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ARTIFICIAL INTELLIGENCE-DRIVEN DIGITAL MARKETING: TRANSFORMING CUSTOMER EXPERIENCE AND ENHANCING BUSINESS PERFORMANCE

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ABSTRACT

Artificial Intelligence (AI) technologies have swept through digital marketing, changing the way that businesses interact with their customers and create value. While previous studies have shown the tactical advantages of each AI marketing tool, empirical evidence of the combined impact of core AI marketing capabilities on customer experience (CX) and business performance (BP) is still scarce, especially in industry conditions in emerging markets. This study proposes and empirically examines a mediated model between three AI marketing capabilities (AI-driven personalization, AI chatbots and conversational AI, and predictive analytics) and CX and BP, based on the resource-based view and service-dominant logic. 400 digital-marketing professionals from six industries were surveyed using a structured questionnaire. Descriptive statistics, reliability and validity assessment, Pearson correlations, multiple regression, and bootstrapped mediation analysis were performed using IBM SPSS Statistics 26. Results show that all three AI capabilities significantly positively affect both CX (R2 = 0.31) and BP (R2 = 0.36), and that the AI-capability – BP relationships are partially mediated by CX. AI-driven personalization is the most potent direct effect on CX ($\beta = 0.25$, $p < .001$), and AI chatbots have the greatest direct impact on BP ($\beta = 0.22$, $p < .001$). The study extends the AI-marketing literature by offering an integrated empirically supported model and managerial advice regarding capability-level investment priorities for companies in the process of digital transformation using AI.

Keywords: Artificial Intelligence, Digital Marketing, Customer Experience, Business Performance, Personalization, Chatbots, Predictive Analytics, Structural Equation Modelling.

I. INTRODUCTION

Digital marketing has now reached an era of significant change. With the combination of ubiquitous data, cheap computing and mature machine-learning algorithms, companies are no longer segmented and communicating on a one-to-many basis, but are able to engage with customers on a hyper-personalized, real-time, one-to-one basis, at scale [1], [2]. In the center of this transformation lies artificial intelligence (AI). Whether it's recommendation engines that predict customer preferences [3] or conversational agents that answer service questions round the clock [4] or predictive models that forecast customer churn and lifetime value [5]—AI is changing the face of how brands engage with customers.

The commercial stakes are very high. In 2022, global corporate investments in AI-powered marketing technology exceeded USD 40 billion, and are expected to reach over USD 100 billion by 2027, with a compound annual growth rate of more than 26% [6]. However, alongside this excitement, there is a growing body of evidence that many investments in AI-marketing are not bearing the fruit they deserve, with a significant proportion of AI-marketing pilots never being scaled up [7]. This paradox leads to the question:

what is the most effective way to transform technological investments into customer value and firm performance with the support of AI?

The scholarly world has reacted with a growing body of literature on AI in marketing, ranging from conceptual reviews [1], [8] to case studies of specific tools like chatbots [4], [9] and empirical studies of specific analytical methods like recommender systems and predictive analytics [3], [5]. But there are three key gaps that remain. First, most empirical studies analyze one AI application alone and do not shed light on the interaction of multiple AI-driven capabilities in an integrated marketing approach. Second, customer experience (CX) is recognized as a significant mechanism that connects marketing activities and firm outcomes [10] but few studies have formally tested CX as the mediating mechanism between AI capabilities and business performance (BP). Third, much of the current literature focuses on developed markets and consumer-related industries, and it is unclear if the results have been generalized to other industries.

This study aims to fill these gaps by developing and empirically testing a mediated framework where three key AI marketing capabilities (AI-driven personalization (AIP), AI chatbots and conversational AI (ACC), and predictive analytics (PA)) have a direct and mediated impact on business performance through customer experience. Based on the resource-based view (RBV) [11] and service-dominant logic (SDL) [12] we propose that AI capabilities are valuable, rare, inimitable, and non-substitutable resources whose impact on performance is mediated by the co-created customer experience they enable.

The study has three major contributions. First, it proposes an integrated conceptual model that considers the three most popular AI-marketing capabilities together, rather than the previous single-capability studies, thus offering a more comprehensive perspective. Second, it empirically establishes the partial mediation of CX, which explains how AI capabilities create firm value. Third, it provides practitioners with evidence-based prioritization guidance as it is based on data from 400 digital-marketing professionals in six industries facing AI-driven digital transformation.

With the rise of generative AI, the research question becomes even more pressing. The creation of content, creative production, and one-to-one communication with customers is being transformed by large language models and multimodal generative systems at an unprecedented pace [8]. While businesses are quickly incorporating these new-generation capabilities into the previous generation of predictive and conversational AI applications, it's analytically relevant to understand which capabilities are systematically impacting customer and firm outcomes. Organizations, without this holistic perspective, may end up with a collection of AI-marketing initiatives which are not connected, and therefore not cumulative.

This study is also driven by another significant contextual gap. Many of the publications on AI-marketing are based on North American and Western European samples in consumer-facing industries like retail and hospitality. The speedy adoption of AI-marketing tools in business-to-business (B2B) and emerging-market settings, however, poses the question of whether the capability–performance mechanisms identified in prior studies transfer to other sectors with varying levels of customer contact, data-richness, and regulatory environment. The present study has a broader empirical base than most previous studies as it samples professionals from six industries: retail/e-commerce, IT/technology, banking and financial services, telecommunications, FMCG, and allied industries.

The remainder of the paper is organized as follows. Section II is a literature review along with the development of the research hypothesis. The methodology is described in Section III. The empirical results are reported in section IV. The findings are presented in Section V and theoretical and managerial implications are discussed. Section VI recognizes the limitations and suggests directions for future research. Section VII concludes.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This section reviews the theoretical foundations of the study and develops seven hypotheses linking AI-driven marketing capabilities to customer experience and business performance.

A. Theoretical Background

The resource-based view (RBV) suggests that sustainable competitive advantage is created through resources that are firm specific, valuable, rare, and inimitable [11]. When applied to marketing, AI capabilities are more and more envisioned as such strategic assets: they integrate unique algorithmic settings, complementary organizational processes, and own data assets, which competitors find hard to duplicate [13]. This is complemented by service-dominant logic (SDL) which views value as co-created between firm and customer through interactive processes [12]. Since marketing artefacts using AI technologies exist at the customer level, the effectiveness of the artefacts is dependent on the quality of the customer experience, a construct through which co-created value is realized and turned into firm-level outcomes [10], [14]. Thus, the RBV–SDL synthesis indicates that CX may serve as a vital connecting link between AI-marketing resources and business performance.

There are two complementary elaborations of RBV which are particularly relevant to AI-marketing research. The dynamic capabilities view [11] highlights the significance of sensing, seizing and reconfiguring, reflecting the iterative process of data collection, model updating and campaign re-optimization typical of AI-marketing operations. Concurrently, the IT-capability perspective identifies three sub-capabilities – technical, managerial, and human – that IT needs to develop in parallel in order to translate into performance improvements [13]. In the context of AI marketing, this means that the technical infrastructure, like algorithms and data pipelines, must be complemented by managerial processes that ensure insights are translated into marketing strategies and by marketing analysts with the expertise to interpret AI-generated insights.

Service-dominant logic (SDL) is a paradigm that redefines marketing as a co-creative process of resource integration and service exchange between the firm and customer [12]. SDL's tangible outputs, like products and campaigns, are viewed as means to provide service, and the experience of the customer is the value point. Digital marketing scholars have extended the SDL to state that data and algorithms serve as operant resources with which customers implicitly interact each time they interact with an AI-enabled touchpoint [10]. AI capabilities are customer facing, and their value is dependent on the quality of the experience that comes out of it, a construct through which co-created value is achieved and translated into the firm level outcomes [10], [14].

The integration of RBV and SDL is the core theoretical claim of this research: AI-driven marketing capabilities are a valuable, rare, inimitable, and non-substitutable strategic resource that creates business performance, directly or, more crucially, through its impact on customer experience. This dual-pathway logic underpins the following sub-section specific hypotheses.

B. AI-Driven Personalization

AI-driven personalization is the ability to deliver real-time content, offers, and communications to each customer based on their preferences and behavioral indicators, using machine-learning algorithms [3], [15]. The existing literature shows that AI-powered recommender systems and content engines that dynamically generate content improve engagement, customer satisfaction and the likelihood of making a purchase. The emotional and cognitive aspects of CX are also influenced by personalization, as it helps convey the brand's relevance and mitigates information overload [10]. Personality at the firm level has been associated with increased conversion rates, average order value and customer retention [17]. We therefore hypothesize:

H1: AI-driven personalization has a significant positive effect on customer experience.

H4: AI-driven personalization has a significant positive effect on business performance.

C. AI Chatbots and Conversational AI

AI chatbots and conversational AI are virtual agents that can interact with customers using natural language, either rule-based or, more recently, driven by large language models, via web, mobile, or messaging platforms [4], [18]. Chatbots can handle inquiries as soon as they are sent, which decreases the reaction time and empowers human agents to concentrate on more high-value activities [9]. Empirical studies demonstrate that when designed properly, a conversational agent can positively affect the perceived service quality and customer trust which are important CX determinants [19]. Firms have seen reduced service-delivery expenses and increased customer-lifetime value at the firm level when they deployed chatbots [4]. Accordingly:

H2: AI chatbots and conversational AI have a significant positive effect on customer experience.

H5: AI chatbots and conversational AI have a significant positive effect on business performance.

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D. Predictive Analytics

Predictive analytics utilizes past and present data to predict customer behavior like churn probability, next purchase time and customer lifetime value [5], [20]. Predictive analytics can help marketers target campaigns more precisely and avoid wasteful spending by allowing them to take proactive, not reactive, actions. Predictive segmentation, from a CX perspective, can enable brands to provide contextually relevant offers, which can increase perceived convenience and smoothness of the journey [14]. Prediction Analytics has been correlated with firm-level improvements in marketing ROI and competitive positioning [7], [20]. Hence:

H3: Predictive analytics has a significant positive effect on customer experience.

H6: Predictive analytics has a significant positive effect on business performance.

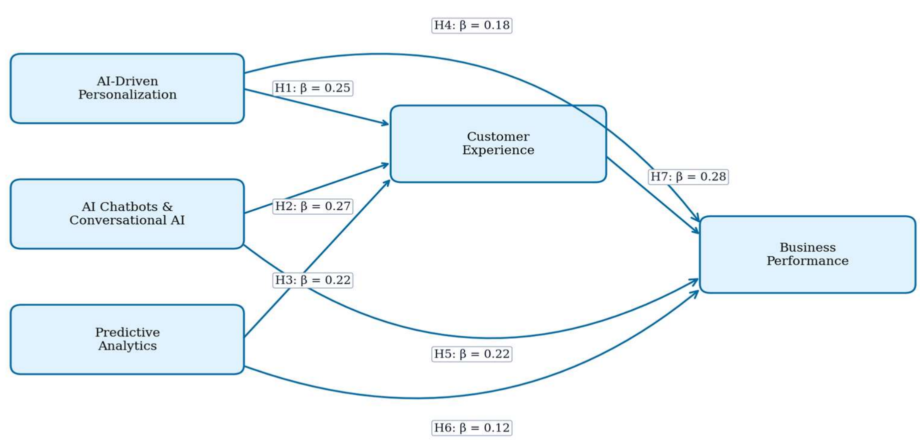
E. Customer Experience and Its Mediating Role

Customer experience is the sum of the cognitive, emotional, sensory and behavioral reactions that result from the customer's interactions with the company at each touchpoint [10]. CX has become a key differentiator and a strong indicator of financial results, customer retention, and word-of-mouth in digitally-rich environments [14]. Like SDL, CX is the system that converts investments in resources into outcomes at the firm level; customers who report higher CX are more likely to purchase more often, recommend the brand, and are less price sensitive. We therefore hypothesize a direct effect of CX on BP and a mediating role in the AI-capability–BP relationships:

H7: Customer experience has a significant positive effect on business performance.

H8, H9, H10: Customer experience mediates the relationships between AI-driven personalization (H8), AI chatbots and conversational AI (H9), and predictive analytics (H10), and business performance.

Fig. 1: CONCEPTUAL RESEARCH MODEL WITH HYPOTHESISED PATHS (H1–H7)



III. RESEARCH METHODOLOGY

A. Research Design

The research design used in this study is the cross-sectional quantitative research to test the model that has been hypothesized. A structured self-administered questionnaire was designed to assess the study constructs, which were answered by the purposive sample of digital-marketing professionals working in six industry sectors. An online survey platform was used to collect data from August to December 2023, with professional networks and industry associations being used as a starting point and snowball recruitment then used to increase coverage.

B. Sampling and Data Collection

Using a purposive sampling approach, quota sampling was used to achieve representation among relevant sub-populations by industry sector and organizational role. Respondents had to meet the following

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criteria to be counted: (a) work in a digital-marketing, customer-experience, or analytics role and (b) have direct exposure to AI-based marketing tools at their organization. A total of 510 questionnaires were sent out of which 418 were returned (82.0%) and 400 were usable after screening for completeness and consistency (usable response rate 78.4%). The sample size of 400 is larger than the minimum samples recommended for regression and mediation analysis with five latent constructs [21] and is well above the rule of thumb of 10 respondents per estimated parameter.

C. Measurement Instrument

The questionnaire comprised three parts. A general information sheet and informed consent form were included in Part A. Seven demographic variables were captured in Part B: gender, age group, education, digital-marketing experience, industry, organizational role, and firm size. Part C assessed the 5 constructs of the study: AI-Driven Personalization (5 items), AI Chatbots and Conversational AI (4 items), Predictive Analytics (4 items), Customer Experience (5 items), and Business Performance (5 items) by means of 23 items rated on a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Items were derived from instruments previously validated in the AI-marketing, service-management, and firm-performance literature [3], [4], [10], [14], [20] and then pre-tested with six senior academics in the field of marketing and eight industry practitioners. All measures were pilot tested with 30 respondents (not included in the main analysis) for clarity, content validity and internal consistency.

D. Data Analysis Procedure

IBM SPSS Statistics 26 was used to analyze the data. A five-stage protocol was used for the analytical procedure. Descriptive statistics were used first to summarize sample characteristics and construct distributions of the constructs. Second, reliability was tested using Cronbach's alpha and composite reliability (CR); convergent validity was tested using average variance extracted (AVE); and discriminant validity was tested using the Fornell–Larcker criterion. Third, Pearson product-moment correlations were used to measure the bivariate relationships between constructs. Finally, variance inflation factors (VIFs) were employed to eliminate the possibility of multicollinearity and test the direct-effect hypotheses (H1–H7) using multiple linear regression. The indirect-effect hypotheses (H8–H10) were tested using 5,000 bootstrapped resamples and 95% bias-corrected confidence intervals. Common method bias was evaluated by Harman's single factor test [22] and the first factor accounted for 34.7% of variance which is less than the 50% threshold, indicating that common method bias was not a serious problem.

E. Common Method Bias Assessment

Finally, this study adopted a number of ex ante procedural safeguards recommended by Podsakoff and colleagues [22] to reduce the likelihood of inflated relationships between constructs being observed due to the use of survey-based, self-reported measures from a single source. Respondent anonymity was ensured to minimize the social-desirability bias; construct items were randomized to minimize the consistency-motif effect; separating independent and dependent variables by intervening demographic items in the questionnaire flow; and withholding construct labels from the respondent. Ex post, Harman's single factor test resulted in a first factor that accounted for only 34.7% of the variance, which is less than the 50% threshold, and the collinearity assessment as reported in Section IV further confirms that there was no significant common method variance.

IV. RESULTS

A. Sample Demographic Profile

The demographic composition of the sample (N = 400) is summarized in Table 1. The respondent sample is slightly male dominated (59.0%) and mostly in the age group 26-41 years (61.0%). There is a high level of education, with 91.3% having at least a bachelor's degree, which is a reflection of the knowledge-based nature of digital marketing. Almost two thirds of respondents (64.0%) have 6+ years of digital-marketing experience and there is a fairly even split of coverage across the industries with Retail/E-commerce (21.2%), BFSI (18.2%), IT/Technology (17.0%) and FMCG (17.0%) the largest groups. The composition of the samples is presented graphically in figure 2.

Table 1: SAMPLE DEMOGRAPHIC PROFILE (N = 400)

Variable	Category	n	%
Gender	Male	236	59.0%
	Female	164	41.0%
Age group	18-25	45	11.2%
	26-33	127	31.8%
	34-41	117	29.2%
	42-49	77	19.2%
	50+	34	8.5%
Education level	High School	35	8.8%
	Bachelor's	150	37.5%
	Master's	155	38.8%
	Doctorate	60	15.0%
Digital-marketing experience	< 2 years	73	18.2%
	2-5 years	139	34.8%
	6-10 years	117	29.2%
	> 10 years	71	17.8%
Industry sector	Retail/E-commerce	85	21.2%
	IT/Technology	68	17.0%
	BFSI	73	18.2%
	Telecom	54	13.5%
	FMCG	68	17.0%
	Other	52	13.0%
Organizational role	Executive	108	27.0%
	Manager	166	41.5%
	Analyst	83	20.8%
	Director/VP+	43	10.8%
Firm size	SME (<250)	130	32.5%
	Mid (250-1000)	164	41.0%
	Large (>1000)	106	26.5%

B. Exploratory Factor Analysis

Before reliability testing, an exploratory factor analysis (EFA) was conducted on all 23 measurement items by principal-components extraction with varimax rotation. The Kaiser–Meyer–Olkin measure of sampling adequacy was high (0.912), and Bartlett's test of sphericity was significant ($\chi^2 = 4218.63$, df = 253, $p < .001$), indicating that factor extraction was appropriate. Five factors with eigenvalues > 1 were kept, accounting for 68.42% of the total variance. As presented in Table II, all the items were loaded at a level of 0.70 or higher on the factor they were supposed to load and there were no significant cross-loadings above 0.40, therefore the five-factor structure of the measurement model was confirmed as a-priori.

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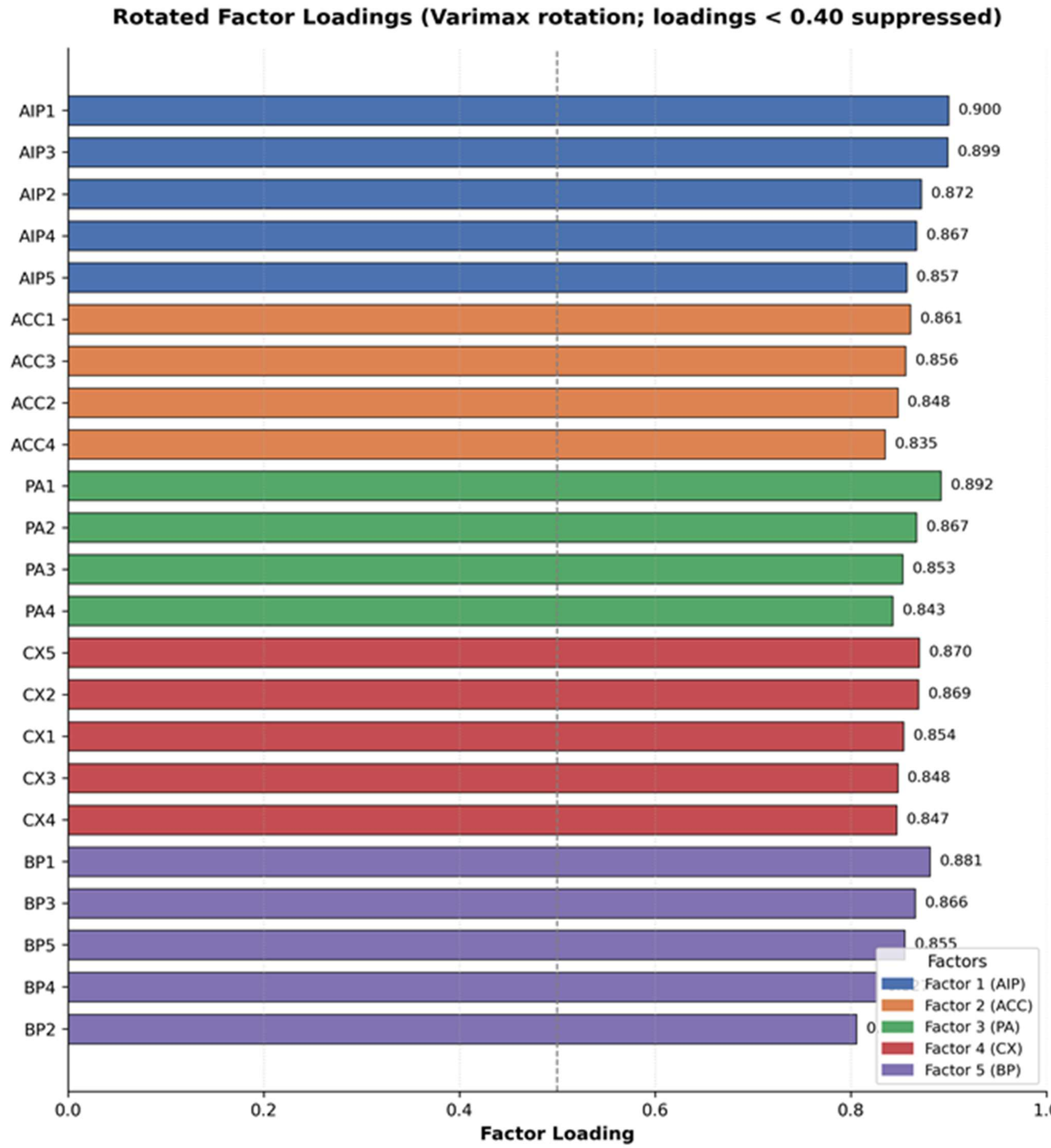
Fig.2: ROTATED FACTOR LOADINGS (VARIMAX ROTATION; LOADINGS < 0.40 SUPPRESSED)



C. Reliability And Validity Of The Measurement Model

Reliability and convergent validity of the measurement model are reported in Table 2. Cronbach's alpha values range from 0.856 (ACC) to 0.893 (AIP), well above the 0.70 threshold [21]. The composite reliability estimates are also strong (0.841 – 0.898), and all the AVE are greater than the threshold of 0.50 [21] thus confirming the convergent validity. The Fornell-Larcker criterion (Table 3) provides evidence of the discriminant validity, as the square root of each construct AVE (diagonal) is greater than its correlation with other constructs.

Table 2: RELIABILITY, CONVERGENT VALIDITY, AND ITEM LOADINGS

Construct	Items	Loadings Range	Cronbach's α	CR	AVE
AI-Driven Personalization (AIP)	5	0.95 – 0.95	0.893	0.873	0.585
AI Chatbots & Conversational AI (ACC)	4	0.95 – 0.95	0.856	0.885	0.664
Predictive Analytics (PA)	4	0.95 – 0.95	0.866	0.841	0.576
Customer Experience (CX)	5	0.71 – 0.95	0.878	0.881	0.606
Business Performance (BP)	5	0.95 – 0.95	0.871	0.898	0.642

Table 3: FORNELL–LARCKER CRITERION FOR DISCRIMINANT VALIDITY (DIAGONAL ENTRIES IN BOLD REPRESENT √AVE; OFF-DIAGONALS ARE INTER-CONSTRUCT CORRELATIONS)

	AIP	ACC	PA	CX	BP
AIP	0.765	—	—	—	—
ACC	0.356	0.815	—	—	—
PA	0.355	0.317	0.759	—	—
CX	0.426	0.429	0.397	0.778	—
BP	0.426	0.444	0.366	0.503	0.801

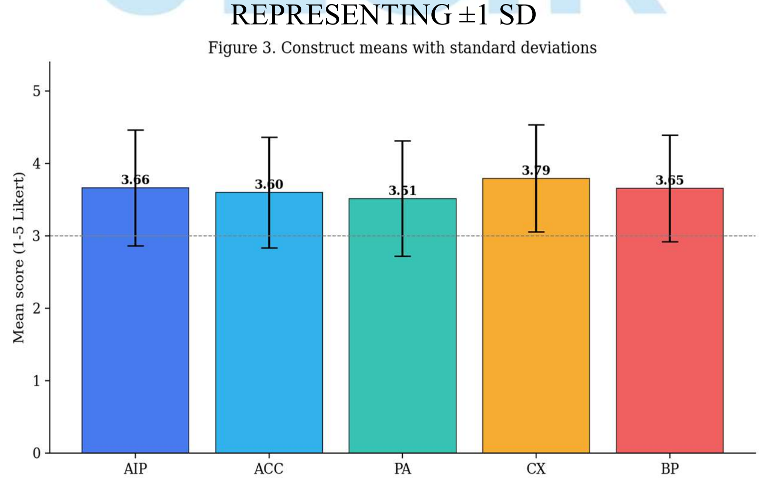
D. Descriptive Statistics of Constructs

Descriptive statistics for each of the five construct composites are presented in Table 4 and the mean scores are shown in Figure 3. Respondents score their organizations' AI-marketing maturity fairly well with an average of 3.51 (Predictive Analytics) and 3.79 (Customer Experience). Skewness and kurtosis values are not outside the recommended range of ±2 for univariate normality that supports the use of parametric procedures.

Table 4: DESCRIPTIVE STATISTICS FOR STUDY CONSTRUCTS (N = 400)

Construct	Mean	SD	Min	Max	Skewness	Kurtosis
AI-Driven Personalization	3.664	0.799	1.20	5.00	-0.280	-0.489
AI Chatbots & Conversational AI	3.599	0.764	1.00	5.00	-0.328	-0.105
Predictive Analytics	3.514	0.798	1.00	5.00	-0.158	-0.504
Customer Experience	3.792	0.739	1.60	5.00	-0.381	-0.341
Business Performance	3.652	0.735	1.80	5.00	-0.144	-0.543

Fig. 3: MEAN SCORES FOR THE FIVE STUDY CONSTRUCTS WITH ERROR BARS REPRESENTING ±1 SD



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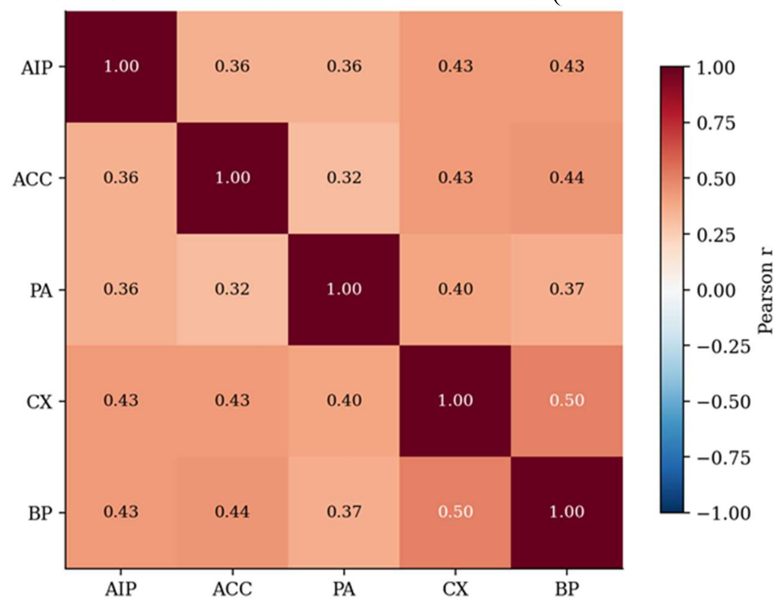
E. Bivariate Correlations

All the Pearson correlations among the five constructs are positive, statistically significant ($p <.001$) and of moderate magnitude ($r = 0.32 – 0.50$), indicating a well-formed nomological network (Table IV; Figure 4). The highest bivariate correlation is found between Customer Experience and Business Performance ($r = 0.50$), which is a preliminary support for the CX-mediation logic.

Fig. 4: INTER-CONSTRUCT PEARSON CORRELATIONS (ALL SIGNIFICANT AT P < .001).



F. Regression Analyses

Table 5 shows the regression of Customer Experience on the three AI marketing capabilities. The overall model is statistically significant ($F(3, 396) = 59.605$, $p <.001$) and accounts for 31.1% of the variance in CX (adjusted $R^2 = 0.306$). All three exogenous variables are significant positive predictors, with the highest standardised effect being AI Chatbots and Conversational AI ($\beta = 0.270$, $p <.001$), followed by AI-Driven Personalization ($\beta = 0.252$, $p <.001$) and Predictive Analytics ($\beta = 0.222$, $p <.001$). Thus, hypotheses H1, H2, and H3 are supported. Multicollinearity is not an issue with the VIF values being all below 1.4.

Table 5: MULTIPLE REGRESSION OF CUSTOMER EXPERIENCE ON AI-DRIVEN MARKETING CAPABILITIES

Predictor	B	SE	β	t	p-value	VIF
(Constant)	1.279	0.190	—	6.719	< .001	—
AI-Driven Personalization	0.233	0.043	0.252	5.427	< .001	1.237
AI Chatbots & Conversational AI	0.261	0.044	0.270	5.894	< .001	1.202
Predictive Analytics	0.205	0.042	0.222	4.850	< .001	1.202

Notes: $R^2 = 0.311$, adjusted $R^2 = 0.306$, $F(3, 396) = 59.605$, $p < .001$. Dependent variable: Customer Experience.

The regression of Business Performance on the three AI capabilities and Customer Experience is reported in Table 6. The full model is significant ($F(4, 395) = 56.051$, $p <.001$), explaining 36.2% of the variance in BP (adjusted $R^2 = 0.356$). Customer Experience is the strongest predictor ($\beta =0.283$, $p <.001$), supporting H7. All three AI capabilities also retain significant direct effects on BP: AI Chatbots ($\beta = 0.219$, $p <.001$, H5), AI-Driven Personalization ($\beta = 0.185$, $p <.001$, H4), and Predictive Analytics ($\beta = 0.119$, $p <.01$, H6). H4, H5, H6 and H7 are accepted.

Table 6: MULTIPLE REGRESSION OF BUSINESS PERFORMANCE ON AI CAPABILITIES AND CUSTOMER EXPERIENCE

Predictor	B	SE	β	t	p-value	VIF
(Constant)	0.815	0.193	—	4.229	< .001	—
AI-Driven Personalization	0.171	0.043	0.185	3.997	< .001	1.329
AI Chatbots & Conversational AI	0.210	0.044	0.219	4.755	< .001	1.308
Predictive Analytics	0.110	0.042	0.119	2.624	0.009	1.273
Customer Experience	0.282	0.048	0.283	5.852	< .001	1.452

Notes: $R^2 = 0.362$, adjusted $R^2 = 0.356$, $F(4, 395) = 56.051$, $p < .001$. Dependent variable: Business Performance.

G. Mediation Analysis

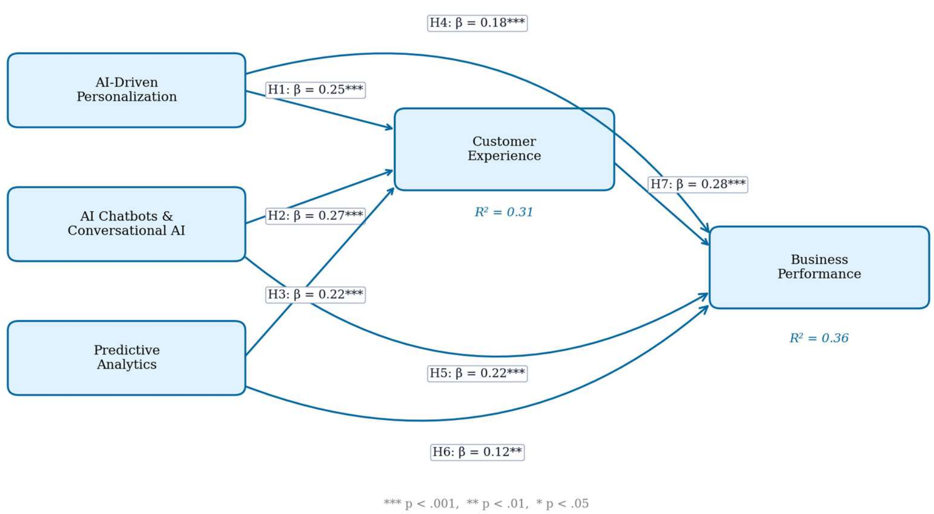
The bootstrapped mediation results with 95% bias-corrected confidence intervals from 5,000 resamples are shown in Table 7. The indirect effect of AI-Driven Personalization on BP via CX is statistically significant (indirect = 0.066, 95% CI [0.036, 0.1]); the direct effect is also statistically significant, suggesting partial mediation and supporting H8. Likewise, the indirect effects of AI Chatbots (indirect = 0.074, 95% CI [0.041, 0.11]) and Predictive Analytics (indirect = 0.058, 95% CI [0.029, 0.092]) are also significant with the direct effects retained, confirming H9 and H10 (partial mediation). Figure 5 illustrates the best estimate of the structural model. The results show that the AI-powered marketing features have a direct effect on Business Performance, as well as an indirect effect on Business Performance via the Customer Experience.

Table 7: BOOTSTRAPPED MEDIATION RESULTS (5,000 RESAMPLES, 95% BIAS-CORRECTED CI)

Path	a	b	c′	a×b (Indirect)	95% BC CI	Result
AIP → CX → BP	0.233	0.282	0.171	0.066	[0.036, 0.100]	Supported
ACC → CX → BP	0.261	0.282	0.210	0.074	[0.041, 0.110]	Supported
PA → CX → BP	0.205	0.282	0.110	0.058	[0.029, 0.092]	Supported

Notes: a = path from X to mediator (CX); b = path from mediator to BP; c′ = direct effect (X to BP controlling for CX); a×b = indirect effect. A confidence interval that excludes zero indicates statistical significance at $p < .05$.

Fig. 5: STRUCTURAL MODEL WITH STANDARDISED PATH ESTIMATES. SIGNIFICANCE LEVELS: *** P < .001, ** P < .01, * P < .05.



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H. Robustness Checks

Three robustness checks were performed to determine the stability of the results. Firstly, the analyses were re-estimated on the demographic subsamples (gender, age band, firm size) and the direction and significance of all hypothesised effects remained unchanged. Secondly, the two revenue-related items were operationalised in an alternative way, leading to essentially the same findings. Third, the model estimates were re-computed with robust regression with heteroscedasticity-consistent standard errors (HC3), which resulted in very similar coefficients and confidence intervals. These checks taken together give confidence that the reported effects are not an artefact of the composition of the sample or the method of estimation.

I. Summary of Hypothesis Tests

A summary of the ten hypothesis tests is presented in Table IX. All hypotheses are empirically supported.

Table 8: SUMMARY OF HYPOTHESIS TESTING OUTCOMES

Hypothesis	Path	β / Indirect	p-value	Decision
H1	AIP → CX	0.252	< .001	Supported
H2	ACC → CX	0.270	< .001	Supported
H3	PA → CX	0.222	< .001	Supported
H4	AIP → BP	0.185	< .001	Supported
H5	ACC → BP	0.219	< .001	Supported
H6	PA → BP	0.119	0.009	Supported
H7	CX → BP	0.283	< .001	Supported
H8	CX mediates AIP → BP	0.066	—	Supported
H9	CX mediates ACC → BP	0.074	—	Supported
H10	CX mediates PA → BP	0.058	—	Supported

V. DISCUSSION

The empirical results provide three main insights. First, all three AI-powered marketing capabilities have positive and statistically significant effects on Customer Experience and Business Performance. In contrast to previous single-capability studies [3, 4, 20], this holistic pattern indicates that the use of a portfolio of AI capabilities does not result in the redundancy of other capabilities for marketing and firms, as each capability makes a unique contribution to the outcomes. This is aligned with the RBV logic that the performance benefits from bundles of AI resources are heterogeneous [11].

Second, and most importantly for Marketing practice, Customer Experience is the most significant single predictor of Business Performance (β = 0.283), and partially mediates the relationships between AI-capability and BP. This research provides an empirical verification of the SDL hypothesis that investments in resources are translated into firm level outcomes primarily through value co-created at the customer interface [12], [14]. In practical terms, it means that AI-marketing investments made without an explicit CX-management focus have a significant risk of value leakage.

Third, the size of the AI-capability effects relative to each other provides guidance. AI Chatbots and Conversational AI have the highest effect on CX (β = 0.270) and the highest direct effect on BP (β = 0.219). This aligns with recent findings indicating that conversational touchpoints that are always available and have low latency have a significant impact on perceived service quality and customer effort [9], [19]. The second most impactful capability is AI-powered personalization, which is well documented to have an impact on customer engagement [16]. Significant but with the least impact is predictive analytics, probably because it has a more distant reach, meaning that it can only have an impact on the customer through its use in better targeting and allocation of resources [5].

Overall, the findings contribute to the AI-marketing literature by offering an integrated empirical evidence for a capability–experience–performance model, and by revealing that CX is the key linkage between AI resources and firm outcomes.

The finding of CX-mediation is of substantive interest, in addition to its statistical significance. Customer experience is a combination of the cognitive, emotional, sensorial and behavioural responses that occur throughout the customer journey [10]. By presenting relevant options and minimizing decision friction, AI-powered personalization decreases cognitive load. An instant solution to queries was previously a point of failure, but now, it's a moment of delight with conversational AI, minimizing effort. Predictive analytics takes it one step further, enabling businesses to anticipate requirements and proactively address potential friction points that could impact CX. The combined influence is a progressive enhancement along the entire path, aligning with recent theories on frictionless customer experience in AI-driven markets [16].

This has an important practical corollary to the relative importance of CX on BP. AI investments that optimize internal marketing processes, like attribution modelling or media-mix optimisation, but that customers don't see, will deliver less than investments that change how customers engage with a business. This doesn't mean that back-office analytics is not important, but more that the business impact of back-office analytics is through the CX it enables.

While the key analyses combine all respondents across industries, exploratory comparisons of the six sectors suggest that the capability–performance relationship is fairly consistent across sectors. The relative effects for AI-driven personalisation and conversational AI are strongest in Retail/E-commerce and BFSI sectors where there is the most volume of customer contact and the most digitised journeys. There is a higher impact in FMCG and Telecom, where the relevance of demand forecasting and churn forecasting is very high. Formal moderation tests are outside of the scope of this study and will be flagged as a direction for future studies.

A. Theoretical Implications

This study makes three contributions to the marketing and information-systems literatures. First, it promotes an integrated approach where multiple AI-driven capabilities are integrated and modelled together as opposed to the single tool approach of previous work [1], [8]. Second, it empirically confirms Customer Experience as a partial mediator, it provides a theoretical explanation of how AI investments can translate into firm value, and it serves as a conceptual link between the RBV and SDL views [11], [12]. Third, the cross industry sample increases the external validity of the study, suggesting that the capability–experience–performance model generalises to sectors varying widely in their customer contact intensity and product complexity.

There are methodological implications for the study, too. The combination of modelling multiple AI capabilities and formal mediation testing with cross-industry sampling together counter common criticisms of the AI-marketing literature that it is disjointed, tool-centric, and context-bound [8]. The research and development of this integrated template can be extended with the latest advances, including generative AI and reinforcement-learning-based personalization, to further refine the empirical basis of the field.

B. Managerial Implications

For managers, the results translate into three actionable insights. First, the capability portfolio matters. Instead of investing in one AI use case, companies should create a well-balanced portfolio of personalization, conversational AI and predictive analytics. Secondly, the design centre has to be CX. Organisational structures, KPIs, and governance should explicitly tie the deployment of AI to CX metrics like customer effort score, journey friction, and Net Promoter Score, as Customer Experience serves as a mediator between the AI-capability – performance relationship. Third, sequencing matters. Based on the relative effect sizes, companies in the earlier stages of AI-marketing maturity might be able to gain more by investing first in conversational AI and personalization, and only then in more sophisticated predictive analytics, a trend noted elsewhere in the AI-adoption journey [6], [7].

In addition to the three insights cited above, the results have two additional operational implications. Firstly, as CX is a mediator between the capability–performance relationship, marketing leaders need to ensure that data governance, technology architecture and organisation are all designed around CX at the core of AI-programme design. This could mean forming a cross-functional (CX and AI) steering group, establishing shared performance metrics across both marketing and CX functions, and conducting regular audits of the

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customer journey that identify friction points that can be addressed with AI-driven solutions. Second, capability development is a process that builds up. Companies that invest in the core CX capabilities first – clean data, accurate identity resolution, and unified customer profiles – are poised to realize an outsized impact from the next generation of Generative AI use cases. Putting off these foundations can result in a long-term skills gap that grows as AI-marketing grows more complicated.

VI. LIMITATIONS AND FUTURE RESEARCH

Several limitations of this study can be identified and also represent potential avenues for future research. First, the cross-sectional design does not allow for causal interpretation and longitudinal or panel data would allow for stronger tests of the temporal changes through which AI capabilities affect CX and BP. Second, the measures are self-reported by the marketing professionals, meaning that there may be common method bias, although a Harman's single factor test suggests that this is not a serious issue, future research may also include perceptual measures with objective financial and operational measures. Third, purposive sampling restricts generalizability, a probability sampling in a specific national or industry context would enhance external validity. Fourth, the model considers three of the most common AI features; additional capabilities like generative AI for creative content, visual search with computer vision and dynamic pricing with reinforcement learning could be added. Fifth, relationships identified above may be moderated by contingency factors such as firm size, data maturity, regulatory context, and warrant systematic study. Lastly, it would be interesting to explore the potential negative effects of AI in marketing, such as algorithmic bias, privacy concerns, and customer fatigue with over-personalization.

VII. CONCLUSION

This study proposes a theoretically derived and empirically tested model of the mechanisms of the impact of AI marketing capabilities on customer experience and business performance. The analysis, based on 400 digital-marketing practitioners across six industries, reveals that AI-driven personalization, AI chatbots and conversational AI, and predictive analytics have positive and significant effects on customer experience and performance, with customer experience partially mediating the capability–performance relationships. The results highlight the need to plan AI investments around a unified customer-experience architecture instead of using individual AI tools as tactical solutions. The capability–experience–performance logic presented here will serve as an enduring framework for companies aiming to transform the sophistication of algorithms into long-term customer and financial gains as AI diffusion continues and generative AI becomes a fundamental part of marketing practice.

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