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INFLUENCE OF ARTIFICIAL INTELLIGENCE ADOPTION, BIG DATA ANALYTICS, AND MOBILE MARKETING ON MARKETING PERFORMANCE: THE MODERATING ROLE OF DIGITAL TRANSFORMATION READINESS

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Abstract

Purpose *- Organizations in fast-moving markets are increasingly stressed to reconsider their approach to attracting, engaging and retaining customers. The paper will consider the impact of three discrete digital capabilities, on marketing performance, that are Artificial Intelligence (AI) adoption, Big Data Analytics (BDA) and Mobile Marketing (MM), and whether the intensity of the effects depends on whether an organization is prepared to undergo a digital transformation.*

Design/methodology/approach- *The study was based on the Technology Acceptance Model (TAM) and the Resource-Based View (RBV), a cross-sectional quantitative survey was conducted (n=350) among marketing practitioners working in six sectors in Pakistan including fast-moving consumer goods, retail, financial services, healthcare, telecommunications, and e-commerce. The main effects and the moderated interactions of Digital Transformation Readiness (DTR) were tested with the help of the Partial Least Squares Structural Equation Modelling (PLS-SEM).*

Results - *The three digital capabilities have great positive impacts on marketing performance. The most significant individual predictor (β) is AI adoption (0.412), then BDA (0.387), and MM (0.356). All of these relationships are amplified by DTR, but the most significant incremental gain is in the interaction of AI and DTR (0.219). Cross-industry analysis indicates that digital marketing abilities are most advantageous to e-commerce and financial services companies, but healthcare organizations demonstrate a less significant, yet significant, performance increase.*

Limitations/ implications of research *- The single country sample and cross-sectional design restrict the generalizability in time and geography. The model should be replicated longitudinally and in various emerging-market environments in future studies to test the boundary conditions.*

Practical implications *- The results indicate that it is not possible to invest in digital tools only. Companies that simultaneously enhance their organizational preparedness, in the terms of infrastructure, talent and culture, get much more out of AI, analytics and mobile marketing programs.*

Originality/value *- The research is one of the first to establish DTR as a moderator, not a mediator in the digital marketing-performance chain, providing a more detailed description of when and to whom digital capabilities pay off. The six-industry design of comparison provides the contextual richness so uncommon to single-sector-based studies.*

Keywords: Adoption of artificial intelligence, Big data analytics, Mobile marketing, Marketing performance, Digital transformation readiness, PLS-SEM, Pakistan.

1. Introduction

There has been a change in how the practitioners approach to marketing in the last decade. Discussions about the creative campaigns and brand positioning have been replaced by discussions about algorithms, dashboards, and platform strategy. The transformation is not just superficial. The instruments that a marketing team will possess in 2024 have very little structural similarity to the one that even a decade ago, and the difference between organizations who have assimilated this fact and those who have not is growing at a rate that is visible in the performance statistics (Kannan and Li, 2017). The given paper is where three of those tools, namely Artificial Intelligence, Big Data Analytics, and Mobile Marketing, cross and where the question, which has not yet been answered with a clean response in the literature, is: does the underlying preparedness of an organization to digital transformation dictate the extent to which each of the mentioned tools can be leveraged?

The question is important because of a number of reasons. To begin with, there has been a rapid growth in the investment in digital marketing technologies. In 2023, global AI expenditure in marketing is estimated to be over USD 27 billion, and this figure is expected to increase by over three times by 2028. But the payoff on that investment is unequal. Companies within the identical industry, with competitive conditions broadly similar, regularly report performance which differs significantly after similar technology investments. One of the most reasonable explanations, which the current research is aiming to empirically test, is that absorptive capacity of the receiving organization mediates what any given technology may or may not be able to do (Zahra and George, 2002). We operationalize that capacity as Digital Transformation Readiness (DTR), which is a construct that reflects the maturity of infrastructure, the depth of human capital, the orientation of leadership, and the willingness to embrace change as a cultural phenomenon.

Second, the current literature addresses AI, Big Data Analytics, and Mobile Marketing in a more or less disconnected manner. Research on AI and personalization seldom interacts with the analytics infrastructure that personalization is realizable (Paschen et al., 2020). The literature on the effectiveness of mobile marketing does not explore smartphone penetration as a strategic ability to be nurtured; instead, it approaches it as an exogenous variable to be assumed (Shankar et al., 2016). And Big Data studies in marketing are commonly done about technical architecture and ignore the organizational circumstances under which findings based on data ever make it to a decision-maker in a format that can be utilized (Gandomi and Haider, 2015). The main theoretical contribution of this paper is the bringing of these three capabilities into one framework, moderated by DTR.

Third, the context of the developing market is also worth consideration. Majority of the empirical studies on effectiveness of digital marketing are based in North America, Western Europe, and East Asia- the markets where digital infrastructure is well developed and the level of DTR is comparatively high. It is a different story in Pakistan: fast smart phone diffusion, young digitally literate labor force and business environment where most organizations are still in the process of formalization of their digital marketing functions. It remains an open question whether the results of high-DTR contexts can be transferred to the situation where readiness is heterogeneous, but it also has some practical policy ramifications to government agencies that aim to enhance SME competitiveness with the help of digital capability programs.

The paper is divided as follows. Section 2 analyses the literature available on the topic and formulates the six hypotheses. In section 3, the conceptual framework is introduced. Section 4 presents the methodology. The results are reported in Section 5, both in the form of the PLS-SEM measure and the structural model results. The findings are discussed in sections 6 and 7, and concluded with implications and limitations.

2. Review of literature and hypothesis development.

2.1 Theoretical grounding

The research model is rooted in two theoretical traditions. Technology Acceptance Model was developed by Davis et al. (1989) and later developed by Venkatesh and Davis (2000) and suggests that the intention to use a technology is influenced mainly by the perceived usefulness and perceived ease of use. These perceptions are in effect in both the organizational marketing environment at individual levels and team levels, where overall evaluations of the credibility of a tool can influence the adoption momentum. The TAM has been widely used in the context of digital technology adoption research and has high explanatory strength in contexts of increasing complexity of technology portfolios (King and He, 2006).

The second pillar is provided through the Resource-Based View (Barney, 1991). In the case of TAM involving adoption behavior, RBV is concerned with the adoption technologies being resources that create enduring competitive advantage. Digital marketing products and services that are based on proprietary AI models trained using first-party customer data, or analytics pipelines that combine CRM, transactional, and behavioral signals in near real-time, are likely to fall into the requirements of being valuable, rare, and difficult to copy. The RBV thus aids in clarifying why companies that have equal access to technology can produce significantly different levels of performance: the structure and embeddedness of digital resources is equally important as the existence of such resources (Wernerfelt, 1984).

DTR is at the cross-section of the two frameworks. In TAM terms, increased preparedness reduces the perceived obstacles to successful technology adoption which enhances the likelihood that adoption will result in altered behavior and not shelf ware. In terms of RBV, even readiness is a higher-order organizational capability a capability to create capabilities that are the determinant of whether particular digital investments become lasting competitive resources or are wasted due to ineffective implementation, lack of talent, or cultural inertia.

2.2 Artificial Intelligence adoption

The applications of AI in marketing are broad and rapidly growing: predictive customer scoring, natural language generation to personalized content, visual search using computer vision, conversational agents, dynamic pricing, and algorithmic media buying, and so on. Davenport et al. (2020) posit that the most significant contribution of AI to marketing, however, is not the automation itself but the possibility to reveal and take action on customer behavior patterns that would not be detected by unassisted analysis. Companies that actualize this capacity have quantifiable increase in conversion rates, customer lifetime value, and cost efficiency in marketing.

Huang and Rust (2021) differentiate between mechanical AI tasks, which are proven to be better executed by the technology than by human and empathetic tasks, which remain at a loss of the technology to rival human judgement. The vast majority of existing marketing applications of AI are more mechanical in nature: segmentation, bid optimization, scales A/B testing, product recommendation. The performance boost is actual and quantifiable in those areas. It is not what AI tools a company buys but whether the company possesses the data governance, talent, and process architecture to run them at production scale that DTR is consequential.

H1. *The use of Artificial Intelligence exerts a major positive impact on the performance of marketing.*

H4. There is a positive moderation of Digital Transformation Readiness in the relationship between AI adoptions and marketing performances, where stronger the relationship is the higher the DTR.

2.3 Big Data Analytics

Big Data Analytics is the organizational ability to gather, store, process and understand vast and heterogeneous data to create insights that guide decisions. Customer interactions, web and application interactions, social media, email, and, most recently, IoT-enabled product usage are the most practically important data sets in marketing, which form a detailed, real-time view of how customers interact with brands across touchpoints (Chen et al., 2012).

Gandomi and Haider (2015) describe the benefits of BDA as the benefits of not only the volume of data but also the speed with which it can be processed and responses can be taken.

Another player who bases his current campaign decisions on the campaign data of the last quarter and you base your current campaign decisions on the data of the last day is not in a qualitatively similar strategic environment. The internal environment to BDA effectiveness is challenging - it needs solid data architecture, skilled analysts, governance structures, and cultures of decision making that are sincerely prepared to allow evidence to prevail over intuition. It is this set of organizational prerequisites that DTR captures.

H2. The impact of Big Data Analytics on marketing performance is very positive.

H5. Digital Transformation Readiness moderates the relationship between Big Data Analytics and marketing performance in a positive direction with the relationship being stronger with greater values of DTR.

2.4 Mobile Marketing

Mobile Marketing is any customer-facing marketing that is executed via or optimized to mobile devices. The tactical repertoire consists of SMS and push notification campaigns, in-app advertising, location-based targeting, QR code integration, mobile-optimized web content, and social commerce through platforms the use of which is dominated by mobile-first (Shankar et al., 2016). In markets where there was a swift transition of feature phones to smartphones, mobile is not just a single channel among many channels, but rather the dominant screen. Pakistan is of this profile.

In 2023, the Pakistan Telecommunication Authority indicated that there were over 120 million mobile broadband subscribers. Mobile marketing capability is a fundamental and not a support competency of the brands that work in this environment. The performance correlation is confirmed by studies of similar markets: mobile-first-customer-engagement strategy companies show increased customer acquisition, more brand recognition, and reduced cost-per-acquisition than companies with mobile as a secondary channel (Lim et al., 2021).

H3. Mobile Marketing has a significant positive effect on marketing performance.

H6. Digital Transformation Readiness moderates positively the relationship between Mobile Marketing and marketing performance, with the relationship being stronger with high levels of DTR.

2.5 Digital Transformation Readiness as moderator.

DTR is an organizational construct that is composite in nature with its constituents having been described differently in the literature. Westernman et al. (2014) discuss digital maturity and determine it to be technology assets, human capital and strategic intent as its key dimensions. In a study that specifically focuses on the setting of the adoption of digital technologies in the public sector, Varzaru (2023) identifies the perceived usefulness and ease of use of digital technologies as being influenced significantly by the level to which an adopting organization has equipped its infrastructure and workforce. In their study on the performance of SMEs in Jordan, Sharabati et al. (2024) put digital transformation at the forefront as a process variable that converts digital marketing strategies into business results.

The decision to model DTR as a moderator, as opposed to a mediator, is what makes the current study unique. The moderation framing suggests that the performance effect of every digital tool depends on the degree of preparedness that the organization has on its implementation. The practical implications of this difference are as follows: a company that implements AI tools without addressing the deficits in readiness should not anticipate returning as much as the theoretical capabilities of this technology would indicate not because the technology cannot work but due to the lack of the organizational conditions required to realize it. Such framing is consistent with the absorptive capacity theory (Zahra and George, 2002) that states that the existing related knowledge and organizational routines dictate the effectiveness with which firms can identify, internalize, and utilize new information.

2. Conceptual framework

The research model places AI adoption, Big Data Analytics, and Mobile Marketing as independent predictors of the marketing performance (DV). DTR is represented as a pure moderator which forms three terms of interaction: AI x DTR, BDA x DTR and MM x DTR. The model is based on TAM of the dynamics of adoption of each of the IV and RBV of the implications of digital resource deployment in terms of performance. The constructs, their theoretical roles, constituent dimensions, and approach of measurement are summarized in table 1. The PLS-SEM structural model – displaying indicator loadings, path coefficients, interaction paths, and model fit statistics – is presented in Figure 1.

Table 1 Research constructs: roles, dimensions, and measurement

Construct	Role	Core dimensions	Items	Scale
AI Adoption	Independent	Tool usage; perceived usefulness; integration depth; trust in AI outputs	5	5-pt Likert
Big Data Analytics	Independent	Data collection scope; processing capability; insight generation; decision integration	5	5-pt Likert
Mobile Marketing	Independent	SMS/push activity; app-based engagement; location targeting; mobile content quality	5	5-pt Likert
Digital Transformation Readiness	Moderator	IT infrastructure; digital talent; leadership commitment; data governance; cultural openness	6	5-pt Likert
Marketing Performance (DV)	Dependent	Market share; customer acquisition; brand equity; ROMI; customer retention; satisfaction	6	5-pt Likert
Industry Sector	Contextual	FMCG; Retail; Financial Services; Healthcare; Telecommunications; E-commerce	—	Categorical

Source: Authors' own elaboration based on Davis et al. (1989), Barney (1991), Gandomi and Haider (2015), Shankar et al. (2016), Paschen et al. (2020), Varzaru (2023), and Sharabati et al. (2024)

Methodology

4.1 Design and philosophical orientation of the research.

The research takes the positivist epistemological position and a quantitative research design. Positivism should be used in situations where the objective is to test specifically formulated hypotheses regarding the causal relationship between measurable constructs (Bryman, 2016). The cross-sectional survey design is used, which is typical of TAM and marketing technology adoption literatures. The analytical method, PLS-SEM, is selected due to its ability to consider both formative and reflective measurement models, works reasonably with moderate sample sizes, and is specifically designed to test theories in management research with multiple interaction terms (Hair et al., 2017).

4.2 Population, sampling and data collection.

The target group is the marketing managers, brand managers, digital marketing specialists and senior marketing officers of organizations operating in Pakistan in the six industry sectors. The respondents must be employed within a professionally oriented marketing field and must be involved directly in making marketing decisions that involve technology in the present job. The sampling is stratified and the six industry sectors are the strata. The data collection will be performed during a ten-week period and two follow-up reminders will be given at week four and seven. Out of 490 surveys that are issued, 378 are returned. The total sample that can be used is 350 after eliminating 28 non-responses or marginally suspicious, which translates to a response rate of 71.44% which is well above the 60 percent mark required by survey-based management research (Baruch and Holtom, 2008).

Table 2 Sample composition by industry sector

Industry sector	Target (n)	Achieved (n)	Achieved (%)
FMCG	65	63	18.0
Retail	60	59	16.9
Financial services	60	61	17.4
Healthcare	55	56	16.0
Telecommunications	55	57	16.3
E-commerce	55	54	15.4
Total	350	350	100.0

Source: Primary survey data

4.3 Measurement instrument

The questionnaire is organized into six sections. Everything is rated on a five-point Likert scale with the anchors being strongly disagree (1) and strongly agree (5). The items are based on the scales previously validated in the literature: AI adoption items are based on Paschen et al. (2020); BDA items are based on Gandomi and Haider (2015); Mobile Marketing items are based on Shankar et al. (2016); DTR items are based on Varzaru (2023); marketing performance items are based on the scale utilized by Sharabati et The wording of the items was reviewed by a panel of three academic reviewers and two industry practitioners. Cronbach alpha values were greater than 0.78 in all constructs in a pilot study with 45 respondents.

4.4 Analytical strategy

The analysis is carried out in three steps. The initial reliability tests and descriptive statistics are performed in SPSS v26. Second, all five constructs are measured by reflective indicators in Smart PLS v4.0. Reliability is discussed in terms of Cronbach alpha and composite reliability (CR); convergent validity in terms of average variance extracted (AVE); and discriminant validity in terms of the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). Third, structural model estimation is done through bootstrapping (using 5,000 subsamples) and using a two-tailed significance of 0.05. The two-stage strategy as suggested by Hair et al. (2017) is used to create interaction terms. Multi-group analysis (MGA) based on permutation test is employed to compare the path coefficients of the six industry strata.

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CJSSR
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5. Results

5.1 Sample characteristics

The sample is composed of 62% male respondents. The age group that is mostly dominant is 3140 years (41%), as per the criteria of seniority. Most of them (52) have bachelors (degree), and the rest are master graduates (36). The distribution of experience is skewed to the middle range: 38% have 610 years in marketing and 22% of them have 1115 years of experience. The professed specialization of the 58% of respondents is marketing, and the rest is spread among business management, digital strategy, and related domains.

5.2 Common method bias assessment

Since the measurements of all constructs are taken at the same time and on the same respondent, common method variance (CMV) should be considered. Harman single factor test is performed by inputting all items in a factor analysis on an exploratory analysis with no rotation restriction. The un rotated greatest factor measures 23.4% of total variance which is far less than the 50% level traditionally considered to be serious CMV (Podsakoff et al., 2003). When a theoretically unrelated construct is used to determine marker variable analysis, it does not show any significant correlations with study variables. Taken together these findings indicate that CMV cannot be a significant confounding factor.

5.3 Measurement model

The results of reliability and validity of all five constructs are shown in Table 3. All Cronbach alpha values lie between 0.812 and 0.901, with composite reliability values ranging between 0.871 and 0.932, both more than comfortable well above the 0.70 and 0.80 levels respectively. The values of AVE are consistently over 0.50, which supports convergent validity. All HTMT ratios are below 0.85 indicating discriminant validity: respondents are making a clear distinction between the constructs and not confusing them.

Table 3 Measurement model: reliability and validity statistics

Construct	Cronbach's α	CR	AVE	HTMT max	Assessment
AI Adoption (IV1)	0.863	0.901	0.644	0.741	Acceptable
Big Data Analytics (IV2)	0.849	0.891	0.621	0.763	Acceptable
Mobile Marketing (IV3)	0.812	0.871	0.612	0.749	Acceptable
Digital Transf. Readiness (Moderator)	0.901	0.932	0.721	0.782	Acceptable
Marketing Performance (DV)	0.889	0.919	0.698	0.771	Acceptable

CR = composite reliability; AVE = average variance extracted; HTMT = heterotrait–monotrait ratio (maximum across all construct pairs). Source: SmartPLS v4.0 output

5.4 PLS-SEM structural model

The entire PLS-SEM model created using Smart PLS v4.0 is shown in figure 1. The diagram illustrates the three independent variable constructs on the left, with their respective indicator loadings (between 0.788 and 0.847 among all the IVs). The Digital Transformation Readiness moderator is displayed in the upper part, and the dashed purple moderation paths are indicated to the nodes of interaction junction on each main effect path. On the right is Marketing Performance showing six indicator loadings (0.797-0.831). The value of R2 (0.674) is displayed in the DV box. Each structural path is presented with path coefficients and hypothesis labels and the significance is annotated with asterisks (*** p <0.001).

5.5 Hypothesis testing results

Table 4 reports path coefficients, standard errors, t-statistics, p-values, and hypothesis decisions. The structural model explains 67.4% of the variance in marketing performance ($R^2 = 0.674$; adjusted $R^2 = 0.668$), indicating strong explanatory power. The predictive relevance statistic Q^2, obtained via blindfolding, is 0.489, substantially above zero and confirming meaningful out-of-sample predictive accuracy (Hair et al., 2017). SRMR is 0.061, below the recommended threshold of 0.08, indicating acceptable model fit.

All six hypotheses are supported at conventional significance levels. Among the main effects, AI adoption returns the largest standardized coefficient ($\beta = 0.412$, $t = 8.92$, $p < 0.001$). BDA follows closely ($\beta = 0.387$, $t = 7.64$, $p < 0.001$), and Mobile Marketing, while the smallest of the three main effects, remains economically and statistically significant ($\beta = 0.356$, $t = 6.89$, $p < 0.001$). All three moderation effects are significant, with the AI×DTR interaction producing the largest incremental coefficient ($\beta = 0.219$), indicating that the performance advantage of AI adoption is particularly pronounced in organizations that have invested in the foundational conditions for digital transformation.

Table 4 Structural model results and hypothesis decisions

Hypothesis	Relationship	β	SE	t	p	Decision
H1	AI Adoption → Marketing Performance	0.412	0.046	8.92	<0.001	Supported
H2	Big Data Analytics → Marketing Performance	0.387	0.051	7.64	<0.001	Supported
H3	Mobile Marketing → Marketing Performance	0.356	0.052	6.89	<0.001	Supported
H4	AI Adoption × DTR → Marketing Performance	0.219	0.051	4.31	<0.001	Supported
H5	BDA × DTR → Marketing Performance	0.198	0.050	3.99	<0.001	Supported
H6	MM × DTR → Marketing Performance	0.183	0.049	3.74	<0.001	Supported

Bootstrap resamples = 5,000; two-tailed test; SE = standard error; DTR = Digital Transformation Readiness. Source: SmartPLS v4.0 output

5.6 Multi group analysis in terms of industry sectors.

Table 5 shows the sector-specific path coefficients and explained variance of MGA based on the permutation test of 5,000 iterations. E-commerce has the largest explained variance ($R^2 = 0.741$), and path coefficients of AI adoption (0.488) and BDA (0.456) are significantly higher compared to those of healthcare ($p = 0.05$) which has the lowest overall model fit ($R^2 = 0.618$). Among all industries, the BDA coefficient ($\beta = 0.441$) in financial services is the highest. Mobile marketing is the largest predictor ($\beta = 0.387$) in FMCG, which supports the strategic rationale of investing in mobile-first campaigns in the industry where the purchase frequency is high, and consumers are ready to make their brand decisions within a short period.

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CJSSR

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Table 5 Multi-group analysis: standardized path coefficients by industry sector

Sector	AI → Perf	BDA → Perf	MM → Perf	DTR mod	R^2
FMCG	0.398	0.341	0.387	Moderate	0.641
Retail	0.421	0.368	0.412	High	0.679
Financial services	0.467	0.441	0.298	Very high	0.712
Healthcare	0.356	0.389	0.312	Moderate	0.618
Telecommunications	0.449	0.421	0.376	High	0.698
E-commerce	0.488	0.456	0.443	Very high	0.741

Sector differences in AI and BDA coefficients between e-commerce and healthcare are significant at $p < 0.05$ (permutation test). Source: SmartPLS v4.0 MGA output

6. Discussion

The performance of all three digital marketing capabilities is positively predicted is consistent with previous literature, but also has a theoretical significance in what the magnitude ordering suggests. The primacy of AI adoption (β = 0.412) demonstrates a qualitative change to what marketing is capable of doing when algorithmic intelligence is incorporated in the execution of campaigns, customer segmentation, and content delivery. It is not merely more rapid execution of existing tasks but rather the ability to execute tasks which would have been impractically challenging to do at scale in the past because AI did not exist commercially. The conclusion echoes Huang and Rust (2021), who claim that the enduring marketing benefit of AI is its ability to manage the complexity of analysis that is beyond the human cognitive bandwidth.

The fact that BDA has a coefficient that follows closely (β=0.387) is not surprising because, in reality, AI and analytics are closely intertwined: AI systems need data, and analytics infrastructure is the means through which data can become decision-relevant. The similar coefficients imply that, in the organizational situations of the sample, AI and BDA capabilities are more likely to co-evolve than to develop separately, which aligns with the data flywheel logic, which has been reported in the strategic management of technology platforms (Parker et al., 2016). The smaller, yet still significant coefficient (β = 0.356) of mobile marketing is what makes it a channel layer, through which the insights created by AI and analytics are finally reported to the customers.

The most significant empirical observation in the study, which is, arguably, the confirmation of all the three moderation hypotheses, is the result obtained. The traditional discourse on the digital marketing literature approaches technology investment as the core driver of performance enhancement, with organizational issues recognized incidentally as implementation issues. The implications of the moderation results are even more basic: the level of digital readiness of the organization is not a secondary factor but the first-order determinant of the extent to which any particular technology can create value.

At the lower end of the DTR distribution, an organization investing in AI capability is likely to experience a significant yet small performance payoff. That investment in a high-DTR organization yields a much greater payoff, not due to the different technology, but due to a different organizational context in which the outputs are trusted, acted on and continually improved. There is an exact equivalent of this finding in the literature of absorptive capacity. Zahra and George (2002) differentiate between potential absorptive capacity- the possibility to obtain and absorb new knowledge - and realized absorptive capacity, the possibility to transform, as well as exploit it. DTR is similar to realized absorptive capacity: access to digital technologies is necessary but not sufficient.

The cross-industry results are educative in the obscured manner of aggregate analyses. The relatively weak R^2 (0.618) and moderate DTR moderation effect indicate a sector in which regulatory restrictions, data privacy considerations, and prioritization of clinical credibility over digital interaction restrain the extent to which digital marketing technologies can, alone, instigate performance outcomes. At the other extreme, e-commerce and financial services are in a domain where digital interaction IS the main customer experience, and the very high DTR moderation effect in both industries validates readiness as the amplifier. The unique profile of FMCG, with mobile marketing the most significant single predictor, is the economic nature of the industry, with mobile-elicited offers, loyalty applications, and social commerce occurring just at the point the most significant influence on purchase is created.

7. Conclusion

The aim of this paper was to explore if and how the adoption of AI, Big Data Analytics, and Mobile Marketing can have an impact on marketing performance in a developing-market setting, and whether these impacts depend on Digital Transformation Readiness. The outcomes of the PLS-SEM give positive responses on both fronts. The three digital capabilities are all important positive predictors of marketing performance and each of them has meaningfully stronger relationships with DTR. The multi-group analysis of six industry sectors shows that there is no uniformity in digital marketing-performance nexus across industries.

Theoretically, the research has three contributions. It is one of the first to conceptualize DTR as a moderator of particular digital marketing capability-performance associations instead of a mediator or direct foreteller. Second, the combination of TAM and RBV would offer a better theoretical foundation compared to either one. Third, the six-sector comparative design makes it known that there are significant contextual conditions of the relationship between digital marketing and performance, beyond the ability of prior single-sector studies to establish.

To the marketing executives, the core practical message is that the investment of technology should be supported by the readiness investment. Companies who buy AI systems, analytics systems, and mobile engagement systems without governing the system, talent capability, and cultural orientation towards data-driven decision-making are unlikely to achieve more than a portion of the potential performance upside. Sequencing is important: readiness-building is not a follow-on process but a precondition to the efficient deployment. The findings highlight to policymakers in developing markets the need to implement ecosystem-level interventions, including cloud infrastructure incentives, data governance frameworks, and digital skills training programs, which can enhance preparedness in the SME sector.

Limitations and future research

There are a number of limitations. The cross-sectional design implies that causality is derived theoretically but not proven by a time sequence; a longitudinal panel would be better to support causal inferences. The one-country sample does not allow generalization to other emerging markets, which are not Pakistan in critical aspects such as the level of digital infrastructure development and regulatory environment. The model should be recreated in at least one more MENA or South Asian market in the future to check the conditions of geographic boundaries. The performance outcome is self-reported, and both independent variables are self-reported, which brings into question the possibility of construct conflation, which can be resolved using objective performance data. Lastly, the fact that DTR can be broken down into its individual dimensions to determine the elements that contribute the most to the moderation effect is an excellent area to pursue, as it would offer more managerial-level advice.

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