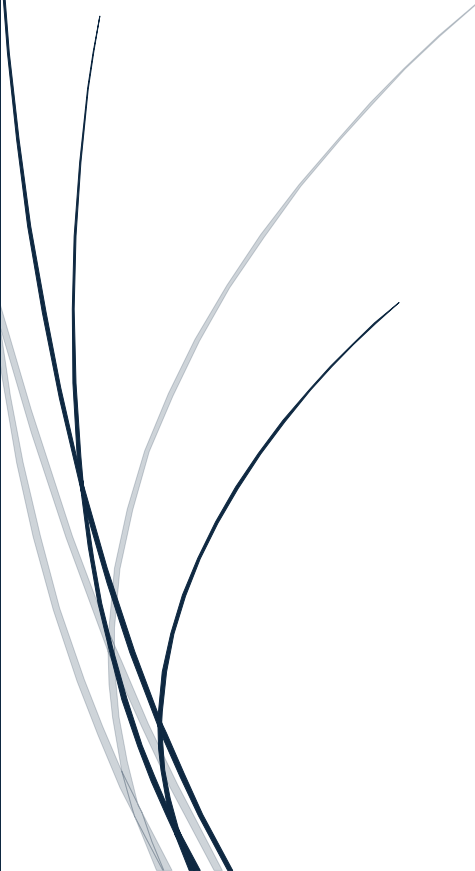


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The Impact of AI on Marketing Performance and Customer Engagement



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Dedication

I dedicated this project to my parents and family for their endless love, encouragement, and support throughout my academic journey. Their belief in my abilities has been my greatest motivation.

I also dedicate this work to everyone who has encouraged me to continue learning, developing my knowledge, and striving for excellence.

Finally, I dedicate this research to all those interested in understanding how Artificial Intelligence is transforming modern marketing and shaping the future of business.

Acknowledgment

I would like to express my sincere gratitude to my supervisor for providing valuable guidance, support, and constructive feedback throughout this research project.

I would also like to thank **Midocean University** and the **Faculty of Management** for providing the academic environment and resources necessary to complete this study.

Finally, I extend my appreciation to my family and friends for their encouragement and continuous support during this research journey.

Abstract

Purpose

The purpose of this research is to examine the impact of Artificial Intelligence (AI) on marketing practices and business performance. The study investigates how AI technologies improve customer engagement, marketing efficiency, personalization, and organizational decision-making while identifying the opportunities and challenges associated with AI adoption in modern marketing.

Methodology

This study adopts a quantitative research approach using a structured questionnaire distributed to marketing professionals, managers, and employees working in different industries. A convenience sampling technique is applied, and the collected data are analyzed using descriptive statistics, reliability analysis, correlation analysis, and regression analysis through SPSS.

Findings

The study is expected to demonstrate that Artificial Intelligence positively influences marketing performance by improving customer experience, increasing operational efficiency, enhancing personalization, and supporting data-driven decision-making. The findings also indicate that successful AI implementation depends on organizational readiness, employee skills, and effective data management.

Originality & Implication

This research contributes to the growing body of knowledge on Artificial Intelligence in marketing by providing empirical evidence regarding its impact on organizational performance. The findings offer practical recommendations for managers seeking to integrate AI technologies into marketing strategies and improve competitive advantage.

Keywords

Artificial Intelligence (AI), Marketing, Digital Marketing, Customer Engagement, Marketing Performance, Machine Learning, Consumer Behavior, Business Performance.

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Study on AI Applications in Marketing

Executive summary. This chapter proposes a rigorous, defensible methodology for examining how artificial intelligence is applied in marketing and how those applications affect marketing performance and customer experience. It treats AI in the OECD sense of a machine-based system that infers from inputs how to generate outputs such as predictions, recommendations, content, or decisions, and it positions AI in marketing as spanning research, segmentation/targeting/positioning, campaign execution, customer interaction, and content generation. The proposed design is a **mixed-methods explanatory sequential study**: a cross-sectional quantitative survey of marketing decision-makers is used first to test hypotheses, followed by semi-structured qualitative interviews to explain mechanisms, barriers, and contextual differences in the quantitative results. This choice fits the practical and socio-technical nature of AI in marketing, where performance effects, data quality, organizational readiness, privacy, and consumer trust are interdependent rather than purely technical issues. [\[1\]](#)

The chapter assumes, because the brief does not specify a context, that the empirical setting is **consumer-facing firms in Saudi Arabia** across retail, e-commerce, banking, telecom, hospitality, and related service sectors. That assumption is methodologically reasonable because Saudi Arabia has an explicit national data and AI strategy, a strong digital transformation agenda, and official business statistics infrastructure that can support frame construction at establishment level. The target respondents are marketing managers, CRM managers, digital marketing specialists, growth leads, and related decision-makers in firms that have used at least one AI-enabled marketing application for at least six months. Under a conservative Cochran calculation for a large population at 95% confidence and 5% error, the minimum quantitative sample is **385 valid responses**,

with oversampling to about **450–500** to protect against unusable questionnaires and subgroup imbalance; the qualitative phase targets **15–20 interviews** or saturation. [2]

Introduction

This methodology chapter is structured to mirror the attached Chapter 3 slide checklist and to provide a full research blueprint for an empirical study on AI applications in marketing. The study is grounded in the view that AI is not a single tool but a family of capabilities that can automate repetitive tasks, produce predictions from large datasets, personalize interactions, and increasingly generate content and service responses. In marketing, recent scholarship consistently locates AI's influence in customer understanding, segmentation and targeting, recommendation systems, advertising optimization, service automation, and generative content workflows. [3]

Because several key details were not specified in the brief, the following assumptions are used and should be disclosed in the thesis methodology chapter itself. First, the **country context** is assumed to be Saudi Arabia. Second, the **industry scope** is assumed to be consumer-facing sectors where measurable campaign, conversion, and service outcomes are available. Third, the **unit of analysis** is the firm's marketing function, represented by a knowledgeable key informant. Fourth, the **time horizon** is assumed to be cross-sectional fieldwork completed within one quarter, with interviews following the survey. These assumptions keep the design coherent while remaining transferable to another country or sector if the researcher later narrows the study scope. Saudi Arabia is an analytically plausible setting because SDAIA identifies data and AI as national priorities, while GASTAT provides establishment-level economic sector statistics suitable for sampling and stratification. [4]

The assumed **study objective** is to determine whether and how major AI marketing applications improve marketing outcomes, and under what organizational and data conditions they do so. In practical terms, the chapter therefore models four focal AI application domains as independent variables: **AI personalization capability**, **AI chatbot capability**, **predictive analytics capability**, and **programmatic advertising optimization capability**. Two substantive outcomes are proposed: **marketing performance** and **customer experience**. Two enabling conditions are modeled as higher-level explanatory factors: **data quality** and **organizational AI readiness**. Control variables are included to reduce omitted-variable bias and to account for sectoral and organizational heterogeneity. This variable architecture reflects leading reviews showing that contemporary AI-in-marketing research clusters around personalization and targeting, customer interaction, predictive analysis, creative/content generation, advertising optimization, and ethics/privacy. [5]

Operational definitions for research variables

The operationalization below is designed for a manager survey using mostly multi-item Likert scales, paired with interview prompts that probe mechanisms and implementation context. The constructs are intentionally defined in firm-capability terms rather than narrow product-feature terms, so that the model remains valid even if respondents use different vendors or combinations of tools.

Construct	Role in model	Operational definition	Indicative operationalization	Proposed scale
AI personalization capability	Independent variable	The extent to which the firm uses AI/ML to tailor products, messages, offers, or content across channels using current and historical customer data. [6]	Real-time recommendations; next-best offer; dynamic content targeting; product/content relevance	7-point Likert composite
AI chatbot capability	Independent variable	The extent to which conversational AI supports customer service, lead qualification, or guided selling with speed, accuracy, and contextual relevance. [7]	Query resolution; response speed; contextual accuracy; escalation quality; lead capture	7-point Likert composite
Predictive analytics capability	Independent variable	The extent to which the firm uses AI/ML to forecast customer	Propensity scoring; churn prediction; budget forecasting; lead scoring; next-best-action models	7-point Likert composite

Construct	Role in model	Operational definition	Indicative operationalization	Proposed scale
		behavior, campaign outcomes, churn, conversion propensity, or next-best actions for marketing decisions. [8]		
Programmatic advertising optimization capability	Independent variable	The extent to which AI automates bidding, targeting, auction-time decisions, and ad delivery optimization to maximize conversion or conversion value. [9]	Auction-time bidding; target CPA/ROAS; audience quality optimization; bid automation	7-point Likert composite
Data quality	Enabling / moderating variable	The degree to which marketing data are accurate, complete, timely, consistent, and usable for AI-supported decision making. [10]	Accuracy; completeness; timeliness; consistency/integration across touchpoints	7-point Likert composite
Organizational AI readiness	Enabling / moderating variable	The degree to which the organization has leadership support, data/infrastructure capability, skills, governance, and confidence to deploy AI in marketing. [11]	Top-management support; skills; infrastructure; privacy/governance; change readiness	7-point Likert composite

Construct	Role in model	Operational definition	Indicative operationalization	Proposed scale
Marketing performance	Dependent variable	Perceived improvement in the efficiency and effectiveness of marketing outcomes attributable to AI-enabled marketing applications. Marketing performance assessment is especially salient in digital environments shaped by automation and customer-experience priorities. [12]	Conversion rate, ROAS, lower CPA/CAC, lead quality, revenue contribution, customer retention	7-point Likert composite ; optional objective KPI fields
Customer experience	Dependent variable	Perceived improvement in relevance, responsiveness, convenience, satisfaction, and trust in customer interactions attributable to AI-enabled marketing. [13]	Relevance, satisfaction, perceived usefulness, trust, responsiveness, ease	7-point Likert composite
Firm size, industry, digital maturity, years using AI, marketing budget intensity	Control variables	Organizational characteristics that may independently influence AI adoption and marketing outcomes. [14]	Employees, sector, digital marketing maturity, AI tenure, budget share	Nominal, ordinal, ratio

A second useful form of operationalization is by **AI marketing approach**, because many respondents think in applications rather than latent constructs. The following comparison table helps define the study domain and offers a defensible basis for questionnaire wording and interview prompts.

AI marketing tool or approach	Purpose	Data required	Strengths	Limitations	Typical metrics	Example vendors
Personalization engines	Deliver individualized recommendations, offers, and dynamic content across web, app, email, and journeys	Clickstream, transaction history, CRM profiles, product catalog, context, identity resolution	High relevance, scalable cross-channel tailoring, stronger conversion potential	Data integration burden; privacy and “creepiness” risks if inference is opaque or overpersonalized	CTR, CVR, AOV, revenue per visitor, retention, recommendation acceptance	Salesforce Personalization; Adobe Experience Platform [15]
AI chatbots and conversational agents	Answer questions, qualify leads, support service, guide purchases, and reduce response time	Conversation logs, FAQs, product/service knowledge, customer profile/context, escalation rules	24/7 availability, speed, consistency, service scalability	Accuracy gaps, poor handling of edge cases, trust loss if human escalation is weak	First-response time, containment rate, resolution rate, CSAT, lead conversion, escalation rate	IBM watsonx Assistant [7]

AI
marketing
tool or
approach

tool or approach	Purpose	Data required	Strengt hs	Limitation s	Typical metrics	Example vendors
Predictiv e analytics and next-best-action models	Forecast behaviors and optimize targeting, timing, spend, retention, and propensity-based offers	Historical campaign data, transactions, customer history, engagement events, churn/conver sion labels	Better prioritiz ation, smarter budget allocati on, earlier interven tion, scalabl e decisio n support	Sensitive to data quality and label quality; may encode historical bias; model drift risk	Propensity lift, churn reduction, forecast accuracy, lead-score precision, uplift, ROI	Adobe Experience Platform; SAS Customer Intelligence 360 [16]
Program matic advertising and AI bidding optimization	Automate bid, audience, and auction-time decisions toward conversion or conversion value	Conversion history, audience signals, contextual signals, auction-time signals, attribution/co nversion-value data	Speed and scale in auction s, continu ous optimiz ation, better cost-efficien cy when tracking is strong	Opaque optimizati on logic, dependen ce on clean conversio n tracking, vulnerabili ty to signal loss	ROAS, CPA, CAC, conversio n value, CPC, impressio n share, qualified traffic	Google Ads Smart Bidding [9]

Research design

This study is best designed as a **mixed-methods explanatory sequential design**. In practical terms, that means quantitative data are collected and analyzed first, and qualitative data are collected afterward to explain the quantitative patterns, subgroup differences, outliers, or unexpected results. That sequencing is particularly suitable for AI in marketing because managerial survey data can show whether relationships exist, but

interviews are often needed to explain **why** some AI applications work in some firms and fail in others, how data quality affects usefulness, and where privacy or governance concerns alter implementation behavior. Explanatory sequential mixed methods are explicitly intended to use qualitative inquiry to elaborate initial quantitative findings. [17]

Under the **research onion**, the chapter adopts the following layered choices. The **research philosophy** is **pragmatism**, because the study is problem-centered and seeks both explanation and managerial usefulness. The **approach to theory development** is **abductive with a predominantly deductive first phase**: the survey tests hypotheses grounded in prior literature, while interviews refine and contextualize interpretation. The **methodological choice** is mixed methods. The **strategy** is a survey followed by semi-structured interviews and limited documentary review. The **time horizon** is cross-sectional. The **techniques and procedures** are questionnaire administration, interviewing, psychometric validation, and multivariate analysis. This sequencing is consistent with Saunders' onion logic, which moves from philosophy and approach to methodological choice, strategy, time horizon, and techniques. [18]

The proposed research questions are as follows. **RQ1**: To what extent do AI personalization, AI chatbots, predictive analytics, and programmatic optimization improve marketing performance? **RQ2**: To what extent do those AI applications improve customer experience? **RQ3**: Do stronger data quality and greater organizational AI readiness strengthen the relationship between AI applications and outcomes? **RQ4**: How do managers explain the mechanisms, barriers, governance issues, and human–AI trade-offs behind the observed quantitative results? These questions are consistent with current literature emphasizing personalization, predictive analysis, customer interaction, and privacy/ethics as core clusters in AI-enabled marketing research. [19]

The quantitative hypotheses can therefore be framed as follows: **H1–H4**: each focal AI application capability positively influences marketing performance; **H5–H8**: each focal AI application capability positively influences customer experience; **H9**: data quality positively strengthens the relationship between AI application capabilities and outcomes; **H10**: organizational AI readiness positively strengthens the relationship between AI application capabilities and outcomes. Because contemporary AI research in marketing also flags ethics, security, and trust as consequential, interviews will probe these themes even if they are not modeled as full latent constructs in the first round of hypothesis testing. [20]

Research population and sampling methods and technique

The **target population** is defined as marketing professionals and decision-makers working in consumer-facing firms operating in Saudi Arabia that use at least one AI-enabled marketing tool or approach. Relevant roles include chief marketing officers, digital marketing managers, growth managers, CRM managers, e-commerce managers, marketing analysts, customer experience managers, and customer service automation leads. The **respondent eligibility criteria** are: direct involvement in marketing decisions, familiarity with at least one AI marketing application, and at least six months of exposure to its use in the focal firm. The **unit of analysis** is the firm's marketing function as reported by a knowledgeable key informant. This design is appropriate because official Saudi economic statistics define establishments across sectors and sizes, allowing the sampling frame to be organized systematically. [21]

The **sampling frame** will be constructed in two stages. First, the researcher compiles a list of eligible firms from establishment directories, chambers and association lists where available, public company websites, sector rankings, and professional business networks, then screens them for evidence of digital marketing operations and AI-related martech usage. Second, the researcher identifies a single qualified marketing key informant within each firm. Because no perfect census of AI-using marketing firms is likely to exist, the most rigorous feasible approach is **multi-stage sampling**: purposive identification of eligible firms, followed by **stratified selection by industry and firm size**, followed by criterion-based selection of one informed respondent within each firm. The strata should, at minimum, distinguish sector and size because both are shown in Saudi business statistics to matter for establishment structure and resource conditions. [22]

For the **quantitative phase**, a conservative sample size is calculated with Cochran's large-population formula:

$$n_0 = \frac{Z^2 p(1-p)}{e^2}$$

Using the standard assumptions of **95% confidence** ($Z = 1.96$), **maximum variability** ($p = 0.50$), and **5% margin of error** ($e = 0.05$), the minimum sample is:

$$n_0 = \frac{1.96^2 \times 0.50 \times 0.50}{0.05^2} = 384.16 \approx 385$$

If the final eligible frame is finite, Cochran's finite-population correction will be applied:

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}}$$

On this basis, the minimum target is **385 usable questionnaires**, but the field target should be increased to **450–500 completed responses** to absorb incomplete data, failed attention checks, and subgroup imbalance. Cochran’s method remains appropriate for large populations and is standard in survey research. [23]

For the **qualitative phase**, the sampling technique should be **purposive maximum-variation sampling** drawn from survey respondents who consent to follow-up interviews. Interviewees should be selected from firms with high, medium, and low AI maturity and from cases showing strong positive effects, weak effects, and contradictory outcomes in the survey. A target of **15–20 interviews** is defensible, with stopping guided by thematic saturation; systematic evidence suggests many interview studies reach meaningful saturation within a relatively narrow range, often around **9–17 interviews**, especially when the sample is reasonably homogeneous and the domain is focused. [24]

The resulting **sampling rationale** is strong. Stratification improves heterogeneity control across sectors and firm sizes. The key-informant design improves construct validity because very few organizations can provide AI marketing information through arbitrary employee sampling. The qualitative follow-up adds contextual depth, identifies mechanism pathways, and reduces the risk of superficial survey interpretation. This is especially important in AI research, where results often depend on governance quality, human oversight, and data readiness rather than tool presence alone. [25]



Data collection methods

The primary data collection instruments are a **structured questionnaire** and a **semi-structured interview guide**. The questionnaire is appropriate for testing relationships among constructs across a sizeable sample, while the interview guide is appropriate for explaining how capabilities are deployed, where models succeed or fail, and why managers trust or distrust specific AI uses. The instruments are not intended to capture the full technical architecture of AI systems; rather, they measure the **organizationally**

meaningful capabilities and outcomes that prior marketing scholarship identifies as consequential: personalization, prediction, interaction quality, experience, performance, and readiness. [26]

The **questionnaire** should consist of five parts: screening questions; organizational profile and control variables; multi-item measures for the four AI application capabilities; multi-item measures for data quality and organizational readiness; and outcome measures for marketing performance and customer experience. Unless the eventual supervisor requires a different convention, a **7-point Likert scale** from strongly disagree to strongly agree is preferable because it provides richer variance than a 5-point scale while remaining straightforward for respondents. If the Saudi field setting requires bilingual administration, an Arabic version may be added after expert review and back-translation. The survey should be delivered online, with firm-level invitations sent by email and professional channels, followed by two to three reminder waves. [27]

Suggested survey items are shown below. They are intentionally phrased for **adaptation**, not verbatim adoption, and should be refined after expert review, cognitive pretesting, and pilot results.

Variable	Suggested questionnaire items mapped to the construct
AI personalization capability	“Our firm uses AI to personalize offers or content in real time.”; “AI recommendations improve the relevance of our customer communications.”; “Customer profiles are updated quickly enough to support timely personalization.” [28]
AI chatbot capability	“AI chatbots resolve routine customer inquiries effectively.”; “Our conversational AI provides accurate and contextually appropriate responses.”; “Using chatbots has reduced response time in customer-facing interactions.” [7]
Predictive analytics capability	“We use AI/ML to predict customer behavior such as churn, conversion, or next best offer.”; “Predictive models meaningfully influence target selection and budget allocation.”; “The predictive outputs we use are sufficiently accurate for campaign decisions.” [29]
Programmatic optimization capability	“Our paid digital campaigns use AI-driven bid optimization.”; “Auction-time optimization improves the quality or value of conversions we obtain.”; “AI helps us reduce spend on low-value impressions or audiences.” [30]
Data quality	“Our customer and campaign data are accurate.”; “Our marketing data are complete enough for AI-driven decisions.”;

Variable	Suggested questionnaire items mapped to the construct
	“Data from different touchpoints are sufficiently integrated and timely.” [31]
Organizational AI readiness	“Top management strongly supports AI use in marketing.”; “We have the skills or external expertise required to deploy AI in marketing.”; “Our organization has governance for privacy, fairness, and monitoring of AI outputs.” [11]
Marketing performance	“AI use has improved our campaign conversion performance.”; “AI use has improved return on ad spend or marketing ROI.”; “AI use has improved lead quality, targeting efficiency, or customer retention.” [12]
Customer experience	“AI-enabled marketing has made our customer interactions more relevant.”; “AI-enabled marketing has improved customer responsiveness and convenience.”; “AI-enabled marketing has improved customer satisfaction and trust overall.” [13]

The **semi-structured interview guide** should be used after preliminary survey analysis so that interviews can explain the strongest, weakest, and most surprising quantitative findings. Suggested interview questions are as follows.

Interview question	Variable or theme mapped
“Which AI applications are most central to your marketing work, and why?”	Overall AI application intensity; tool mix
“Can you describe one campaign or journey where AI clearly improved results?”	Marketing performance; mechanism identification
“What kinds of customer and campaign data are most critical for these AI applications?”	Data quality
“Where do data quality or integration problems reduce AI usefulness?”	Data quality constraints
“How do chatbots, personalization, prediction, or bidding tools affect customer experience in practice?”	Customer experience; use-case comparison
“What internal capabilities made AI implementation easier or harder?”	Organizational AI readiness
“How do privacy, bias, explainability, or governance concerns shape tool use?”	Governance, ethics, trust
“When do humans override AI recommendations or decisions?”	Human oversight; augmentation versus replacement

Interview question	Variable or theme mapped
“Why do some AI applications produce stronger results than others in your organization?”	Cross-case explanation; contingency mechanisms
“What would need to change for AI in marketing to create more value in your firm?”	Readiness, barriers, future roadmap

Pilot testing, validity, and reliability are essential. The instrument-development sequence should be: literature-derived draft items; expert review by **5–7 subject and methods experts**; cognitive pretesting with **8–10 target respondents** to assess wording and response interpretation; then a **pilot survey of around 30–50 respondents**. Cognitive interviewing is a recognized method for identifying response problems before main fieldwork, and Lawshe-type expert-judgment procedures remain useful for content validity assessment. For pilot reliability work, recent guidance indicates that **about 30 pilot respondents** may be adequate for assessing whether a questionnaire’s reliability is likely to be acceptable before the full study. [32]

For **validity**, the study should establish face validity through expert review, content validity through CVR/CVI, construct validity through factor analysis, convergent validity through factor loadings and AVE, and discriminant validity through HTMT-based checks. For **reliability**, Cronbach’s alpha may be reported for continuity with much of the marketing literature, but composite reliability should be treated as the stronger primary indicator for latent constructs. Recent best-practice recommendations in SEM explicitly favor reporting composite reliability and using multiple criteria for convergent and discriminant validity rather than relying on a single cutoff or single statistic. [33]

The study should also proactively address **common method bias**, since key independent and dependent variables are collected from the same respondent at one point in time. Procedural remedies should include anonymity assurances, concise and unambiguous items, separation of predictor and outcome blocks, randomized item order within blocks, and clear instructions that there are no right answers. Statistical remedies can include a marker-variable approach or full-collinearity diagnostics as a robustness check. Recent reviews are explicit that common method bias is real, complex, and not easily fixed after the fact, so prevention during instrument design is critical. [34]

Finally, the Saudi field setting requires explicit **ethical and data-protection safeguards**. Consent should be obtained before both survey and interview participation. The study should avoid collection of any customer personal data from respondents; it only needs manager perceptions and optional aggregated firm-level performance indicators. If interviews are recorded, audio files and transcripts should be stored securely, anonymized, and retained only for the approved research period. For Saudi-based fieldwork, the study should explicitly state compliance with the PDPL, which applies

broadly to personal-data processing in the Kingdom and to processing related to individuals residing in the Kingdom. [35]

Types of data

The study uses both **primary** and **secondary** data. The core empirical evidence comes from **primary survey data** and **primary interview data**. Secondary data are used for contextualization, frame construction, instrument refinement, and interpretation rather than as the main hypothesis-testing dataset. Appropriate secondary sources include official Saudi statistics, policy documents, firm websites and annual reports, and official product documentation from AI marketing vendors. This combination is methodologically sound because marketing performance and customer-experience evidence often require both perception-based measures and contextual or archival support. [36]

Data type	Example in this study	Measurement scale or format	Main analytical use
Primary quantitative	Survey responses on AI capabilities, readiness, data quality, outcomes	Mostly ordinal Likert items combined into interval-like composite construct scores; some nominal and ratio controls	Hypothesis testing, descriptives, multivariate analysis
Primary qualitative	Semi-structured interview transcripts	Textual data	Thematic explanation, mechanism discovery, contextualization
Secondary official/policy	SDAIA strategy and PDPL guidance; GASTAT business statistics	Documentary / textual	Context, sampling frame support, governance discussion
Secondary organizational	Firm websites, annual reports, case descriptions, optional aggregated KPI dashboards	Text, ratio metrics if shared	Descriptive triangulation and interview follow-up

Data type	Example in this study	Measurement scale or format	Main analytical use
Secondary technical/vendor	Official product documentation from Google, Salesforce, Adobe, IBM, SAS	Documentary / textual	Instrument wording, use-case specification, approach classification

The scales of measurement should be handled as follows. **Nominal** variables include industry, role, and AI tools currently used. **Ordinal** variables include raw Likert responses and self-rated AI maturity categories. **Interval-like composite** variables arise when multiple Likert items are combined into validated latent-construct scores for parametric analysis. **Ratio** variables include years of AI use, number of employees, ad spend share where reported, and optional objective KPIs such as conversion rate or ROAS. This scale structure is sufficient for descriptive statistics, factor analysis, regression, and SEM if the measurement model is validated appropriately. [37]

Statistical analysis procedures

The quantitative analysis should proceed in stages. First, the researcher performs **data screening**: missing-value diagnostics, duplicate checks, straight-lining checks, response-time outlier review, and basic univariate descriptives. Second, the researcher tests **measurement quality** through reliability and validity procedures. Third, the researcher estimates the **structural relationships** among constructs. Fourth, the qualitative results are used to explain the statistical findings through thematic analysis and joint interpretation. This staged logic is especially appropriate in AI-in-marketing work because contemporary reviews emphasize not only the substantive effects of AI but also the role of data quality, privacy, readiness, and contextual contingencies. [38]

The preferred statistical software stack is **R** for reproducible quantitative analysis and **IBM SPSS Statistics** for initial cleaning, descriptives, and straightforward screening if the researcher prefers a GUI. R is an established environment for statistical computing and graphics, while SPSS provides a comprehensive statistical analysis platform suited to management and social-science workflows. If the researcher or institution prefers a dedicated SEM package, the structural model can equivalently be estimated in R's SEM ecosystem or in Stata/AMOS, but the methodological logic remains the same. [39]

For measurement evaluation, the questionnaire data should first be checked for **factorability** and then subjected to **EFA** if the item pool has been heavily adapted, followed by **CFA** on the full sample to confirm the latent structure. Reliability should be reported using Cronbach's alpha and, more importantly, composite reliability. Convergent validity should be assessed using loadings and AVE; discriminant validity should be checked using HTMT-style criteria. Best-practice recommendations in recent SEM work advise using **multiple criteria** and accounting for sampling error rather than treating any single threshold as decisive. [33]

For hypothesis testing, the primary inferential approach should be **structural equation modeling** because the model uses multiple latent constructs, potentially correlated predictors, and two outcome constructs. If multivariate normality is acceptable, covariance-based SEM with robust standard errors is appropriate. If normality is weak or the realized sample is smaller than planned, the researcher can still estimate the structural model with robust estimators and bootstrapped confidence intervals, while keeping regression-based robustness checks in reserve. Standard assumptions include adequate sample size, reasonable linearity among latent relationships, acceptable multicollinearity, and residual diagnostics where appropriate. Multicollinearity can be checked with VIFs; non-normality can be handled with robust estimation or bootstrapping. [40]

The qualitative analysis should use **thematic analysis** focused on mechanisms, contextual moderators, and governance themes. Coding should begin with a hybrid structure: deductive codes derived from the survey constructs and literature, then inductive codes that capture unanticipated issues such as data fragmentation, organizational politics, or consumer backlash. Trustworthiness can be improved through codebook discipline, analytic memos, peer debriefing or second-coder review on a subset, and member checking where feasible. Contemporary discussions of qualitative rigor continue to emphasize credibility, dependability, confirmability, and transferability as trustworthiness criteria. [41]

The table below maps the main research questions and hypotheses to specific analyses.

Research question or hypothesis	Variables involved	Main analysis	Key assumptions and diagnostics	Output
Measurement quality precondition	All multi-item constructs	Descriptive stats; EFA if needed; CFA on full sample;	Factorability, internal consistency, convergent/discriminant validity, low common method bias	Validated measurement model

Research question or hypothesis	Variables involved	Main analysis	Key assumptions and diagnostics	Output
		CR, AVE, HTMT		
RQ1 / H1–H4: AI application capabilities → marketing performance	Personalization , chatbot, predictive analytics, programmatic optimization → marketing performance; controls included	SEM path analysis; robustness with hierarchical multiple regression	Adequate sample; acceptable VIF; residual checks; robust SE or bootstrap if needed	Standardized path coefficients, confidence intervals, effect sizes
RQ2 / H5–H8: AI application capabilities → customer experience	Same IVs → customer experience; controls included	SEM path analysis	Same as above	Estimated effects on CX construct
RQ3 / H9–H10: moderation by data quality and AI readiness	AI capability constructs × data quality / AI readiness → outcomes	Latent-interaction SEM or mean-centered hierarchical regression interactions	Interaction specification; multicollinearity; bootstrap CIs	Moderation slopes, interaction plots
Subgroup exploration	Sector, firm size, AI tenure, digital maturity	ANOVA / MANOVA or multigroup SEM where sample sizes permit	Group balance; measurement invariance if multigroup SEM is used	Sectoral and size-pattern comparison
Nonresponse / response-quality checks	Early vs late respondents; screened vs retained cases	t-tests, chi-square tests, response-pattern checks	Comparable groups, no severe imbalance	Bias assessment notes

Research question or hypothesis	Variables involved	Main analysis	Key assumptions and diagnostics	Output
RQ4: mechanisms, barriers, governance, trade-offs	Interview transcripts and contextual documents	Thematic analysis and joint display with survey results	Trustworthiness procedures; documented coding logic	Explanatory themes integrated with quantitative results

If the researcher wishes to state explicit decision rules, they may do so in the final thesis draft. However, the stronger position is to emphasize **holistic model evaluation** rather than rigid cutoff worship: report global fit indices, inspect modification logic cautiously, retain theory as the primary guide, and interpret results with effect sizes and confidence intervals rather than p-values alone. Similarly, the final write-up should clearly distinguish **statistical significance**, **practical significance**, and **managerial significance**, because AI tools can produce statistically detectable effects that remain too small, too costly, or too governance-heavy to justify adoption at scale. [42]

Conclusion

This chapter proposes a coherent and rigorous methodology for studying AI applications in marketing under realistic organizational conditions. It is rigorous because it uses explicit assumptions, theory-informed constructs, formal sample-size logic, psychometric validation, sequential mixed methods, and a clear analytical pathway from measurement validation to structural inference and qualitative explanation. It is also practical because it focuses on the AI use cases that dominate current scholarship and managerial deployments: personalization, chatbots, predictive analytics, and programmatic optimization. Recent research makes clear that these capabilities matter, but also that their value depends on data quality, readiness, trust, and governance. A methodology that measures only tool presence would therefore be too weak; a methodology that measures capability, readiness, data quality, and outcomes together is stronger and better aligned with current evidence. [43]

The design is especially suitable if the empirical study ultimately seeks not only to ask **whether** AI improves marketing but also **how**, **when**, and **under what organizational conditions** it does so. If the later thesis narrows the context to a single industry, the same methodology can be retained with minimal adaptation: revise the strata, refine some

control variables, and adjust interview prompts toward sector-specific metrics. If the country changes, only the frame construction, privacy-law references, and contextual secondary sources need to be replaced. In that sense, the chapter is both contextually grounded and portable. [44]

Prioritized sources used to ground this chapter

Source	Why it is prioritized
OECD Recommendation and updated definition of an AI system [45]	Primary policy definition of AI used to state the study's conceptual domain
Davenport, Guha, Grewal, and Bressgott, <i>Journal of the Academy of Marketing Science</i> [46]	Foundational peer-reviewed paper on how AI changes marketing strategy and behavior
Huang and Rust, <i>Journal of the Academy of Marketing Science</i> [47]	Core framework for AI use in marketing research, STP, and actions
Grewal, Saturnino, and Guha on generative AI in marketing [48]	Recent top-tier source connecting GenAI to marketing practice and future research
Cillo and Rubera on GenAI in innovation and marketing [49]	Current roadmap for GenAI opportunities in marketing processes
Lakshika, Chathuranga, and Jayarathne, <i>Journal of Marketing Analytics</i> review [50]	Recent systematic review identifying major AI/ML clusters in digital promotion
Nicolescu and Tudorache on AI chatbots and customer experience [51]	Useful peer-reviewed synthesis for chatbot-related constructs and interview prompts
Morgan et al. on marketing performance assessment [52]	Strong basis for outcome measurement logic in digital/automation contexts
Cheung et al. on reliability, convergent validity, and discriminant validity in SEM [53]	Recent best-practice source for measurement validation
Podsakoff et al. on common method bias [54]	Critical methodological source for single-respondent survey design risks
GASTAT Structural Business Statistics and SDAIA PDPL guidance [27]	Primary Saudi official sources for frame construction and ethics/data protection
Official product documentation from Salesforce, Google, IBM, Adobe, and SAS [55]	Primary sources for defining the focal AI marketing applications and their practical metrics

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