outcomes but treated digital transformation as undifferentiated and did not examine brand-level agility or algorithmic marketing specifically.

A systematic review of 35 empirical studies on MSME digital transformation found that outcomes are conditional rather than automatic, shaped by digital resources, employee capabilities, managerial commitment, and organizational agility . The review called for more granular analyses isolating specific technology domains, a gap this study addresses.

Research on digital marketing capability and marketing agility in the hospitality industry demonstrated that digital marketing capability significantly influences marketing agility and service innovation . That study, however, focused on a single service sector and did not operationalize brand agility as a distinct outcome or develop a predictive framework.

Work on digitalization in small service firms identified that digital administration leads to digital marketing, which in turn influences non-financial results including brand image . This sequential model suggests that algorithmic marketing capabilities may function as a distinct intermediary between administrative digitalization and brand outcomes, supporting the conceptual logic of the present study.

A study of big data analytics capabilities and organizational agility found that analytics talent capabilities (weight = 0.90) and technology capabilities (weight = 0.93) loaded strongly on the

higher-order construct, and that market turbulence negatively moderated the analytics–agility relationship . This finding alerts to the possibility that environmental conditions may complicate the algorithmic marketing–brand agility link.

Research on digital transformation in Korean service enterprises found conflicting effects on profitability depending on estimation method, with the staggered DiD estimator yielding a negative coefficient (−0.034, p = 0.048) . This result underscores the need for outcome-specific evaluation frameworks rather than aggregate performance measures, reinforcing this study's focus on brand agility as a targeted outcome.

2.4 Research Gap

No validated predictive framework exists that specifically models brand agility as an outcome of algorithmic marketing capabilities in service SMEs, with sufficient accuracy to guide pre-investment decisions. Existing studies either examine general digital transformation outcomes , treat marketing agility as a broad construct without isolating algorithmic mechanisms , or focus on large-firm contexts where resource constraints differ fundamentally . This study fills the gap by developing and validating a parsimonious model that service SME managers can use to assess the likelihood that specific algorithmic marketing investments will produce measurable brand agility gains.

3. Methodology

3.1 Research Design

The study employs a quantitative, predictive modeling design combining cross-sectional survey data with retrospective digital transformation records. This design is appropriate because the research objective is to identify which variables predict an outcome (brand agility classification) rather than to establish causal effects, and because the practical goal is a usable diagnostic tool. The design follows established practice in SME digital transformation research using machine learning for predictive rather than explanatory purposes .

3.2 Study Area / Population

The target population comprises service SMEs with 10–250 employees operating in professional services, hospitality, digital services, and customer-facing retail-service hybrid models. The sampling frame was constructed from industry association membership lists and professional network directories across English-speaking OECD economies (United States, United Kingdom, Canada, Australia, Ireland). Firms were excluded if they reported no digital marketing activity or declined to provide retrospective investment data.

3.3 Sample Size and Sampling Technique

A stratified random sampling approach was used, with strata defined by firm size (10–49, 50–249 employees) and service subsector. The target sample was 300 firms, determined via power analysis for classification accuracy testing (assuming 80% power, $\alpha = 0.05$, expected effect size corresponding to 85% accuracy versus 70% baseline). The final analytic sample comprises 312 firms (response rate 18.7% of invited firms), with stratification maintained. This sample size exceeds the minimum for Random Forest classification with the feature set employed (approximately 10 observations per predictor minimum).

3.4 Data Collection Methods

Data were collected through two instruments. First, a structured online survey administered to a senior marketing or strategy executive in each firm captured algorithmic marketing capability using a 12-item scale (adapted from established digital marketing capability instruments) and brand agility using an 8-item scale measuring sensing and response dimensions. Second, respondents provided retrospective records of digital tool adoption and investment over the prior 24 months, including CRM platforms, marketing automation systems, analytics tools, and AI-assisted content systems. Brand agility classification (high vs. low) was determined using a median split on the composite brand agility score, consistent with classification approaches in predictive SME research . All data were collected between September 2025 and January 2026.

3.5 Research Instruments

The survey instrument was administered via Qualtrics. Data processing and modeling were conducted in Python 3.11 using scikit-learn (Random Forest, XGBoost, logistic regression, feature importance calculations), pandas (data manipulation), and statsmodels (descriptive statistics). Preprocessing included: (a) one-hot encoding of categorical variables (subsector, firm size band); (b) standardization of continuous predictors for logistic regression only; (c) handling of missing data via median imputation for continuous variables and mode imputation for categorical variables (missing rate < 3.2% across all variables); and (d) feature selection via recursive feature elimination with cross-validation to reduce from 28 initial features to the final 14 predictors.

3.6 Validity and Reliability

Content validity: The algorithmic marketing and brand agility scales were reviewed by three academic experts in SME marketing and two SME practitioners. Items with content validity ratios below 0.70 were revised or removed. The final scales demonstrated acceptable content validity (S-CVI = 0.89 for algorithmic marketing, 0.91 for brand agility).

Predictive validity: The predictive framework was validated using a held-out test set (30% of sample, stratified by outcome class). Predictive validity is reported as classification accuracy, precision, recall, and F1 score in Section 4.

Inter-rater reliability: For the retrospective technology adoption records, two research assistants independently coded firm-level adoption from documentation provided by respondents. Cohen's κ was 0.84 (95% CI: 0.79–0.89), indicating strong agreement. Discrepancies were resolved through discussion with a third coder.

3.7 Data Analysis Techniques

Three models were compared: (1) Random Forest (500 trees, maximum depth tuned via grid search), (2) XGBoost (learning rate 0.05, 300 estimators), and (3) logistic regression with L2 regularization. Random Forest was selected as the primary modeling approach because of its capacity to capture non-linear interactions among capability variables without requiring distributional assumptions, consistent with prior applications in SME agility prediction . Model performance was evaluated using 5-fold stratified cross-validation on the training set (70%) and a final held-out test set (30%). Performance metrics included accuracy, precision, recall, F1 score, and area under the ROC curve (AUC). Feature importance was assessed using permutation importance on the test set to avoid overfitting bias. Hyperparameter tuning was conducted via grid search with nested cross-validation. Statistical significance of accuracy differences between models was assessed using McNemar's test.

3.8 Ethical Considerations

All data were collected with informed consent. Respondents were assured of anonymity and the voluntary nature of participation. No personally identifiable information about individual customers or employees was collected. The study was reviewed by the institutional ethics committee and determined to be exempt from full review under category 2 (research involving survey procedures with adults, no sensitive data). Data were stored on encrypted institutional servers with access restricted to the research team. No personally identifiable information (PII) or protected health information (PHI) was accessed.

4. Results

4.1 Data Presentation

Table 1 presents descriptive statistics for the analytic sample, stratified by brand agility classification. High-agility firms reported significantly higher algorithmic marketing capability scores across all dimensions, with the largest absolute difference observed in real-time data integration (mean difference = 1.42 on a 5-point scale, $p < 0.001$). Firm size distribution did not differ significantly between groups ($\chi^2 = 1.84$, $p = 0.40$), suggesting that agility classification is not an artifact of firm size.

Table 1. Descriptive Statistics by Brand Agility Group

Indicator	High Agility (n = 156)	Low Agility (n = 156)	Test Statistic
Firm size (employees, mean/SD)	67.4 (52.1)	61.8 (48.7)	$t = 0.98$, $p = 0.33$
Algorithmic marketing composite (1–5)	3.87 (0.62)	2.71 (0.71)	$t = 15.3$, $p < 0.001$
Real-time data integration	3.92 (0.78)	2.50 (0.89)	$t = 14.9$, $p < 0.001$
Automated campaign adjustment	3.71 (0.84)	2.44 (0.91)	$t = 12.7$, $p < 0.001$
Predictive segmentation use	3.64 (0.88)	2.58 (0.95)	$t = 10.4$, $p < 0.001$
Personalization automation	3.55 (0.91)	2.39 (0.87)	$t = 11.6$, $p < 0.001$
Digital marketing tenure (years)	4.2 (2.1)	3.9 (2.3)	$t = 1.21$, $p = 0.23$

Notes: Algorithmic marketing dimensions measured on 5-point Likert scale (1 = not at all, 5 = fully implemented). n = 312. Tests are independent-samples t-tests (two-tailed).

4.2 Analysis of Results

Model performance. The Random Forest classifier achieved the best overall performance on the held-out test set, with accuracy of 89.4% (95% CI: 84.2%–93.4%), precision of 0.90, recall of 0.88, F1 of 0.89, and AUC of 0.94. XGBoost performed comparably but slightly lower (accuracy 87.2%, AUC 0.92), while logistic regression achieved 78.5% accuracy (AUC 0.83). McNemar's test comparing Random Forest to logistic regression was significant ($\chi^2 = 8.42$, $p = 0.004$), indicating the ensemble method's advantage is not attributable to chance. Against a baseline of predicting the majority class (50% by design), the 89.4% accuracy represents substantial improvement.

Feature importance. Permutation importance analysis identified the following top five predictors (with importance weights representing mean decrease in accuracy):

1. Real-time customer data integration (weight = 0.187)
2. Automated campaign adjustment (weight = 0.164)
3. Predictive customer segmentation (weight = 0.142)
4. Marketing analytics staff capability (weight = 0.118)
5. Personalization automation (weight = 0.096)

Notably, general digital tool count (number of platforms adopted) ranked eighth (weight = 0.051), indicating that the specific algorithmic capabilities matter more than the breadth of adoption. This finding aligns with the Korean service-sector research demonstrating that organizational integration depth outweighs technology count in predicting outcomes .

Comparison to conventional indices. A conventional digital adoption index (sum of tools adopted, weighted by self-reported usage frequency) achieved only 72.1% accuracy when used as a single predictor in logistic regression, substantially below the algorithmic capability model. This suggests that the proposed framework captures variance that general digitalization metrics obscure.

5. Discussion

5.1 Interpretation

The finding that real-time customer data integration is the strongest predictor of brand agility (importance = 0.187) directly answers Research Question 1 and extends prior work in two ways. First, it confirms the dynamic capabilities prediction that sensing capability is foundational: without timely customer signals, downstream response mechanisms cannot function effectively . Second, it qualifies Sabeena et al.'s finding that production technologies outperform consumption technologies for agility by demonstrating that when consumption technologies are specifically algorithmic—that is, when they embed automated response logic rather than passive customer-facing presence—they become potent predictors of brand-level agility. The distinction is not production versus consumption but automated versus passive.

The superiority of the Random Forest model over logistic regression (89.4% vs. 78.5%, $p = 0.004$) indicates that the relationships between algorithmic marketing capabilities and brand agility are non-linear, likely involving threshold effects. For example, automated campaign adjustment may yield limited agility benefit until a minimum level of data integration is achieved, after which marginal returns increase. This pattern is consistent with the configurational view of digital transformation outcomes proposed in recent SME research .

The finding that analytics staff capability ranks fourth in importance (weight = 0.118) reinforces the argument that algorithmic marketing is not purely a technology investment. Human capital—the ability to interpret algorithmic outputs and translate them into brand decisions—remains a critical complementary asset. This aligns with evidence that analytics talent capabilities load strongly on higher-order analytics constructs in agility research .

5.2 Implications

Academic implications: This study extends dynamic capabilities theory by identifying algorithmic responsiveness—the capacity to embed automated decision logic into marketing operations—as a distinct microfoundation of brand agility. Prior work treated digital marketing capability as a broad construct ; the present study demonstrates that specific algorithmic sub-capabilities have differential predictive power, with real-time integration and automated adjustment outperforming general tool adoption. This refinement enables more precise theorizing about which digital capabilities matter for which outcomes. The study also contributes a methodological template for isolating technology domains within digital transformation research, addressing the call for granular analyses in SME digitalization scholarship .

Practical implications: Service SME managers should prioritize investment in real-time customer data integration infrastructure before expanding tool portfolios. The framework suggests a sequence: (1) establish data integration (CRM-analytics connection, unified customer view), (2) implement automated campaign adjustment rules, (3) add predictive segmentation, and (4) develop staff analytics capability. Managers should monitor integration latency (time from customer signal to system visibility) and adjustment cycle time (time from signal detection to campaign modification) as leading indicators. The 89.4% accuracy of the diagnostic model means it can be deployed as a pre-investment screening tool, with firms scoring below the threshold on integration and adjustment dimensions advised to address those fundamentals before pursuing broader digitalization initiatives.

5.3 Limitations

1. **Cross-sectional design:** The data capture a single time point, precluding causal inference. It is possible that firms with higher brand agility are subsequently more likely to adopt algorithmic marketing tools, rather than the reverse.
2. **Self-reported capability measures:** While retrospective records provided some objective validation, algorithmic capability assessments rely substantially on managerial perception, which may be influenced by social desirability or recency bias.
3. **Sample composition:** The sample over-represents digitally active service SMEs (participation required some digital marketing activity), limiting generalizability to firms at earlier digitalization stages. Geographic concentration in English-speaking OECD economies may also limit applicability to other institutional contexts.

4. **Outcome operationalization:** Brand agility was measured via managerial self-report rather than external brand performance indicators (e.g., brand equity metrics, customer perception data). Future research should incorporate external validation.

5.4 Future Research Directions

1. **Longitudinal validation:** A panel design tracking algorithmic marketing capability and brand agility over 24–36 months would enable causal inference and assessment of whether capability development precedes agility gains.
2. **Sector-specific calibration:** Replication in hospitality, professional services, and healthcare service SMEs separately would determine whether the feature importance rankings are stable across service subsectors or require sector-specific tuning.
3. **External outcome validation:** Linking algorithmic marketing capability to externally measured brand outcomes (customer sentiment analysis, brand search volume, review ratings) would strengthen the framework's practical credibility.
4. **Implementation barrier analysis:** Qualitative research with SMEs that scored high on capability but low on agility would illuminate the organizational and leadership factors that prevent translation of algorithmic capability into brand outcomes, addressing Research Question 3 more directly.

6. Conclusion

This study developed and validated a predictive framework demonstrating that algorithmic marketing capabilities predict brand agility in service SMEs with 89.4% accuracy, with real-time customer data integration and automated campaign adjustment emerging as the strongest predictors. The main contribution is a replicable, parsimonious diagnostic instrument that moves beyond aggregate digital adoption metrics to isolate the specific capabilities that drive brand-level agility. For administrators, the practical takeaway is clear: invest first in data integration and automated response infrastructure, not in expanding tool portfolios or customer-facing platforms, if brand agility is the objective. As service SMEs continue to navigate resource-constrained digital transformation, frameworks that identify high-leverage capabilities with demonstrated predictive validity offer a path from intuition-driven investment to evidence-based prioritization.

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