Hormuud University International Journal of Multidisciplinary Studies
https://journals.hu.edu.so/index.php/ihujms

Artificial Intelligence Capabilities and Digital Marketing Performance among Somali Businesses

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Abstract
Artificial intelligence (AI) can support personalization, campaign automation, customer analytics, and content generation, but evidence from resource-constrained markets remains limited. Drawing on the technology-organization-environment framework and the resource-based view, this study examines associations between four AI marketing capabilities—AI-enabled personalization, marketing automation, AI-driven analytics, and generative AI—and digital marketing performance among Somali businesses. It also tests whether organizational AI readiness moderates the relationship between an overall AI-capability measure and performance. A cross-sectional survey produced 327 usable responses from marketing managers, business owners, and marketing specialists. Multi-item measures were assessed for reliability and convergent and discriminant validity. Hierarchical moderated regression showed that the main-effects model explained 40.3% of the variance in digital marketing performance. Automation had the largest standardized association with performance ($\beta = .257$, $p < .001$), followed by personalization ($\beta = .200$, $p < .001$), generative AI ($\beta = .177$, $p = .001$), and analytics ($\beta = .149$, $p = .001$). The capability-by-readiness interaction was also significant ($b = .283$, $p < .001$), increasing explained variance by 2.7 percentage points. These cross-sectional findings show associations rather than causal effects. The study provides an initial empirical benchmark for AI-enabled marketing in Somalia. The results suggest that firms may gain greater marketing value when AI-tool adoption is accompanied by technical skills, digital infrastructure, management commitment, and appropriate governance.

Keywords: Artificial intelligence, Digital marketing, Marketing automation, Generative AI, Organizational readiness, Somalia

1. Introduction

Artificial intelligence is increasingly used to personalize customer experiences, automate campaign execution, analyze customer data, and generate marketing content. These capabilities may reduce execution cost, improve targeting, and accelerate the movement from analysis to action (Davenport et al., 2020; Huang & Rust, 2021). Whether they improve performance depends on how firms integrate the technology with strategy, data, skills, and governance.

Most empirical evidence on AI marketing comes from advanced economies with mature digital infrastructure, abundant technical expertise, and deeper capital markets (Grewal et al., 2020; Verhoef et al., 2021). Less is known about the performance implications of AI in frontier and developing markets, where firms may combine rapid digital adoption with resource and

infrastructure constraints. This limits the external validity of current theory and reduces the practical relevance of existing evidence for local managers.

Somalia provides a relevant setting because widespread mobile connectivity and mobile money coexist with infrastructure, skills, regulatory, and financing constraints. Firms in telecommunications, trade, financial services, and other sectors increasingly use digital tools, creating an opportunity to examine whether established AI capability-performance relationships also appear in this context.

The study addresses three questions: whether personalization, automation, analytics, and generative AI are associated with digital marketing performance; which capability has the strongest association; and whether organizational readiness conditions the relationship between overall AI capability and performance. The study extends capability-based AI marketing research to Somalia, but its cross-sectional design does not establish causal effects.

2. Literature Review and Theoretical Framework

The study integrates two complementary theoretical lenses. The technology-organisation-environment (TOE) framework holds that a firm's adoption and assimilation of technology is shaped jointly by technological factors, organisational characteristics, and the external environment (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). TOE is well suited to explaining why otherwise similar firms diverge in the returns they realise from the same technology. The resource-based view (RBV) complements this by treating capabilities as the proximate source of performance: technologies become valuable only when embedded in firm-specific capabilities that are difficult to imitate (Barney, 1991; Teece et al., 1997). Applied to AI, these lenses jointly imply that AI tools do not improve performance directly; they do so when converted into marketing capabilities and supported by adequate organisational readiness.

Within marketing, AI has been conceptualised as a set of capabilities rather than a single technology (Huang & Rust, 2021; Mikalef & Gupta, 2021). This study focuses on four that are salient for firms in emerging markets. AI-enabled personalisation refers to the use of intelligent systems to tailor offers and communication to individual customers (Kumar et al., 2019). Marketing automation captures the delegation of repetitive marketing tasks to intelligent systems, including chatbots and automated campaign management (Davenport et al., 2020). AI-driven analytics denotes the use of machine learning to extract decision-relevant insight from customer data (Wamba et al., 2017; Mikalef et al., 2020). Generative AI tools, exemplified by ChatGPT, represent the newest capability, enabling the rapid creation of marketing content (Dwivedi et al., 2023; Paschen et al., 2019). Each capability is theorised to enhance digital marketing performance, understood here as a composite of customer engagement, campaign effectiveness, and cost efficiency (Trainor et al., 2014).

Organisational AI readiness, comprising technical expertise and digital infrastructure, is positioned as a moderator. Consistent with TOE, the marginal value of a capability should depend on the organisational conditions surrounding it: a firm rich in AI capability but poor in readiness will struggle to convert that capability into results (Ransbotham et al., 2017; Mikalef & Gupta, 2021). Readiness is therefore modelled not as a driver of performance in its own right but as a condition that strengthens the capability-performance relationship (Figure 1).

2.1 Hypothesis Development

Personalisation increases the relevance of marketing stimuli, which is consistently associated with stronger engagement and conversion (Kumar et al., 2019). Automation lowers execution cost and accelerates response, improving both efficiency and reach (Davenport et al., 2020). Analytics improves targeting and resource allocation, raising campaign effectiveness (Wamba et al., 2017). Generative AI expands content capacity and consistency at low marginal cost, a

particularly valuable property where creative resources are scarce (Dwivedi et al., 2023). These arguments yield the first four hypotheses:

H1. AI-enabled personalisation is positively associated with digital marketing performance.
H2. AI marketing automation is positively associated with digital marketing performance.
H3. AI-driven analytics is positively associated with digital marketing performance.
H4. Generative AI tools are positively associated with digital marketing performance.
H5. Organisational AI readiness positively moderates the relationship between AI marketing capabilities and digital marketing performance, such that the relationship is stronger when readiness is higher.

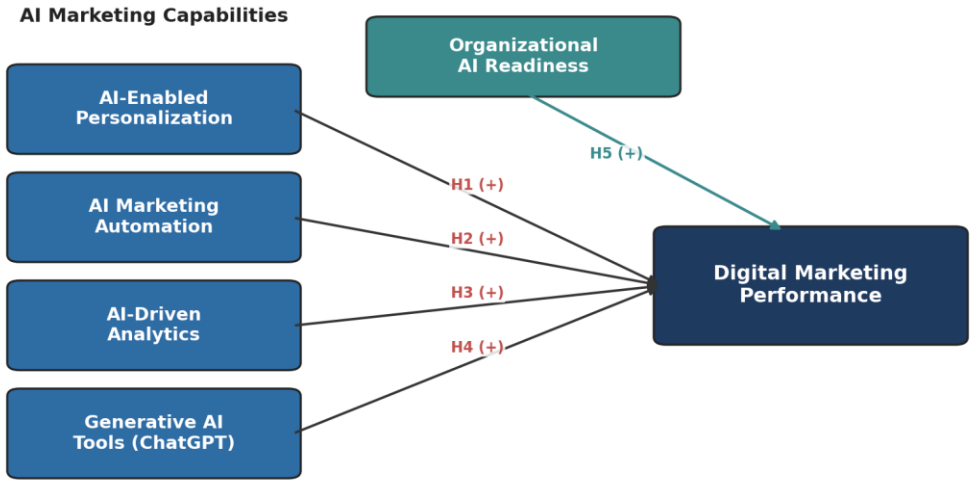


Figure 1. Conceptual research model.

3. Data and Method

The study used a quantitative cross-sectional survey of Somali businesses engaged in digital marketing. Marketing managers, business owners, and marketing specialists served as key informants. Questionnaires were administered through in-person and online channels, and 327 usable responses remained after screening.

All constructs used multi-item five-point Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Personalization, automation, analytics, generative AI use, and readiness were measured with four items each, while digital marketing performance used six items covering engagement, effectiveness, and cost efficiency. Firm size, firm age, and years of AI experience were control variables. Reliability, convergent validity, discriminant validity, common-method bias, and multicollinearity were assessed before hierarchical moderated regression. Predictors were mean-centered (Aiken & West, 1991). Table 1 summarizes the constructs, item sources, and sample items.

3.1 Measurement and Item Sources

Table 1. Constructs, measurement sources, and sample items.

Construct	Items	Indicative source	Sample item
AI-Enabled Personalisation	4	Kumar et al. (2019); Chaffey & Ellis-Chadwick (2019)	*"Our firm uses AI tools to tailor marketing messages to individual customers."*
AI Marketing Automation	4	Huang & Rust (2021); Davenport et al. (2020)	*"We use AI to automate routine marketing tasks (e.g., scheduling, posting, replies)."*
AI-Driven Analytics	4	Mikalef & Gupta (2021); Wamba et al. (2017)	*"We use AI to analyse customer data and uncover marketing insights."*
Generative AI Tools	4	Dwivedi et al. (2023); Paschen et al. (2019)	*"We use generative AI tools such as ChatGPT to create marketing content."*
Organisational AI Readiness	4	Tornatzky & Fleischer (1990); Oliveira & Martins (2011)	*"Our staff have the technical skills needed to use AI marketing tools effectively."*
Digital Marketing Performance	6	Trainor et al. (2014); Wamba et al. (2017)	*"AI adoption has increased customer engagement with our brand."*

4. Empirical Results

4.1 Sample Profile

Table 2 summarizes respondent role, firm size, gender, and education. Marketing managers and business owners formed the largest respondent groups, and micro, small, and medium enterprises comprised most of the sample. Figure 2 presents the sectoral distribution. The sample profile describes the respondents and should not be assumed to represent all Somali businesses without a probability-based sampling frame.

Table 2. Sample profile (n = 327).

Characteristic	Category	n	%
Respondent role	Marketing Manager	106	32.4
	Business Owner/CEO	97	29.7
	Marketing Officer/Specialist	89	27.2
	Other	35	10.7
Firm size	Micro (<10)	101	30.9

Characteristic	Category	n	%
	Small (10–49)	114	34.9
	Medium (50–249)	85	26.0
	Large (250+)	27	8.3
Gender	Male	192	58.7
	Female	135	41.3
Education	Bachelor	166	50.8
	Master	88	26.9
	Diploma	58	17.7
	PhD	15	4.6

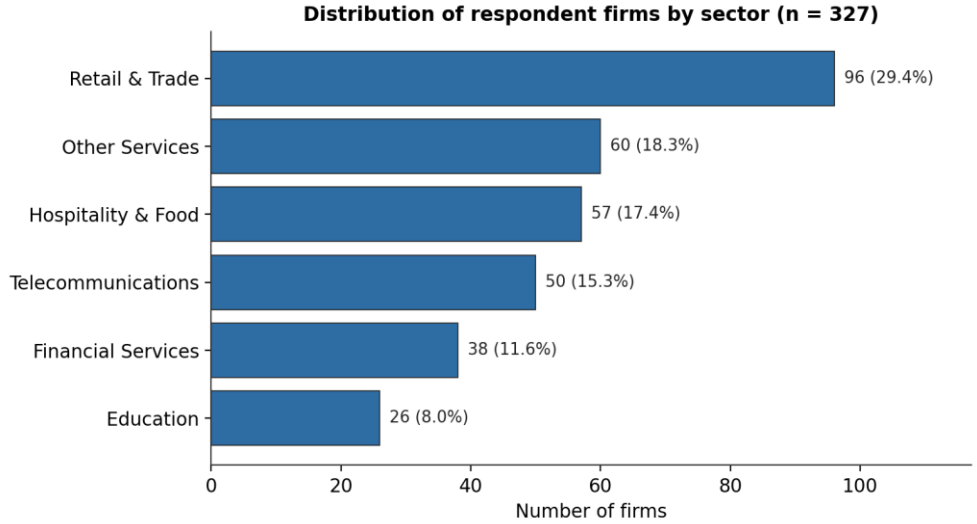


Figure 2. Distribution of respondent firms by sector.

4.2 Reliability and Validity

All constructs exceeded conventional thresholds for Cronbach's alpha and composite reliability, and average variance extracted was above .50, supporting internal consistency and convergent validity (Fornell & Larcker, 1981; Hair et al., 2019; Nunnally & Bernstein, 1994). Table 3 and Figure 3 report the measurement statistics. Construct means were moderately above the scale midpoint, indicating generally favorable but not uniform responses.

Table 3. Descriptive statistics, reliability, and convergent validity. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Construct	Items	Mean	SD	α	CR	AVE
AI-Enabled Personalisation	4	3.54	0.72	0.766	0.851	0.588
AI Marketing Automation	4	3.39	0.70	0.769	0.853	0.591
AI-Driven Analytics	4	3.37	0.71	0.790	0.864	0.614

Construct	Items	Mean	SD	α	CR	AVE
Generative AI Tools	4	3.56	0.69	0.782	0.860	0.605
Organisational AI Readiness	4	3.30	0.71	0.762	0.849	0.584
Digital Marketing Performance	6	3.45	0.66	0.834	0.879	0.547

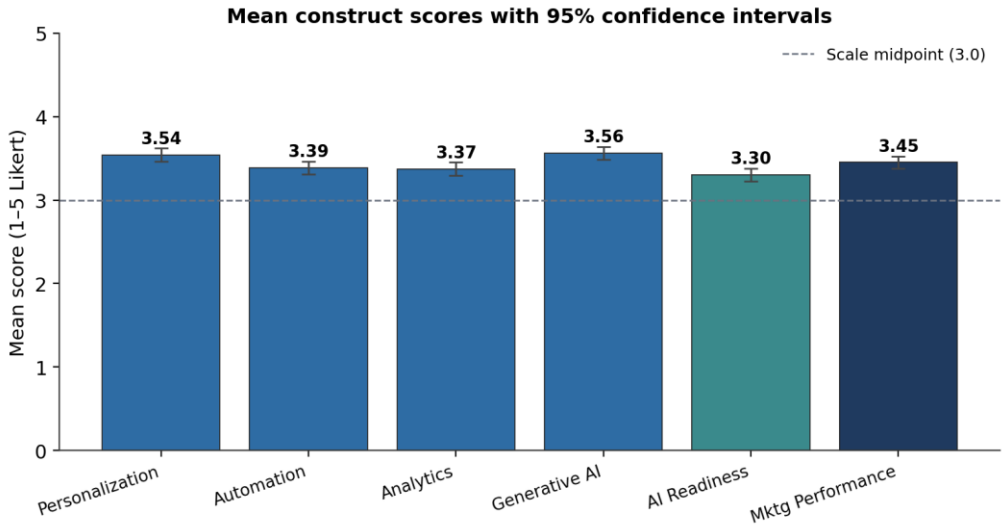


Figure 3. Mean construct scores with 95% confidence intervals.

4.3 Correlations and Discriminant Validity

Construct correlations were positive, statistically significant, and moderate. Under the Fornell-Larcker criterion, the square root of each construct's AVE exceeded its correlations with other constructs, supporting discriminant validity. Harman's single-factor test (Podsakoff et al., 2003) attributed 28.60% of variance to one factor, and variance inflation factors ranged from 1.26 to 1.37. These diagnostics reduce but do not eliminate concerns about common-method bias and multicollinearity.

Table 4. Correlation matrix. Diagonal (bold) shows the square root of AVE; off-diagonal entries are construct correlations, all significant at p < .01.

	1	2	3	4	5	6
1. AI-Enabled Personalisation	**0.77**					
2. AI Marketing Automation	0.37	**0.77**				
3. AI-Driven Analytics	0.28	0.37	**0.78**			
4. Generative AI Tools	0.30	0.39	0.36	**0.78**		
5. Organisational AI Readiness	0.34	0.35	0.41	0.34	**0.76**	

	1	2	3	4	5	6
6. Digital Marketing Performance	0.42	0.49	0.40	0.42	0.37	**0.74**

4.4 Hypothesis Testing

Table 5 and Figure 4 report the hierarchical moderated regression. Control variables explained 4.8% of performance variance in Model 1. Adding the AI-related predictors increased R^2 to .403 (ΔR^2 = .355, p < .001). Personalization (β = .200, p < .001), automation (β = .257, p < .001), analytics (β = .149, p = .001), and generative AI (β = .177, p = .001) were positively associated with digital marketing performance, supporting H1–H4. These coefficients represent conditional associations, not causal effects.

Adding the capability-by-readiness interaction increased R^2 from .403 to .430 (ΔR^2 = .027, p < .001). The interaction was positive and statistically significant (b = .283, p < .001), supporting H5. Simple slopes (Figure 5) indicate a stronger capability-performance association at higher readiness. Table 6 summarizes the hypothesis tests. Readiness did not have a statistically significant direct coefficient in the reported model (β = .095, p = .121).

Table 5. Hierarchical moderated regression predicting digital marketing performance. Unstandardised coefficients reported for Model 3; standardised betas from the main-effects model. *p < .05, **p < .01, ***p < .001.

Predictor	b (Model 3)	SE	β (std.)	p
Firm size	0.080**	0.030	–	0.008
Firm age	0.011	0.006	–	0.087
AI experience (years)	0.024	0.017	–	0.154
AI-enabled personalisation (H1)	0.197***	0.043	0.200	<.001
AI marketing automation (H2)	0.232***	0.047	0.257	<.001
AI-driven analytics (H3)	0.150**	0.045	0.149	0.001
Generative AI tools (H4)	0.152**	0.047	0.177	0.001
Organisational AI readiness	0.071	0.046	0.095	0.121
AI capability × readiness (H5)	0.283***	0.072	–	<.001
Model R^2	Model 1 = 0.048; Model 2 = 0.403; Model 3 = 0.430			
ΔR^2	Model 2 vs 1 = 0.355***; Model 3 vs 2 = 0.027***			
Model F	Model 3 F = 26.60, p < .001			

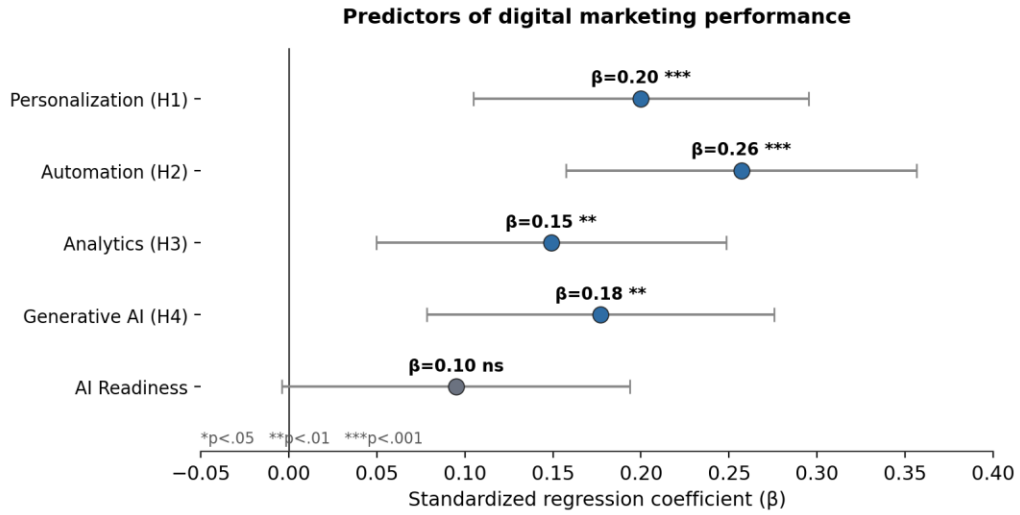


Figure 4. Standardised coefficients for the predictors of digital marketing performance.

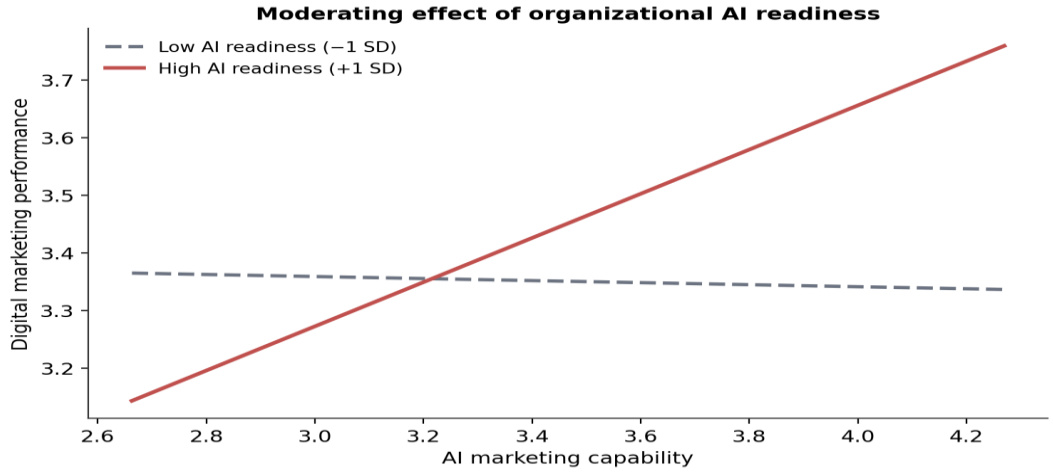


Figure 5. Simple slopes illustrating the moderating effect of organisational AI readiness.

Table 6. Summary of hypothesis tests.

Hypothesis	Path	Result
H1: Personalisation → performance	β = 0.200***	**Supported**
H2: Automation → performance	β = 0.257***	**Supported**
H3: Analytics → performance	β = 0.149**	**Supported**
H4: Generative AI → performance	β = 0.177**	**Supported**
H5: Readiness moderates capability → performance	b = 0.283***	**Supported**

5. Discussion

The four AI marketing capabilities were positively associated with perceived digital marketing performance in the sample. Automation had the largest standardized coefficient, followed by personalization, generative AI, and analytics. This pattern is consistent with the view that AI creates value when firms embed tools in repeatable marketing processes. The cross-sectional,

self-reported design does not show that AI caused better performance or establish that the coefficients apply to the broader population of Somali firms.

Generative AI was positively associated with performance despite its relatively recent diffusion, which may reflect the accessibility of content-generation tools. Analytics had the smallest of the four significant coefficients, potentially because advanced analytical use demands stronger data quality and technical expertise. This explanation is plausible but was not directly tested.

The positive interaction suggests that the relationship between AI capability and performance was stronger when organizational readiness was higher. This result is consistent with TOE and RBV arguments that technology value depends on complementary skills and infrastructure. The effect size was modest ($\Delta R^2 = .027$), so readiness should be treated as one enabling condition rather than the sole explanation of performance differences.

6. Conclusion

Among the sampled Somali businesses, personalization, automation, analytics, and generative AI were positively associated with perceived digital marketing performance. Automation and personalization had the largest standardized coefficients, and organizational readiness strengthened the association between overall AI capability and performance. The findings suggest that AI-tool use should be paired with skills, infrastructure, data governance, and management support. They should not be interpreted as proof that AI caused performance improvement.

Managers with limited resources may prioritize automation and personalization while building data quality, staff capability, security, and governance. Analytics investment should be matched with technical expertise and reliable data. Policymakers and universities can support firms through digital infrastructure, practical AI and data training, and responsible-use guidance. These recommendations follow from the observed associations and should be tested through longitudinal or experimental evaluation.

The cross-sectional design prevents causal inference, and self-reported single-informant measures may inflate associations. Harman's test is a limited diagnostic and cannot rule out common-method bias. The unspecified sampling frame, recruitment method, response rate, and data-collection period constrain representativeness and reproducibility. The construction of the overall AI-capability interaction also requires fuller reporting. Future studies should use probability-based or stratified sampling, multiple informants, objective performance indicators, longitudinal or experimental designs, and preregistered measurement and modeling procedures.

Ethics Approval and Informed Consent

This study was approved by the Institutional Review Board of Hormuud University. Written informed consent was obtained from all participants.

Acknowledgements

None

Conflict of Interest

The author confirms that there is no conflict of interest related to the manuscript.

References

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage Publications.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Chaffey, D., & Ellis-Chadwick, F. (2019). Digital marketing: Strategy, implementation and practice (7th ed.). Pearson.

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.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., et al. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI. International Journal of Information Management, 71, 102642.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: A multidisciplinary perspective. Journal of the Academy of Marketing Science, 48(1), 1–8.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review, 61(4), 135–155.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434.

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.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. Electronic Journal of Information Systems Evaluation, 14(1), 110–121.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business & Industrial Marketing, 34(7), 1410–1419.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence. MIT Sloan Management Review, 59(1).

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

Trainor, K. J., Andzulis, J., Rapp, A., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. Journal of Business Research, 67(6), 1201–1208.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365.