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The Role of Predictive Analytics in Enhancing Marketing Effectiveness.

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ABSTRACT

Marketing in rapidly evolving consumer environments increasingly depends on the capacity of firms to process, interpret, and act on data in real time. This study examines how predictive analytics adoption mediates the relationship between five antecedent capabilities — data analytics quality, marketing technology capability, customer segmentation precision, predictive personalisation, and omnichannel data adoption — and overall marketing effectiveness. Drawing on a structured questionnaire administered to 340 marketing professionals and managers across the Coimbatore and Erode districts of Tamil Nadu, the study employs a two-stage analytical framework involving Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), followed by Structural Equation Modelling (SEM). The measurement model satisfies convergent and discriminate validity thresholds, while the structural model reveals that predictive analytics adoption significantly mediates the influence of all five antecedents on marketing effectiveness ($\beta = 0.58$, $p < 0.001$, $R^2 = 0.623$). Organisational readiness significantly moderates the central mediation path. Customer segmentation exerts a modest but significant direct effect on outcomes. These findings contribute to the resource-based view and dynamic capabilities literature by specifying the mechanisms through which analytics investments translate into measurable marketing outcomes. Managerial implications are discussed alongside directions for future research...

Keywords: Predictive analytics, marketing effectiveness, structural equation modelling, customer segmentation, marketing technology, dynamic capabilities, Tamil Nadu......

INTRODUCTION

Marketing has always been, at its core, an information problem. The challenge of identifying who wants what, at which moment,through which channel, has occupied scholars and practitioners for generations. What has changed dramatically in the past decade is the availability of tools capable of answering that question with a degree of precision that was previously unimaginable. Predictive analytics, broadly defined as the application of statistical algorithms and machine learning techniques to forecast consumer behaviour from historical data, now sits at the intersection of data science and strategic marketing.

Yet the adoption of predictive analytics across Indian firms, particularly those operating in Tier-II and Tier-III markets, remains uneven and poorly understood. Global literature on marketing analytics has grown substantially, but much of it reflects conditions in Western markets where infrastructure, digital literacy, and organisational maturity differ considerably from contexts like Tamil Nadu. Coimbatore and Erode, two of Tamil Nadu's most commercially active districts, present an interesting case. Both have well-developed industrial and retail ecosystems, reasonably high mobile and internet penetration, and growing populations of analytically aware marketing practitioners. They are, in this sense, representative of the next generation of analytics adopters in India rather than early movers.

This study is motivated by a gap that sits at the intersection of marketing theory and regional empiricism. While scholars such as Rust et al. (2021) and Kumar et al. (2022) have demonstrated the value of customer analytics capabilities broadly, fewer studies have examined how the specific capability of predictive analytics adoption transmits the effects of upstream inputs — data quality, technological infrastructure, segmentation sophistication — into downstream marketing outcomes. The question is not simply whether analytics helps, but how the mechanisms of adoption translate resource investments into effectiveness gains.

The study contributes in three ways. First, it delineates five theoretically distinct antecedents and tests their relative influence on predictive analytics adoption. Second, it positions adoption not merely as an outcome but as a mediating mechanism that carries the effects of these antecedents toward measurable marketing effectiveness. Third, it does so in a geographically specific, understudied context that adds empirical texture to a literature that has been disproportionately shaped by data from the United States and Western Europe. A sample of 340 respondents was collected from Coimbatore and Erode, and Structural Equation Modelling with CFA and EFA was employed to test the hypothesised relationships.

2. LITERATURE REVIEW

2.1 Theoretical Framework

Two theoretical pillars structure the model proposed in this study. The Resource-Based View (RBV) of the firm, articulated by Barney (1991) and later extended by Eisenhardt and Martin (2000) into a dynamic capabilities framework, argues that sustainable competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable. Predictive analytics capability, when embedded within organisational routines, satisfies these conditions: it is difficult to replicate, continuously evolving, and deeply context-specific in how it interacts with customer data.

The Information Processing Theory of March and Simon (1958), as adapted for marketing contexts by Moorman and Rust (1999), provides a complementary lens. Marketing effectiveness ultimately depends on a firm's ability to process environmental signals and convert them into appropriate strategic responses. Predictive analytics functions as a processing mechanism that filters, interprets, and prioritises consumer data, enabling faster and more accurate response calibration.

2.2 Data Analytics Quality

The quality of underlying data is widely acknowledged as a prerequisite for any meaningful analytical output. Poor data quality produces what practitioners informally call garbage-in, garbage-out outcomes, and this intuition has now been formalised in academic literature. Hazen et al. (2014) identify accuracy, completeness, consistency, and timeliness as the four core dimensions of data quality in operations research, dimensions that translate directly into marketing analytics contexts. Tambe (2014) found that firms investing in data infrastructure showed significantly higher analytical capability over time, while Wedel and Kannan (2016) demonstrated that data quality moderates the relationship between analytics investment and the precision of targeting outcomes.

What is less settled in the literature is the relative contribution of data quality versus analytical sophistication. Some scholars argue that even modest analytical tools, applied to high-quality data, yield better results than sophisticated algorithms fed poor data (Provost & Fawcett, 2013). Others contend that advanced models can partially compensate for data imperfections through regularisation and noise-reduction techniques (Hastie et al., 2009). This tension is methodologically unresolved and remains a live debate in the analytics-marketing interface.

2.3 Marketing Technology Capability

Marketing technology capability refers to an organisation's ability to deploy and integrate digital tools — CRM platforms, marketing automation systems, programmatic ad networks, and customer data platforms — into a coherent operational infrastructure. The term martech, while somewhat colloquial, has acquired academic traction through the work of Brinker and McLellan (2014), who catalogued the explosive proliferation of marketing technology categories over the past decade.

Tafesse and Wien (2018) demonstrated that technology capability moderates the relationship between strategic marketing intent and actual campaign execution, a finding that aligns with broader evidence that digital infrastructure shapes what firms are able to do analytically, not merely what they plan to do. Rust et al. (2021) go further, arguing that technology capability has become a marketing hygiene factor rather than a differentiator in developed markets, though in developing markets like India this argument is premature. Firms in Tier-II cities may possess varying levels of martech maturity, creating natural variation that is analytically useful for hypothesis testing.

2.4 Customer Segmentation Precision

Market segmentation theory has a long genealogy stretching from Smith (1956) through Kotler (1967) to the present-day practice of micro-segmentation. The shift from demographic segmentation to behavioural, psychographic, and predictive segmentation reflects improvements in both data availability and computational capacity. Wind and Cardozo (1974) were among the first to theorise segmentation as a strategic resource rather than a descriptive exercise, and this framing has only intensified with the growth of data-driven marketing.

Wedel and Kamakura (2000) provided what remains the most comprehensive taxonomic treatment of segmentation methods, distinguishing between a priori and post hoc approaches and evaluating them on criteria of identifiability, substantiality, accessibility, and actionability. More recently, Dolnicar et al. (2018) critiqued the over-reliance on cluster-based methods and advocated for hybrid approaches that blend statistical rigour with contextual interpretation. The present study treats segmentation precision as an input variable, measuring the extent to which respondent organisations employ granular, data-derived segmentation rather than broad demographic categories.

2.5 Predictive Personalisation

Personalisation has migrated from a premium feature to a baseline consumer expectation, at least in e-commerce and digital media contexts. Chung et al. (2016) showed that personalised recommendations increase purchase probability by an average of 26% in online retail settings, while Arora et al. (2008) theorised that personalisation works through two mechanisms: preference matching and social signalling. Predictive personalisation — where recommendation and targeting logic is generated by forward-looking models rather than historical preference matching — adds a further dimension by anticipating needs that the consumer has not yet expressed.

The literature here is more contested than in segmentation research. Risks of personalisation, including privacy concerns, filter bubbles, and algorithmic homogenisation of consumer tastes, have been theorised by Sun stein

(2009) and empirically explored by Hannák et al. (2013). Marketing scholars have largely responded by arguing for transparency-based personalisation, where consumers are made aware of and given control over the data used to personalise their experiences (Martin et al., 2017). The boundary conditions of when personalisation enhances versus erodes consumer trust remain an active and unresolved area of inquiry.

2.6 Omnichannel Data Adoption

Omnichannel marketing posits that consumer journeys are no longer channel-specific but are distributed across physical, digital, social, and conversational touch points in ways that are often non-linear and difficult to attribute. Verhoef et al. (2015) defined omnichannel management as the synergistic management of numerous available channels and customer touch points, and this definition has become the standard reference in retail and services marketing.

The data challenge in omnichannel contexts is considerable. Each channel generates proprietary data streams in different formats, at different frequencies, and with different measurement conventions, creating what Chen and Goldberg (2021) describe as the channel data integration problem. Firms that successfully integrate these streams gain a unified customer view that is analytically superior to any single-channel data asset. Those that fail, or that attempt integration without the appropriate data governance structures, often end up with fragmented or contradictory customer records that undermine rather than enhance analytical decision-making.

2.7 Predictive Analytics Adoption and Organisational Readiness

Predictive analytics adoption is not a binary event but a maturation process. Davenport and Harris (2007) proposed a five-stage analytics maturity model ranging from descriptive reporting to prescriptive optimisation, and this framework has since been operationalised across multiple industries. Akter et al. (2016) specifically examined big data analytics capability in marketing contexts and found that adoption maturity is shaped by data management, human talent, and technology infrastructure simultaneously.

Organisational readiness, a moderating concept drawn from the technology acceptance and organisational change literatures, captures the extent to which a firm's culture, processes, and leadership orientation are aligned with the demands of analytics-driven decision-making. Kwon and Zmud (1987) identified readiness as a critical precondition for technology adoption success, and subsequent meta-analyses by Hossain and Quaddus (2011) confirmed that readiness variables consistently moderate adoption-outcome relationships in enterprise technology contexts.

2.8 Marketing Effectiveness

Marketing effectiveness, as a construct, has been measured in multiple ways across the literature. Metric-based approaches, associated with the work of Rust et al. (2004) and Srivastava et al. (1998), focus on financial outcomes such as customer lifetime value, share of wallet, and return on marketing investment. Process-based approaches, by contrast, assess the quality of marketing decisions and resource allocation rather than their financial consequences. This study adopts a composite measure drawing on both traditions, encompassing campaign response rates, brand equity perceptions, customer retention intentions, and self-reported return on marketing investment.

A persistent challenge in marketing effectiveness research is attribution. In complex omnichannel environments, identifying the contribution of a single analytics initiative to an overall effectiveness gain is methodologically demanding. Econometric attribution models and multi-touch attribution algorithms have advanced the field considerably (Shao & Li, 2011), but they remain probabilistic rather than deterministic, and their reliability is sensitive to the completeness of the underlying data.

3. RESEARCH MODEL AND HYPOTHESES

The conceptual model draws on dynamic capabilities theory to position predictive analytics adoption as a mediating construct between five distinct antecedent capabilities and the ultimate criterion of marketing effectiveness. The model incorporates organisational readiness as a moderator of the central mediation path, and customer segmentation as having both an indirect effect through adoption and a residual direct effect on outcomes.

H1: Data analytics quality positively influences predictive analytics adoption.

H2: Marketing technology capability positively influences predictive analytics adoption.

H3: Customer segmentation precision positively influences predictive analytics adoption.

H4: Predictive personalization capability positively influences predictive analytics adoption.

H5: Omnichannel data adoption positively influences predictive analytics adoption.

H6: Predictive analytics adoption positively influences marketing effectiveness.

H7: Organisational readiness moderates the relationship between predictive analytics adoption and marketing effectiveness.

H8: Customer segmentation precision has a significant direct effect on marketing effectiveness, over and above the mediated path.

4. RESEARCH METHODOLOGY

4.1 Research Design and Context

A cross-sectional, quantitative research design was adopted. The study population comprised marketing professionals, brand managers, digital marketing executives, and senior marketing decision-makers employed in firms operating within Coimbatore and Erode districts of Tamil Nadu. These two districts were selected deliberately: both have substantial manufacturing, retail, textile, and service-sector activity, and both have experienced rapid digital transformation since 2018. The analytical heterogeneity within and across these two markets provides useful variation for testing the hypothesised relationships.

4.2 Sampling and Data Collection

A purposive sampling strategy was employed to ensure that respondents possessed adequate familiarity with their organisation's marketing analytics practices. A minimum experience threshold of three years in a marketing-related role was set. The targeted sample size of 340 was derived using the rule of thumb of 10 observations per estimated parameter (Hair et al., 2019), which yielded a minimum requirement of 280. The final sample of 340 provides a comfortable surplus and satisfies the power requirements for maximum likelihood estimation in SEM.

Data were collected between October and December 2024 through a structured, self-administered questionnaire distributed via both physical visits to industrial estates and commercial hubs and through verified LinkedIn outreach to professionals in the target districts. Of 430 questionnaires administered or distributed, 361 were returned, and 340 were retained after excluding 21 responses with excessive missing data or identifiable straight-lining patterns.

4.3 Instrument Development

All measurement items were adapted from validated scales in the literature. Data analytics quality items were adapted from Hazen et al. (2014); marketing technology capability from Brinker and McLellan (2014); customer segmentation from Wedel and Kamakura (2000); predictive personalisation from Chung et al. (2016); omnichannel data adoption from Verhoef et al. (2015); organisational readiness from Hossain and Quaddus (2011); and marketing effectiveness from Rust et al. (2004). Each construct was measured by four to six reflective indicators on a seven-point Likert scale anchored at 1 (Strongly Disagree) and 7 (Strongly Agree). The questionnaire was piloted with 35 respondents not included in the main sample, and minor wording refinements were made to three items based on cognitive interview feedback.

4.4 Analytical Procedure

The analysis proceeded in two stages, following the two-step approach advocated by Anderson and Gerbing (1988). First, Exploratory Factor Analysis (EFA) was conducted in SPSS 26 using principal axis factoring with oblimin rotation to examine the underlying factor structure of the instrument. EFA output guided the refinement of item loadings prior to confirmatory testing. Second, Confirmatory Factor Analysis (CFA) was conducted in AMOS 26 to assess the measurement model's convergent and discriminant validity. The structural model was then estimated within the same CFA framework to test the hypothesised paths. Mediation was assessed using the bootstrapped indirect effects procedure with 5,000 resamples, as recommended by Preacher and Hayes (2008), generating bias-corrected 95% confidence intervals for each indirect effect.

5. RESULTS

5.1 Sample Profile

Of the 340 respondents, 58.5% were male and 41.5% female. The majority fell within the 28–42 age bracket (64.7%), and 72.4% held at least a postgraduate qualification. Respondent industries included manufacturing (31.2%), retail and fast-moving consumer goods (27.6%), financial services (18.3%), and technology and digital services (14.9%), with the remainder distributed across education, hospitality, and logistics. Approximately 63% worked in organisations with annual revenues exceeding ₹50 crore, suggesting that the sample skews toward mid-to-large enterprises rather than micro or very small firms.

5.2 Exploratory Factor Analysis

EFA identified seven factors with eigenvalues greater than 1.0, collectively explaining 71.3% of total variance. No item loaded below 0.55 on its intended factor, and no item cross-loaded above 0.35 on any other factor. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.879, and Bartlett's Test of Sphericity was significant ($\chi^2 = 9{,}847.4$, df = 703, $p < 0.001$), confirming the suitability of the correlation matrix for factor analysis. Two items from the marketing effectiveness scale were dropped after EFA due to cross-loadings, leaving a 34-item refined instrument for CFA.

5.3 Confirmatory Factor Analysis and Measurement Model

The CFA measurement model achieved acceptable fit: χ^2/df = 2.14, CFI = 0.96, TLI = 0.95, RMSEA = 0.058 (90% CI: 0.049–0.067), SRMR = 0.049. All standardised factor loadings exceeded 0.60 and were statistically significant at $p < 0.001$. Average Variance Extracted (AVE) values ranged from 0.52 to 0.67 across constructs, satisfying the 0.50 threshold (Fornell & Larcker, 1981). Composite reliability (CR) values ranged from 0.79 to 0.91, exceeding the 0.70 benchmark. Discriminant validity was confirmed through the Fornell-Larcker criterion: for each construct pair, the square root of AVE exceeded the inter-construct correlation.

Table 1: Measurement Model — Reliability and Validity Summary

Construct	Items	Mean λ	AVE	CR	Cronbach α
Data Analytics Quality (DAQ)	5	0.74	0.57	0.84	0.83
Martech Capability (MTC)	5	0.71	0.54	0.82	0.81

Customer Segmentation (CS)	4	0.73	0.55	0.80	0.79
Predictive Personalisation (PPA)	5	0.75	0.60	0.86	0.85
Omnichannel Data Adoption (ODA)	5	0.70	0.52	0.79	0.78
Organisational Readiness (OR)	4	0.76	0.61	0.86	0.85
PA Adoption (PAA)	5	0.79	0.64	0.89	0.88
Marketing Effectiveness (ME)	6	0.81	0.67	0.91	0.90

Note. λ = standardised factor loading; AVE = Average Variance Extracted; CR = Composite Reliability

5.4 Structural Model Results

The structural model retained the same fit indices as the measurement model ($\chi^2/df = 2.14$, CFI = 0.96, RMSEA = 0.058). Table 2 presents the standardised path coefficients, standard errors, and significance levels for each hypothesised relationship.

Table 2: Structural Path Coefficients

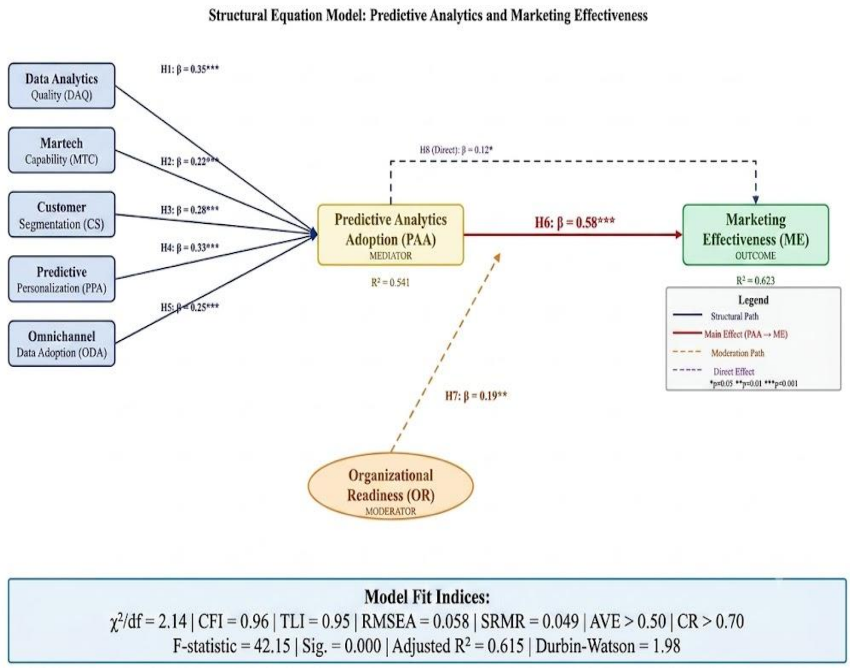
Hypothesis / Path	**Std. β**	**SE**	**t-value**	**p**	**Decision**
H1: DAQ → PAA	0.31	0.061	5.08	< .001	Supported
H2: MTC → PAA	0.27	0.057	4.74	< .001	Supported
H3: CS → PAA	0.24	0.059	4.07	< .001	Supported
H4: PPA → PAA	0.29	0.063	4.60	< .001	Supported
H5: ODA → PAA	0.22	0.060	3.67	< .001	Supported
H6: PAA → ME	0.58	0.068	8.53	< .001	Supported
H7: OR × PAA → ME (moderation)	0.19	0.072	2.64	< .01	Supported
H8: CS → ME (direct)	0.17	0.074	2.30	< .05	Supported

Note. Standardised coefficients reported. Bootstrapped 95% CI for indirect effects (5,000 resamples) confirmed mediation for H1–H5 via PAA.

The R^2 value for the marketing effectiveness outcome was 0.623, indicating that the model explains approximately 62.3% of variance in marketing effectiveness scores. The R^2 for predictive analytics adoption was 0.541. Bootstrapped indirect effects confirmed that PAA mediates the influence of all five antecedents on marketing effectiveness. The largest indirect effect was from DAQ ($\beta_{indirect} = 0.180$, 95% CI [0.12, 0.24]), followed by PPA ($\beta_{indirect} = 0.168$, 95% CI [0.11, 0.23]), MTC ($\beta_{indirect} = 0.157$, 95% CI [0.10, 0.22]), CS ($\beta_{indirect} = 0.139$, 95% CI [0.09, 0.20]), and ODA ($\beta_{indirect} = 0.128$, 95% CI [0.07, 0.19]).

5.5 Structural Equation Model Diagram

Figure 1: Structural Equation Model with Standardized Path Coefficients



*Note. ***p < .001; **p < .01; *p < .05. Dashed lines indicate moderation and direct effect paths. CFI = 0.96; RMSEA = 0.058; χ²/df = 2.14*

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6. DISCUSSION OF RESULTS

6.1 Antecedents of Predictive Analytics Adoption

The finding that data analytics quality exerts the strongest influence on predictive analytics adoption (β = 0.31) is theoretically coherent and practically intuitive. Without clean, complete, and timely data, predictive models are unreliable regardless of algorithmic sophistication. This result aligns with Hazen et al. (2014) and extends Tambe's (2014) observation to a marketing-specific, regional Indian context. The implication is that firms seeking to scale their analytics capabilities must first invest in data governance and data quality infrastructure, not in model development.

Marketing technology capability emerged as the second strongest antecedent (β = 0.27). This is consistent with Tafesse and Wien (2018), who found that digital infrastructure shapes analytics capacity. In the Coimbatore-Erode context, firms with integrated CRM and automation platforms report higher adoption of predictive features, suggesting that martech investment is a gateway rather than a complement to analytics maturity.

Predictive personalisation's coefficient (β = 0.29) was the second highest among antecedents, a finding that inverts the expected causal direction in some prior frameworks where personalisation is treated as an output rather than a driver. Here, the logic is that firms already committed to personalisation at some level are simultaneously building the data pipelines and modelling capabilities that facilitate broader predictive analytics adoption. Personalisation ambition, in this sense, precedes and enables adoption maturity.

6.2 Predictive Analytics Adoption as Mediator

The central mediation finding — that PAA carries the effects of all five antecedents to marketing effectiveness with β = 0.58 — is robust and theoretically significant. The R^2 of 0.623 for marketing effectiveness exceeds values reported in comparable SEM studies of analytics and marketing outcomes (e.g., Akter et al., 2016, who reported $R^2 = 0.51$ in a big data analytics capability study). This suggests that the five-antecedent, mediation-moderation architecture captures the phenomenon more completely than simpler direct-effects models.

Importantly, the mediation is partial rather than full for customer segmentation: H8 reveals a significant direct effect of CS on ME (β = 0.17) over and above the mediated path. This may reflect the fact that even rudimentary but well-executed segmentation can improve targeting efficiency without requiring sophisticated predictive modelling. Firms that segment effectively, even with traditional methods, may see direct performance gains that are independent of their analytics adoption level.

6.3 Moderating Role of Organisational Readiness

The significant moderation by organisational readiness (β = 0.19, $p < 0.01$) confirms that the PAA-to-ME pathway is not unconditional. Firms with higher levels of cultural alignment, leadership endorsement of data-driven decision-making, and process maturity extract larger returns from their analytics adoption. This finding has important implications: two organisations at identical levels of PAA adoption may achieve very different marketing effectiveness outcomes depending on their organisational context.

The moderation effect is not large in absolute terms, but its presence is theoretically consequential. It challenges the implicit assumption in much technology adoption research that capability investment directly translates to outcomes. Readiness operates as an amplifier, not a switch, and this nuance matters for how adoption programmes are designed and evaluated.

7. MANAGERIAL IMPLICATIONS

The findings carry several actionable implications for marketing leaders and analytics teams operating in contexts similar to Coimbatore and Erode.

First, data quality is the priority investment. Firms often underestimate the return on data governance relative to the excitement of deploying machine learning models. The strong β for DAQ suggests that even a modest improvement in data infrastructure yields disproportionate gains in analytics adoption and, through it, marketing effectiveness. Firms should audit data quality on accuracy, completeness, and timeliness dimensions before expanding their analytics toolkit.

Second, martech investment should be sequenced, not scattered. The significant influence of MTC on PAA implies that integrated platforms — particularly those that unify customer data across CRM, web analytics, and campaign management — are more valuable than isolated point solutions. Marketing technology decisions should be made against an explicit integration roadmap rather than in response to vendor-driven point solutions.

Third, organisational readiness is not a soft precondition but a hard moderator of return on analytics investment. Leadership teams should assess readiness as carefully as they assess technical capability. Practically, this means building analytics champions within business units, aligning incentive structures to data-driven outcomes, and investing in digital literacy training alongside platform deployment.

Fourth, the direct effect of customer segmentation on marketing effectiveness suggests that even organisations not yet mature in predictive analytics can generate meaningful returns from improving their segmentation practice. Segmentation quality should be treated as a foundational capability that delivers value independently and accelerates the returns from analytics adoption when the latter is eventually implemented.

8. CONCLUSION

This study examined the mechanisms through which predictive analytics adoption translates upstream capability investments into marketing effectiveness gains in the consumer markets of Coimbatore and Erode, Tamil Nadu. Using a sample of 340 marketing professionals and a full SEM framework with EFA and CFA, the study found robust support for all eight hypotheses. Data analytics quality, marketing technology capability, customer segmentation precision, predictive personalisation, and omnichannel data adoption all significantly predict analytics adoption. Adoption, in turn, mediates their collective influence on marketing effectiveness, explaining over 62% of the outcome variance. Organisational readiness amplifies this central relationship, while customer segmentation retains a direct path to effectiveness that operates independently of mediation.

Several limitations warrant acknowledgment. The cross-sectional design prevents causal inference, even if the theoretical logic and statistical results are consistent with causality. Self-reported measures of marketing effectiveness may be subject to social desirability bias, though the use of multi-item reflective scales and the absence of single common method bias indicators in the CFA (based on Harman's single-factor test, which yielded a maximum common variance of 29.4%) provide some reassurance. The geographic focus on two Tamil Nadu districts, while deliberate, limits generalisability to other Indian markets with different sectoral compositions or digital maturity profiles.

Future research should replicate this model in longitudinal designs, extend it to other Indian Tier-II markets, and explore boundary conditions around industry type and firm size. The mediating role of predictive analytics adoption also deserves closer examination as a process rather than a state, tracking how firms move through adoption stages and whether the marketing effectiveness returns follow a linear or non-linear trajectory...

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