Role of Artificial Intelligence in Marketing for Entrepreneurs

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ABSTRACT

This study examines how specific applications of artificial intelligence in marketing relate to entrepreneurial outcomes in Kerala. Using a cross-sectional survey of owner-managers across regions and sectors, the instrument captured Likert-type composites on overall AI use, AI-driven personalisation, AI-based segmentation and targeting, chatbot practice, marketing performance, and service responsiveness. Data were screened for completeness and polarity alignment, and analyses were conducted in EDUSTAT. Hypotheses were tested with straightforward inferential procedures appropriate for composite scales. The results show a consistent pattern: broader AI use is associated with stronger overall marketing performance; personalisation aligns with higher conversion; segmentation aligns with greater targeting accuracy; and chatbot adoption corresponds to faster responses and higher customer satisfaction. These associations are theoretically coherent with the roles each capability plays in the marketing funnel and practically meaningful for micro and small enterprises. The study offers a concise, state-level evidence base that can guide entrepreneurs toward high-leverage use-cases—prioritising personalisation at the point of decision, disciplined segmentation for qualified enquiries, and well-configured chatbots for responsiveness—supported by basic data hygiene and routine tracking of core metrics. Limitations include the cross-sectional design and reliance on self-reports, suggesting opportunities for longitudinal and objective-metric extensions.

KEYWORDS: Artificial Intelligence; Entrepreneurial Marketing; Chatbots.

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INTRODUCTION

Artificial intelligence (AI) has moved from experimentation to mainstream use in marketing, enabling firms to automate campaign optimisation, personalise content at scale, and augment frontline service through conversational agents. Conceptual and review work in marketing shows that AI systems affect the entire funnel—improving targeting (through machine-learning segmentation), increasing relevance at the point of decision (through personalisation and recommendation), and reshaping service encounters (through chatbots and decision support) (Davenport, Guha, Grewal, & Bressgott, 2020; Jain, 2024). These capabilities map to measurable outcomes: targeting precision, conversion, cost-efficiency, and service responsiveness.

Evidence on two mechanisms is particularly salient for entrepreneurs. First, personalisation tends to raise engagement and conversion when executed with adequate relevance and timing, although effects depend on trust and perceived intrusiveness (Bleier & Eisenbeiss, 2015; Boerman, 2021). Second, AI chatbots can improve responsiveness and purchase outcomes in some settings, while design choices (e.g., disclosure, handover to humans) shape satisfaction and effectiveness (Luo, Tong, Fang, & Qu, 2019; Adam, Wessel, & Benlian, 2021). Together, these strands suggest testable links between AI practice and marketing results that are actionable at the small-firm level.

India's digital context strengthens the case for examining AI in entrepreneurial marketing. National digital public infrastructure—most visibly UPI—has accelerated online transactions and lowered frictions for small firms, creating data and channels where AI can operate (Bank for International Settlements, 2024). Public policy has also emphasised diffusion of AI: the National Strategy for Artificial Intelligence articulated priority domains and ethical guardrails, and the IndiaAI Mission (approved in 2024) aims to scale compute, datasets, and skilling to enable MSME adoption (NITI Aayog, 2018; Press Information Bureau, 2024). Within this landscape, micro, small and medium enterprises (MSMEs) are economically pivotal and increasingly exposed to digital markets (Ministry of MSME, 2024). Kerala, in particular, has an active startup and MSME ecosystem—supported by Kerala Startup Mission—that engages with AI, data, and automation tools (Kerala Startup Mission, 2024). Yet rigorous, state-level empirical evidence on how AI use links to small-firm marketing outcomes remains limited.

This study addresses that gap by focusing on entrepreneurs in Kerala. We test four simple hypotheses that tie specific AI practices to their most relevant outcomes: (H1) broader AI use to overall marketing performance; (H2) AI-driven personalisation to conversion; (H3) AI-based segmentation to targeting accuracy; and (H4) chatbot deployment to service responsiveness and satisfaction. The aim is practical and cumulative: to offer clear, evidence-based associations that entrepreneurs and support agencies can act on—and that future research can extend with longitudinal designs, objective platform metrics, and richer causal identification. The Kerala setting provides policy and ecosystem relevance while complementing the largely large-enterprise and global-north emphasis in prior literature. The results that follow should thus be read as grounded, context-specific evidence on how AI relates to marketing effectiveness in micro and small firms.

Research Questions

1. How is the overall use of AI in marketing associated with overall marketing performance among entrepreneurs in Kerala?
2. How is AI-driven personalisation associated with conversion outcomes?
3. How is AI-based segmentation and targeting associated with targeting accuracy (share of qualified enquiries)?
4. How is chatbot adoption associated with service responsiveness and customer satisfaction?

Research Objectives

- To examine the association between overall AI use in marketing and overall marketing performance among Kerala entrepreneurs.
- To assess the association between AI-driven personalisation and conversion outcomes.
- To analyse the association between AI-based segmentation/targeting and targeting accuracy.
- To determine the association between chatbot adoption and (a) service responsiveness and (b) customer satisfaction.

Hypotheses

1. Higher AI use in marketing is associated with higher overall marketing performance among entrepreneurs in Kerala.
2. Greater intensity of AI-driven personalisation is associated with higher conversion rates.
3. Greater use of AI-based segmentation/targeting is associated with higher targeting accuracy (higher share of qualified enquiries).
4. Chatbot adoption is associated with faster service responses and higher customer satisfaction.

METHODOLOGY

Research design

The study employed a cross-sectional, explanatory survey design to examine associations between the use of artificial intelligence (AI) in marketing and key marketing outcomes among entrepreneurs in Kerala. The unit of analysis was the firm, and the respondent was the owner, founder, or marketing decision-maker. All hypotheses were tested with two-tailed statistics at $\alpha = .05$.

Population and sample

The population comprised micro and small enterprises, including early-stage startups, operating in Kerala and conducting identifiable marketing activities (online and/or offline). Inclusion criteria required at least six months of continuous operation and the respondent's direct involvement in marketing decisions. A total of 200 firms constituted the final sample, providing adequate statistical power for correlation tests and group comparisons.

Sampling procedure

A multi-source frame was assembled from district-level entrepreneur networks, incubators, and business associations. To improve coverage and comparability, light quotas were applied across Kerala's three regions (North, Central, South) and across sectors (manufacturing, services, retail). Within each cell, respondents were recruited using random starts and rolling replacement to address non-response while maintaining the intended distribution.

Measures

Data were collected using a structured questionnaire with 5-point Likert responses (1 = strongly disagree to 5 = strongly agree) anchored to the preceding 30-day period. AI use in marketing was captured by the AI Marketing Use Index (AMUI), formed by averaging multiple items that reflect the breadth and depth of AI adoption across campaign optimisation, content assistance, and workflow integration. AI-driven personalisation (AIPP) and AI-based segmentation and targeting (AISP) were measured as separate multi-item composites reflecting the intensity of practice in each domain. Chatbot adoption and quality (CAQ) was captured with items on availability, containment, handover, and monitoring, alongside a binary indicator of adoption for group comparisons. Marketing performance was operationalised as four brief composites: conversion, targeting accuracy, ROI/CAC, and retention; an overall performance score was computed as the mean of all performance items. Targeting accuracy was measured with a two-item subscale reflecting the proportion and stability of qualified enquiries. Service responsiveness and satisfaction (SRS) summarised perceived first-response speed, resolution, and customer ratings. Firm-level controls included sector, region, years in operation, employee band, monthly ad-spend band, and market scope. Items were reverse-coded where required before averaging; higher scores indicate more of the construct.

Instrument development and data quality

The instrument was reviewed for content relevance and wording clarity and piloted with a small group of entrepreneurs to verify comprehension and response ranges. The final form included brief definitions/examples under numeric or technical terms, an attention-check item, and an optional non-identifying KPI section (bands for conversion rate, qualified-lead share, ROAS, and median first-response time) to triangulate self-reports. Returned forms were screened for completeness, patterned responding, and out-of-range entries. Missing data were minimal and handled via listwise deletion within each test; no imputation was required.

Data collection and Analysis procedure

Data were collected over a defined window using an online form distributed through regional entrepreneur groups, incubator lists, and association channels. Where necessary, short assisted calls were used to clarify definitions and reduce item non-response. No personally identifying information was required beyond optional contact details for sharing aggregate findings.

Composite scores were computed as the mean of their constituent items after reverse coding. Preliminary analyses profiled the sample by region, sector, and chatbot adoption. Hypotheses H1–H3 were tested using Pearson correlations with 95% confidence intervals. Hypothesis H4 compared chatbot adopters and non-adopters with Welch's unequal-variance t-tests on SRS and on median first-response time (minutes; lower values indicate better performance), and a supportive comparison on CSAT. Effect sizes were reported as correlation coefficients (r) and Hedges' g. All analyses were conducted in EDUSTAT.

Ethical considerations

Participation was voluntary with informed consent recorded at the start of the form. The study avoided collection of sensitive personal identifiers, assured confidentiality, and reported only aggregated statistics. Respondents could decline any item without penalty.

DATA ANALYSIS AND INTERPRETATION

This section presents the tests conducted on survey data from Kerala-based entrepreneurs (n = 200). Analyses were carried out in EDUSTAT using two-tailed tests with $\alpha = .05$. Multi-item Likert responses were reverse-coded where required and averaged into composite scores, which were treated as approximately continuous. Preliminary checks covered sample profiling and item polarity to ensure consistent construct direction. Hypotheses H1–H3 were examined using Pearson correlations with 95% confidence intervals. Hypothesis H4 compared chatbot adopters and non-adopters using Welch's unequal-variance t-tests, reporting mean differences, 95% confidence intervals, and Hedges' g. Missing data were minimal and handled via listwise deletion for each test.

Preliminary analysis

Table 1

Distribution of Respondents by Region (n = 200)

Region	n	%
North	66	33.0
Central	66	33.0
South	68	34.0

The sample is evenly spread across Kerala—North (33.0%), Central (33.0%), and South (34.0%). This near-uniform distribution limits regional skew and supports state-wide inference.

Table 2

Distribution of Respondents by Industry (n = 200)

Industry	n	%
Manufacturing	49	24.5
Services	95	47.5
Retail	56	28.0

Services constitute the largest share (47.5%), followed by Retail (28.0%) and Manufacturing (24.5%). This mix reflects the predominance of service-oriented enterprises in Kerala and provides sectoral heterogeneity for analysis.

Table 3
Distribution of Respondents by Chatbot adoption (n = 200)

Chatbot Adopted	n	%
Yes	97	48.5
No	103	51.5

Chatbot adopters (48.5%) and non-adopters (51.5%) are closely balanced. This yields comparably sized groups, enabling reliable tests of chatbot-related differences in responsiveness and satisfaction.

Hypothesis testing
H1: Higher AI use in marketing is associated with better overall marketing performance.
H2: AI-driven personalization is associated with higher conversion.
H3: AI-based segmentation is associated with greater targeting accuracy.

Table 4
Pearson correlations for H1–H3

Hypothesis	Predictor → Outcome	r	95% CI	p	n
H1	AMUI Score → MP Overall	0.758	[0.693, 0.812]	< .001	200
H2	AIPP Score → MP Conversion	0.678	[0.596, 0.747]	< .001	200
H3	AISP Score → MP Targeting	0.555	[0.452, 0.645]	< .001	200

All three correlations are positive and statistically significant ($p < .001$). The association between overall AI use and marketing performance is strong ($r = 0.758$), supporting H1. Personalization shows a large positive link with conversion ($r = 0.678$), supporting H2. AI-based segmentation relates moderately-to-strongly to targeting accuracy ($r = 0.555$), supporting H3.
H4: Deploying AI chatbots is associated with faster responses and higher service satisfaction.

Table 5
SRS — Chatbot adopters vs non-adopters (Welch t-test)

Chatbot	n	Mean	t	df	p	95% CI	Hedges g
Chatbot	97	3.332	8.726	197.0	< .001	[0.533, 0.844]	1.230
No chatbot	103	2.644					

Chatbot users report higher service responsiveness/satisfaction than non-users (Mean 3.332 vs 2.644), with a large effect

(Hedges g = 1.230) and a significant mean difference (t(197.0) = 8.726, p < .001; 95% CI [0.533, 0.844]). This supports H4 on perceived service quality.

Table 6
Median First Response — Chatbot adopters vs non-adopters (Welch t-test)

Chatbot	n	Mean	t	df	p	95% CI	Hedges g
Chatbot	97	62.53	−14.847	196.8	< .001	[−31.73, −24.29]	−2.094
No chatbot	103	90.54					

Chatbot adoption is associated with substantially faster responses (Mean 62.53 min vs 90.54 min), a very large effect (Hedges g = −2.094) and a significant difference (t(196.8) = −14.847, p < .001; 95% CI [−31.73, −24.29]). This further supports H4 on operational responsiveness.

Table 7
CSAT — Chatbot adopters vs non-adopters (Welch t-test)

Chatbot	n	Mean	t	df	p	95% CI	Hedges g
Chatbot	97	2.506	7.538	194.4	< .001	[0.421, 0.719]	1.056
No chatbot	103	1.936					

Customer satisfaction is higher among chatbot adopters (Mean 2.506 vs 1.936), with a large effect (Hedges g = 1.056) and a significant mean difference (t(194.4) = 7.538, p < .001; 95% CI [0.421, 0.719]). This provides additional support for H4.

Overall conclusion
Across 200 Kerala entrepreneurs, higher AI adoption in marketing is strongly associated with overall performance; AI-driven personalization aligns with higher conversion; AI-based segmentation aligns with improved targeting accuracy; and chatbot adoption aligns with faster responses and higher service satisfaction. All four hypotheses are supported.

DISCUSSION OF THE RESULTS

The findings indicate a coherent pattern of positive associations between artificial intelligence (AI) use in marketing and entrepreneurial outcomes in Kerala. General AI use relates strongly to overall marketing performance (r = 0.758), AI-driven personalisation aligns with higher conversion (r = 0.678), AI-based segmentation aligns with improved targeting accuracy (r = 0.555), and chatbot adoption associates with both faster responses (≈28 minutes quicker on average) and higher service responsiveness/satisfaction. Together, the results support all four hypotheses and suggest that targeted AI capabilities map onto the parts of the marketing funnel they are designed to influence.

The strong AI use–performance association is consistent with mechanisms such as automated optimisation, faster learning cycles, and closer integration of marketing with sales workflows. While the design is correlational, the magnitude of the association and its consistency across multiple performance facets (conversion, ROI/CAC, retention) point to a meaningful linkage rather than a trivial statistical artefact. A prudent reading recognises alternative explanations, including that more capable firms both adopt AI and perform better; nonetheless, the observed pattern remains practically significant for micro and small enterprises.

Personalisation shows a large association with conversion. This aligns with how timing, content selection, and dynamic creative optimisation reduce friction for ready-to-buy prospects. In practical terms, firms that deploy even basic send-time optimisation, recommendation widgets, or triggered journeys report better conversion experiences. Segmentation's link with targeting accuracy also makes conceptual sense: propensity models, refreshed clusters, and quality scoring raise the share of qualified enquiries and reduce time lost on mismatched leads.

Service outcomes exhibit particularly large differences for chatbot adopters. Reported first-response times are substantially lower and satisfaction higher among adopters, with large effect sizes. That pattern likely reflects 24×7 availability, automatic triage, and smoother handover to human agents. Notably, mean satisfaction levels, while higher with chatbots, still leave room for improvement, implying that configuration quality, language handling, and containment/handover tuning matter for realising the full benefit.

The Kerala context of micro and small enterprises provides important boundary conditions. The sample spans North, Central, and South regions almost evenly, and includes manufacturing, services, and retail firms, improving coverage for state-level inference. Services form the largest share, which fits the operating profile of many small Kerala firms that market through digital channels. Balanced representation of chatbot adopters and non-adopters supports credible group comparisons.

Causal inference is limited by the cross-sectional design and reliance on self-reported Likert composites for several outcomes. Objective key performance indicators were captured only in coarse bands, which constrains precision. Confounding is possible: digitally mature firms may both adopt AI and perform better for reasons not fully measured (e.g., higher ad spend, stronger brands). Sectoral and spending heterogeneity may moderate effects, but the study did not estimate moderated or multivariate models. The 30-day reference window balances recall with recency but may not capture seasonality.

Longitudinal tracking of the same firms; quasi-experimental adoption comparisons; direct platform exports for objective KPIs; multivariate models that adjust for ad spend, firm size, and sector; mediation tests for data-driven decision capability and personalisation intensity; moderation by data quality, entrepreneurial orientation, or market turbulence; and replication across Indian states to assess external validity.

Across 200 Kerala entrepreneurs, the evidence shows that AI adoption aligns with better overall marketing performance, personalisation aligns with higher conversion, segmentation aligns with more accurate targeting, and chatbots align with faster and better-rated service. The pattern is theoretically coherent and practically actionable for micro and small enterprises aiming to strengthen marketing effectiveness with manageable, high-leverage AI capabilities.

IMPLICATIONS OF THE STUDY

The results indicate that broad, integrated use of AI across the marketing workflow associates with stronger overall performance. Entrepreneurs should treat AI not as a one-off tool but as a set of connected practices—campaign optimisation, content assistance, segmentation, and service—linked to sales/CRM so that insights move quickly from targeting to conversion to follow-up.

Personalisation shows a clear link with conversion. Firms gain most by prioritising use-cases that touch the moment of decision: send-time optimisation for e-mails/WhatsApp, on-site/app recommendations, and triggered journeys (welcome, cart-abandon, re-engagement). These work best with concise creative, clear offers, and transparent consent; over-personalisation without value or permission risks disengagement.

Segmentation relates to targeting accuracy. Practical steps include defining what counts as a "qualified lead," collecting a small set of reliable first-party signals (recency, frequency, monetary value; basic behaviour events), and refreshing segments on a schedule. Even simple propensity or look-alike models reduce wasted impressions and raise the share of relevant enquiries.

Service outcomes strongly favour chatbot adopters, highlighting responsiveness as a competitive lever. Effective deployments pair 24×7 availability with Malayalam-English handling, clear escalation to human agents, and monitoring of containment rate, first-response time, and CSAT. Chatbots should address the top 10–15 intents well rather than attempting everything; periodic review of transcripts keeps quality high.

Capability building matters as much as tools. Owner-managers and small teams benefit from short, hands-on upskilling on data hygiene, prompt design for creative variants, and simple experimentation. Incubators and associations can lower adoption frictions by offering curated tool lists, vendor due-diligence checklists, shared templates, and office-hours for implementation support.

A measurement discipline is essential. Maintain a lightweight dashboard that tracks conversion rate, qualified-lead share, CAC, ROAS, median first-response time, and CSAT. Run small A/B tests when introducing AI features; keep changes reversible. Clean inputs (consistent naming, de-duped contacts, tagged campaigns) amplify AI gains and make results auditable.

For the Kerala ecosystem, targeted support can accelerate impact: subsidised access to MSME-friendly AI tools, cloud credits tied to training completion, and sandbox programmes that let firms pilot chatbots and personalisation with technical guidance. Public–private efforts that improve data literacy and privacy-by-design practices strengthen trust while enabling performance gains.

Overall, the evidence supports a practical roadmap: start with high-leverage use-cases (personalisation at conversion, chatbot responsiveness), ensure basic data readiness and measurement, and expand to segmentation and broader AI-assisted optimisation as capabilities mature.

CONCLUSION

The study shows a clear, coherent pattern linking artificial-intelligence practices to marketing outcomes among Kerala entrepreneurs. Broader AI use aligns strongly with higher overall marketing performance, AI-driven personalisation aligns with higher conversion, and AI-based segmentation aligns with greater targeting accuracy; chatbot adoption corresponds to markedly faster responses and higher service satisfaction. These results, based on a state-wide sample of 200 firms and tested with simple, transparent statistics, indicate that practical AI capabilities map to the specific points in the funnel they are designed to influence. While the cross-sectional design and reliance on self-reports limit causal inference, the magnitudes observed are substantive and operationally meaningful for micro and small enterprises. Taken together, the evidence supports prioritising personalisation at the point of conversion, disciplined segmentation for qualified leads, and well-configured chatbots for responsiveness—underpinned by basic data hygiene and monitoring of conversion, qualified-lead share, CAC/ROAS, and response times.

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