Artificial Intelligence Applications and Customer Engagement among Microcredit Recipient Entrepreneurs in Selangor, Malaysia

Nasharuddin Mohammad[1]*, Siriaupa Salleh[2]

[1]Academy of Contemporary Islamic Study, Universiti Teknology MARA, 40450 Shah Alam, Selangor, Malaysia

[2]Centre for Languages and Pre-University Academic Development (CELPAD), International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia

DOI: https://doi.org/10.47772/IJRISS.2026.101000814

Received: 25 October 2026; Accepted: 30 October 2026; Published: 18 November 2026

ABSTRACT

Artificial intelligence (AI) offers opportunities to support customer interactions, yet its relevance to customer engagement among microcredit recipient entrepreneurs requires context-specific investigation. This study examines the associations between personalization, chatbots and virtual assistants, predictive analytics, natural language processing (NLP), and customer engagement performance (CEP) among microcredit recipient entrepreneurs in Selangor, Malaysia. Cross-sectional survey data from 308 entrepreneurs were analysed using partial least squares structural equation modelling in SmartPLS 4, with 5,000 bootstrap subsamples and 95% bias-corrected and accelerated (BCa) confidence intervals. All four application dimensions were positively associated with CEP. Predictive analytics exhibited the largest estimated coefficient ($\beta = 0.303$, $p < 0.001$), followed by chatbots and virtual assistants ($\beta = 0.232$, $p < 0.001$), NLP ($\beta = 0.221$, $p < 0.001$), and personalization ($\beta = 0.122$, $p = 0.041$). The model explained 59.6% of the variance in CEP. Internal consistency and convergent validity were satisfactory; however, construct overlap and unfavourable model-fit evidence constrained interpretation. Support for personalization was sensitive to the confidence interval method. The findings provide provisional evidence linking entrepreneurs' favourable evaluations of AI applications with reported engagement-related evaluations and practices, rather than establishing improvements in observed customer behaviour. They suggest that enterprise-support initiatives could pilot task-specific AI applications alongside customer-outcome monitoring. Further research should refine construct measurement and use longitudinal, multi-source data to assess whether these associations translate into sustained engagement outcomes.

Keywords: Artificial intelligence; customer engagement; microcredit recipient entrepreneurs; digital marketing; PLS-SEM; Malaysia.

1.0 INTRODUCTION

For microcredit recipient entrepreneurs, obtaining finance addresses only one aspect of sustaining a business. Maintaining customer interest, responding to enquiries, and adapting offers to customer needs constitute a separate managerial challenge. Customer engagement is therefore relevant to understanding how entrepreneurs maintain relationships within digital marketplaces. Brodie et al. (2011) conceptualise engagement through interactive customer experiences and distinguish it from related concepts such as participation and involvement. This perspective directs attention beyond the completion of an individual transaction towards the continuing relationship between a business and its customers.

Artificial intelligence (AI) introduces potential ways of supporting these interactions. Applications can assist businesses in interpreting customer information, automating communication, and tailoring marketing activities. Davenport et al. (2020) identify substantial implications of AI for marketing strategy and customer behaviour, while Huang and Rust (2021) distinguish its roles in automation, analytical decision-making, and interaction-

related understanding. These perspectives suggest that the relevance of AI depends on the marketing function it supports, rather than on technological adoption alone.

For microcredit recipient entrepreneurs, this raises a practical question: how are different AI-related marketing applications associated with customer engagement? The availability of an application does not establish that an entrepreneur can use it effectively or that customers respond favourably. Moreover, an entrepreneur's satisfaction with a tool is distinct from independently observed improvement in customer behaviour. Examining these relationships therefore requires attention to both the functions attributed to AI and the perspective from which engagement is measured. This study examines four application dimensions: personalization, chatbots and virtual assistants, predictive analytics, and natural language processing (NLP). These dimensions capture different aspects of customer-facing activity, including adapting communication, handling enquiries, anticipating preferences, and interpreting language. They may nevertheless operate together within a single platform. Their conceptual and empirical distinction is consequently an issue to be examined rather than assumed.

The research problem concerns the relationship between entrepreneurs' evaluations of these application dimensions and their reported customer engagement performance (CEP). Existing conceptual and application-specific literature provides explanations for why AI may support marketing activities, but does not itself establish how the four dimensions relate to CEP within the population examined here. The study addresses this contextual question without assuming that findings from other industries or customer populations transfer directly to microcredit recipient entrepreneurs. Accordingly, the objective is to examine the associations between personalization, chatbots and virtual assistants, predictive analytics, NLP, and CEP among microcredit recipient entrepreneurs in Selangor, Malaysia. Using survey responses from 308 entrepreneurs, the study estimates the four relationships simultaneously through partial least squares structural equation modelling (PLS-SEM). Its contribution is to provide contextual evidence about differentiated AI-related marketing perceptions, identify the boundaries of the measurement framework, and inform the design of subsequent research and enterprise-support initiatives. The analysis concerns reported perceptions and practices; it does not estimate the causal effects of AI adoption on customer behaviour, business income, or microcredit outcomes.

2.0 LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1 Customer engagement in the entrepreneurial context

Customer engagement provides a relational perspective on interactions between customers and businesses. Brodie et al. (2011) emphasise its interactive and context-dependent character, indicating that engagement cannot be reduced to a single purchase or equated automatically with satisfaction. This distinction is important when evaluating digital marketing applications: a tool may improve the efficiency of communication without necessarily generating deeper customer involvement.

In an entrepreneurial setting, engagement-related activities may include responding to enquiries, encouraging feedback, maintaining relevant communication, and adapting marketing practices to customer responses. These activities provide a useful context for investigating AI applications because they involve information processing and repeated interaction. However, the current study observes these activities through entrepreneurs' reports rather than through customers' accounts or behavioural records.

The dependent construct retains the label customer engagement performance used in the questionnaire. Operationally, its four indicators cover the perceived importance of engagement, satisfaction with achieved engagement, monitoring of engagement metrics, and efforts to improve engagement. CEP is therefore interpreted as an entrepreneur-reported measure combining engagement-related evaluations and management practices. It should not be treated as equivalent to a customer-level engagement scale or an objective performance index. This operational boundary is maintained throughout the interpretation of the results.

2.2 AI applications in digital marketing

The marketing relevance of AI arises from the tasks it can support. Huang and Rust (2021) propose a strategic framework linking different forms of AI to marketing research, strategy, and action. Their distinction between automation, analytical processing, and interaction-related capabilities offers a useful organising perspective for examining application functions. Davenport et al. (2020) similarly discuss AI in relation to marketing decisions and customer behaviour, drawing attention to both opportunities and implementation questions.

The present study focuses on four dimensions associated with these functions. Personalization concerns the adaptation of content and offers to customer preferences. Chatbots and virtual assistants concern automated conversational assistance. Predictive analytics concerns the use of information to anticipate customer needs and inform decisions. NLP concerns the processing of customer language and the preparation or interpretation of communication.

These categories do not represent mutually exclusive technologies. Personalization is a marketing practice, chatbots are application interfaces, predictive analytics is an analytical function, and NLP is an enabling capability. For example, a conversational application may use NLP to interpret an enquiry and predictive models to recommend a response. The four constructs are therefore treated as related application dimensions whose empirical separation requires assessment.

2.3 Conceptual rationale for the research model

The model is informed by AI-in-marketing and customer engagement literature rather than presented as a direct test of a single established behavioural theory. Its central proposition is that favourable evaluations of AI-related application functions are associated with favourable engagement-related evaluations and practices.
Four mechanisms provide the conceptual rationale. Personalization may increase the relevance of communication; conversational assistance may support responsiveness; predictive analytics may improve anticipation of customer needs; and NLP may support the interpretation and expression of customer information. These mechanisms explain the expected direction of the hypotheses, but are not separately measured as mediators in the study.

The framework of Huang and Rust (2021) provides an interpretive foundation for distinguishing marketing functions, while Brodie et al. (2011) provide a relational understanding of engagement. Neither framework is reproduced in full by the current instrument. The study consequently evaluates a literature-informed model of associations, with claims bounded by the questionnaire's operational definitions.

The model specifies four direct paths to CEP. Estimating these paths simultaneously allows each relationship to be considered in the presence of the other application dimensions. No mediation, moderation, or higher-order AI construct is specified. This approach preserves the study's focus while allowing the measurement assessment to identify whether the proposed dimensions are sufficiently distinguishable.

3.0 HYPOTHESES DEVELOPMENT

3.1 Personalization and customer engagement performance

Personalization involves adapting marketing content, offers, or recommendations to customer preferences and needs. Its proposed relationship with engagement rests on relevance: communication that corresponds more closely to a customer's interests may provide a stronger reason to attend, respond, or continue an interaction.
However, personalization does not guarantee a favourable response. Aguirre et al. (2015) show that the effectiveness of personalized advertising depends on information-collection practices and trust-building conditions. Their findings indicate that relevance must be considered alongside how customers perceive the use of their information. Thus, personalization is best understood as a potentially beneficial practice whose effectiveness depends on its implementation.

In this study, PER captures entrepreneurs' assessments of the relevance and effectiveness of personalized marketing and their satisfaction with personalized offers. Entrepreneurs who evaluate these activities favourably may also report more favourable engagement-related outcomes and practices. This reasoning motivates a positive association while leaving its magnitude open to empirical assessment.

H1: Personalization is positively associated with customer engagement performance among microcredit recipient entrepreneurs in Selangor, Malaysia.

3.2 Chatbots and virtual assistants and customer engagement performance

Chatbots and virtual assistants provide conversational interfaces through which customers can obtain information or assistance. Their potential relevance to engagement lies in supporting the continuity and responsiveness of customer communication. By handling routine enquiries, such applications may facilitate interaction when an entrepreneur is occupied with other business activities.

Customer responses nevertheless depend on the perceived quality of the interaction. Luo et al. (2019) demonstrate that chatbot disclosure can influence purchasing behaviour, with perceptions of knowledge and empathy helping to explain customer reactions. Their findings indicate that technical competence alone does not ensure customer acceptance. Although purchasing behaviour differs from CEP as measured here, the study establishes the importance of considering customer-facing evaluations when examining conversational applications.

The CVA indicators assess entrepreneurs' perceptions of enquiry handling, responsiveness, likely customer interaction, and customer experience. Favourable evaluations of these functions are expected to be associated with more favourable assessments of engagement. The proposed relationship concerns perceived conversational assistance rather than an assumption that all chatbots improve customer outcomes.

H2: Chatbots and virtual assistants are positively associated with customer engagement performance among microcredit recipient entrepreneurs in Selangor, Malaysia.

3.3 Predictive analytics and customer engagement performance

Predictive analytics uses patterns in available information to estimate future outcomes and inform decisions. In customer-facing activities, its potential value concerns anticipating needs, identifying relevant offers, and supporting the timing or targeting of communication. The analytical role described by Huang and Rust (2021) provides a conceptual basis for connecting information processing with marketing decisions.

For an entrepreneur, the proposed engagement mechanism is improved anticipation. If analytical information helps identify what customers may require, marketing activities may become more responsive to those requirements. This is a proposed pathway rather than an observed mechanism in the present study. Predictive accuracy, the quality of underlying data, and the entrepreneur's interpretation of recommendations may affect whether the anticipated benefit is realised.

The PA indicators capture perceived usefulness, satisfaction with recommendations, beliefs about customer responses, and confidence in anticipating needs. They do not independently establish forecasting capability. Within this operational scope, favourable evaluations of predictive analytics are expected to be associated with favourable CEP.

H3: Predictive analytics is positively associated with customer engagement performance among microcredit recipient entrepreneurs in Selangor, Malaysia.

3.4 Natural language processing and customer engagement performance

NLP supports the processing of human language, including the interpretation of enquiries and feedback and the

preparation of communication. Its proposed relevance to engagement concerns the ability to make customer language usable for marketing decisions and responses. Berger et al. (2020) describe how textual information from marketplace interactions can generate marketing insight, supporting the view that language contains information about customers and their experiences.

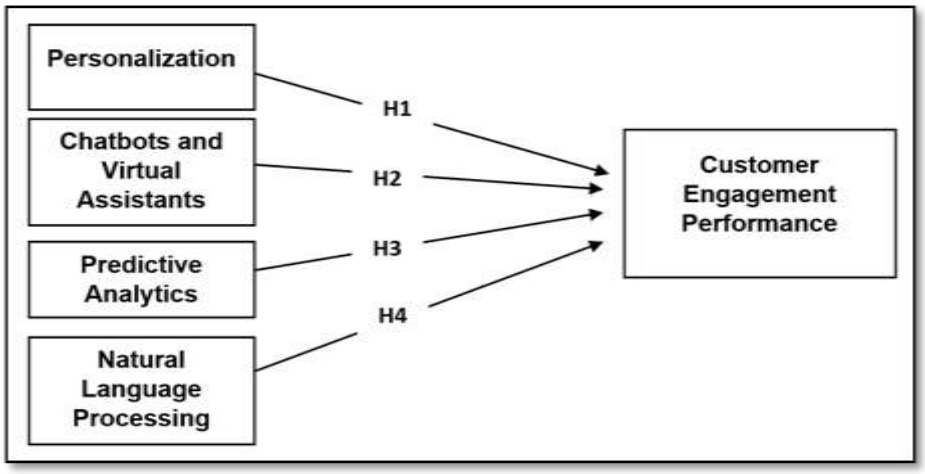
For entrepreneurs, language-processing applications may assist in identifying recurring concerns, preparing relevant messages, and responding to customer feedback. These functions could support engagement by improving the alignment between what customers communicate and how businesses respond. Their value nevertheless depends on accurate interpretation and contextually appropriate communication.
The NLP indicators assess perceived assistance in understanding enquiries, communication effectiveness, social media interaction, and relevant content generation. A positive relationship with CEP is therefore anticipated, while recognising that NLP may also operate within the other application dimensions.

H4: Natural language processing is positively associated with customer engagement performance among microcredit recipient entrepreneurs in Selangor, Malaysia.

The proposed framework comprises four direct relationships from PER, CVA, PA, and NLP to CEP. The hypotheses concern associations between the measured constructs and do not imply that the applications operate independently in practice or that the survey design establishes causal effects.

Thus, based on the developed hypotheses, the proposed research model is shown in Figure 1:

Figure 1: Proposed research model.



4.0 RESEARCH METHODOLOGY

4.1 Research design and context

The study employed a quantitative survey design to examine associations between AI-related application dimensions and CEP among microcredit recipient entrepreneurs in Selangor, Malaysia. The analytical dataset contained 308 respondents. Data were collected using a self-administered questionnaire distributed through Google Forms during March 2025–May 2026, as recorded in the study documentation. The analysis treats the responses as cross-sectional observations and estimates relationships between entrepreneurs' reported perceptions and practices. It does not examine changes within the same respondents over time. Consequently, the results are interpreted as associations within the sample rather than estimates of the causal effects of AI applications.

4.2 Participant Recruitment and Sampling

The study employed a non-probability recruitment approach through entrepreneur associations, with eligibility

screening applied to the submitted responses. A Google Forms questionnaire was circulated to association members operating their own businesses. Recruitment targeted business owners rather than individuals participating solely as employees or gig workers. The recruitment context included online AI-related training activities conducted through SME Corp Malaysia and Universiti Teknologi MARA during the three-year period preceding and overlapping with the study. These activities recorded approximately 500 participations; however, this approximate figure did not constitute a verified sampling frame or a count of unique survey invitees. Consequently, an invitation-based response rate could not be established. Eligibility required respondents to own a business operating in Selangor and to have previously received microcredit, including financing from TEKUN or microcredit facilities offered by banks. Eligibility was established through respondents' self-reported answers rather than independent verification against lender or agency records. Selangor-based operations were defined by the location of the business, including roadside stalls and home-based enterprises, rather than the owner's residential address alone. An active business registration was not imposed as an inclusion requirement, allowing participation by operating businesses whose SSM registration had expired.

A total of 342 questionnaire responses were received. Following eligibility screening, 34 responses were excluded because the respondents had not received microcredit or operated outside Selangor, leaving 308 cases for analysis. The final sample included business owners operating across all nine districts of Selangor, although respondents were concentrated in Shah Alam and the wider Klang Valley. This geographical coverage did not arise from a probability-based district selection procedure and should not be interpreted as proportional representation of the state's entrepreneur population. The recruitment approach and reliance on self-reported eligibility therefore delimit the generalisability of the findings.

4.3 Measurement Instrument and Data Collection

Data were collected using a self-administered bilingual questionnaire in Bahasa Melayu and English, distributed electronically through Google Forms. The questionnaire included explanations and examples of the AI applications under investigation, drawing on applications encountered in the training activities while allowing respondents to consider other relevant tools and practices. Examples included conversational tools for responding to online customer enquiries and applications such as ChatGPT and Gemini for preparing advertising copy and other digital marketing content. These examples supported interpretation of the questions without restricting responses to a particular software provider.

The instrument contained 21 indicators representing five constructs. Personalization, chatbots and virtual assistants, natural language processing, and customer engagement performance were each measured using four indicators, while predictive analytics was measured using five. Responses were recorded on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The indicators were coded PER1–PER4, CVA1–CVA4, PA1–PA5, NLP1–NLP4, and CEP1–CEP4, respectively.

Before the main survey, the instrument was piloted with 80 student entrepreneurs in Selangor. No items were removed following the pilot. The pilot population differed from the main study population in its student-entrepreneur composition; accordingly, pilot results were not treated as establishing the measurement properties of the instrument in the final sample. Reliability and validity were assessed again using the main-study data.

The predictor indicators captured entrepreneurs' evaluations of AI-related application functions, including perceived usefulness, satisfaction, confidence, and anticipated customer responses. They did not independently verify technical proficiency, usage intensity, or experience with every application dimension. CEP combined perceived engagement importance, satisfaction with achieved engagement, monitoring practices, and improvement efforts. It was therefore interpreted as an entrepreneur-reported measure of engagement-related evaluations and practices rather than a direct measure of observed customer behaviour.

All five constructs were specified reflectively in the reported PLS-SEM model, and all 21 indicators were retained in the main analysis. The indicator wording and codes are presented in the accompanying

measurement-item table. Statistical assessment was considered alongside item content when interpreting the scope and limitations of the constructs.

4.4 Measurement items

The questionnaire contained 21 indicators representing five constructs. PER, CVA, NLP, and CEP were each measured using four indicators, while PA was measured using five. Responses were recorded on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The indicator codes were PER1–PER4, CVA1–CVA4, PA1–PA5, NLP1–NLP4, and CEP1–CEP4. The predictor measures captured entrepreneurs' evaluations of AI-related application functions, including perceived usefulness, satisfaction, confidence, and expected customer responses. CEP captured engagement-related evaluations and management practices. These measures were not treated as direct observations of technical capability, adoption intensity, or customer behaviour.

All five constructs were specified reflectively in the reported model. This specification represents the analytical treatment of the indicators and does not, by itself, establish their conceptual interchangeability or unidimensionality. The interpretation therefore considers indicator content alongside statistical reliability and validity.

Each item that is an instrument of study is encoded with a specific series of figures and is a reference for the link between the constructs in the PLS-SEM analysis. In testing the validity of each factor, a preliminary test was conducted as below:

Table 1.0: Coding of factorial items

Construct	Questions Based On Thematic Items	Code
Personalization (PER)	I believe that personalizing the digital marketing content aligns with the specific needs and preferences of target audience.	PER1
	I am satisfied with the level of personalization in the marketing offers I deliver to my customers.	PER2
	Personalizing my marketing efforts enhances the engagement and satisfaction of my customers.	PER3
	I believe that offering personalized product recommendations increases customer engagement with my campaigns.	PER4
Chatbots and Virtual Assistants	The use of chatbots and virtual assistants helps me effectively address customer inquiries or concerns.	CVA1
(CVA)	I am satisfied with the responsiveness and efficiency of the chatbots and virtual assistants.	CVA2
	I believe that customers are likely to engage with chatbots and virtual assistants to obtain product information.	CVA3
	The presence of chatbots and virtual assistants enhances the overall experience of my customers.	CVA4
Predictive Analytics	The utilization of predictive analytics enables me to better understand and fulfill the specific needs and preferences of my customers.	PA1
(PA)	I am satisfied with the accuracy and relevance of personalized recommendations and targeted marketing campaigns based on predictive analytics.	PA2
	I believe that customers are likely to engage with my digital marketing campaigns that utilize predictive analytics for personalized content and offers.	PA3
	Insights and recommendations derived from predictive analytics play a significant role in influencing my customers' purchasing decisions.	PA4

	I am confident in my ability to understand and fulfil my customers' future needs and preferences by effectively utilising predictive analytics in my digital marketing strategies.	PA5
Natural Language Processing (NLP)	The use of Natural Language Processing (NLP) enables me to better understand and respond to customer inquiries or feedback.	NLP1
	I am satisfied with the accuracy and effectiveness of NLP-based language employed in my communication through digital marketing channels.	NLP2
	I believe that customers are more likely to engage in social media interactions with my business when NLP is employed to monitor and respond to customer feedback.	NLP3
	The customized and relevant content generated through NLP positively enhances my customers' engagement with my digital marketing efforts.	NLP4
Customer Engagement Performance	1. I believe that customer engagement performance is a crucial indicator of the success of my digital marketing strategies.	CEP1
(CEP)	2. I am satisfied with the level of customer engagement achieved through my digital marketing efforts.	CEP2
	3. I actively track and measure customer engagement metrics to assess the effectiveness of my digital marketing strategies.	CEP3
	4. I continuously strive to improve customer engagement by incorporating feedback and adjusting my digital marketing approaches accordingly.	CEP4

* Note: In the Likert scale, respondents are typically asked to rate their level of agreement or disagreement with a statement using a scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).

4.5 Data analysis

PLS-SEM was conducted using SmartPLS 4. The method was used to estimate the relationships between the multi-item constructs and to examine the explanatory performance of the proposed model. The assessment followed the measurement-model and structural-model sequence discussed by Hair et al. (2019). The use of PLS-SEM was not taken to remove the need for satisfactory measurement or to establish causal inference.

Internal consistency was assessed using Cronbach's alpha, rho_A, and composite reliability (rho_C). Indicator loadings and AVE were examined for convergent validity. Values around or above 0.70 for reliability and 0.50 for AVE were used as conventional reference points, with indicator retention considered alongside content and the overall measurement evidence.

Discriminant validity was assessed using HTMT and bootstrap confidence intervals, drawing on Henseler et al. (2015). The assessment distinguished between point-estimate thresholds and confidence-bound evidence. Exclusion of unity was not treated as equivalent to an entire interval remaining below 0.90. Cross-loadings provided supplementary diagnostic information.

The structural assessment examined standardised path coefficients, bootstrap standard errors, t statistics, p values, and 95% BCa confidence intervals. Bootstrapping used 5,000 subsamples, a fixed seed, and two-tailed tests at a significance level of 0.05. The final output also provided percentile intervals, which were inspected to identify sensitivity in the inferential conclusions.

Explanatory performance was assessed using R^2 and adjusted R^2, while f^2 described the incremental contribution of individual predictors. SRMR, d_ULS, and d_G were examined as complementary evidence concerning model fit, including comparison with the bootstrap reference values. No out-of-sample predictive assessment or formal comparison between path coefficients was included in the reported analysis. Conclusions were therefore restricted to the estimated associations and explanatory performance within the analysed sample.

5.0 RESULTS

The analysis examined the relationships between four dimensions of artificial intelligence applications, namely personalization (PER), chatbots and virtual assistants (CVA), predictive analytics (PA), natural language processing (NLP) and customer engagement performance (CEP) among 308 microcredit recipient entrepreneurs. Partial least squares structural equation modelling was performed using SmartPLS 4. Following the assessment sequence outlined by Hair et al. (2019), the measurement model was evaluated before interpreting the structural relationships. Statistical inference employed 5,000 bootstrap subsamples, two-tailed tests at the 5% significance level, and 95% bias-corrected and accelerated (BCa) confidence intervals. All 21 indicators were retained in the reported model.

5.1 Measurement Model Assessment

Internal consistency reliability was assessed using Cronbach's alpha, rho_A, and composite reliability (rho_C), while convergent validity was examined through indicator loadings and average variance extracted (AVE). As presented in Table 1, Cronbach's alpha ranged from 0.808 to 0.893, rho_A from 0.816 to 0.893, and composite reliability from 0.874 to 0.926. These results exceeded the conventional minimum of 0.70. AVE values ranged from 0.621 to 0.759, indicating that each construct accounted for more than half of the variance in its indicators.

Table 2.0: Internal consistency reliability and convergent validity

Construct	Indicators	Loading range	Cronbach's α	rho_A	rho_C	AVE
Personalization	4	0.804–0.901	0.893	0.893	0.926	0.759
Chatbots and virtual assistants	4	0.755–0.848	0.808	0.816	0.874	0.635
Predictive analytics	5	0.696–0.871	0.846	0.85	0.891	0.621
Natural language processing	4	0.789–0.865	0.85	0.862	0.898	0.687
Customer engagement performance	4	0.733–0.915	0.832	0.845	0.889	0.669

Note. Values represent original-sample estimates from the final bootstrap output. AVE = average variance extracted.

Twenty indicators recorded loadings above 0.70. The remaining indicator, PA2, had a loading of 0.696, marginally below this benchmark. PA2 was retained in the reported specification, with its weaker indicator reliability explicitly acknowledged. Although the PA construct demonstrated satisfactory composite reliability and AVE, these construct-level results do not eliminate concerns about the distinctiveness of individual indicators. More broadly, satisfactory reliability and convergent validity do not independently establish that all indicators adequately represent their intended conceptual domains.

5.2 Discriminant Validity

Discriminant validity was examined using the heterotrait–monotrait ratio of correlations (HTMT), following Henseler et al. (2015). Table 2 presents the HTMT estimates and their 95% BCa confidence intervals. Point estimates ranged from 0.701 to 0.893 and were below the 0.90 benchmark. However, the PA–CVA estimate of 0.893 exceeded the more conservative threshold of 0.85, indicating that the distinction between these two constructs requires particular caution.

Table 3.0: HTMT estimates and bootstrap confidence intervals

Construct pair	HTMT	95% BCa lower bound	95% BCa upper bound
CVA–CEP	0.8328	0.7417	0.9051

NLP–CEP	0.7735	0.6998	0.8336
NLP–CVA	0.7834	0.6934	0.8629
PA–CEP	0.8371	0.758	0.8999
PA–CVA	0.8931	0.8267	0.9503
PA–NLP	0.8176	0.728	0.8909
PER–CEP	0.7131	0.6189	0.7948
PER–CVA	0.8163	0.74	0.8774
PER–NLP	0.7015	0.6136	0.782
PER–PA	0.7513	0.643	0.8384

Note. Four decimal places are retained to distinguish the PA–CEP upper confidence bound from 0.9000.

All confidence intervals excluded unity. Nevertheless, the upper bounds for PA–CVA and CVA–CEP exceeded 0.90, while the PA–CEP upper bound approached this threshold. Consequently, the results do not provide uniform support for discriminant validity under a criterion requiring the entire confidence interval to remain below 0.90. The structural coefficients are therefore interpreted with recognition of the empirical overlap between certain constructs, particularly PA and CVA.

5.3 Structural Relationships and Hypothesis Testing

Table 3 summarises the estimated relationships between the four AI application constructs and CEP. All four path coefficients were positive, their two-tailed p values were below 0.05, and their BCa confidence intervals excluded zero. Accordingly, H1–H4 received statistical support under the BCa inference procedure used in this analysis.

Table 4.0: Structural relationships and hypothesis testing

Hypothesis	Relationship	β	Bootstrap SE	t	p	95% BCa CI	f^2	Decision
H1	PER → CEP	0.122	0.059	2.049	0.041	[0.011, 0.244]	0.017	Supported
H2	CVA → CEP	0.232	0.059	3.922	<0.001	[0.106, 0.339]	0.045	Supported
H3	PA → CEP	0.303	0.059	5.153	<0.001	[0.188, 0.418]	0.081	Supported
H4	NLP → CEP	0.221	0.065	3.411	<0.001	[0.101, 0.353]	0.055	Supported

Note. β = standardised path coefficient; SE = standard error; CI = confidence interval. Decisions concern the estimated associations within the specified model. †Support for H1 is sensitive to the confidence interval method.

Predictive analytics exhibited the largest estimated positive association with CEP ($\beta = 0.303$, $p < 0.001$), followed by chatbots and virtual assistants ($\beta = 0.232$, $p < 0.001$) and NLP ($\beta = 0.221$, $p < 0.001$). Personalization showed a smaller positive association ($\beta = 0.122$, $p = 0.041$). These coefficients represent the conditional relationships estimated with the other predictors included in the model. Their numerical ordering does not establish statistically significant differences between the coefficients, as pairwise coefficient comparisons were not conducted.

The evidence for H1 warrants additional qualification. Its BCa confidence interval excluded zero, whereas the corresponding percentile interval included zero [−0.0013, 0.2327]. Thus, although the BCa results supported H1, this conclusion was sensitive to the interval estimation method. Personalization also had the smallest f^2 value (0.017), compared with CVA (0.045), NLP (0.055), and PA (0.081). Statistical significance should therefore be distinguished from the magnitude of each predictor's incremental contribution.

5.4 Explanatory Power and Model Fit

The four predictors jointly accounted for 59.6% of the variance in CEP ($R^2 = 0.596$; adjusted $R^2 = 0.590$). The 95% BCa confidence interval for R^2 was [0.508, 0.660]. This result describes the model's explanatory performance within the analysed sample; it does not establish out-of-sample predictive accuracy or causal effects.

Overall model fit presented a less favourable assessment. The saturated and estimated models both produced an SRMR of 0.1038. The observed SRMR exceeded the bootstrap 95th-percentile reference value of 0.0503 and the 99th-percentile reference value of 0.0528. Similarly, the observed d_ULS value of 2.4896 exceeded its 99th-percentile reference value of 0.6448, while d_G of 0.8869 exceeded its corresponding value of 0.3048. These results indicate discrepancies between the observed and model-implied correlation structures.

Taken together, the analysis identified positive associations between the four AI application constructs and CEP, alongside satisfactory internal consistency and convergent validity. However, construct overlap, sensitivity in the personalization result, and unfavourable model-fit evidence limit the strength of the conclusions. The supported paths are therefore treated as conditional associations within the retained specification rather than conclusive validation of the proposed model.

6.0 DISCUSSION

This study examined the associations between four dimensions of artificial intelligence applications and customer engagement performance among microcredit recipient entrepreneurs in Selangor, Malaysia. The results supported positive relationships for personalization, chatbots and virtual assistants, predictive analytics, and natural language processing under the reported BCa bootstrap procedure. Together, these constructs explained 59.6% of the variance in CEP. However, the findings require a differentiated interpretation: the estimated relationships varied in magnitude, the personalization result was sensitive to the confidence interval method, and the measurement assessment identified construct overlap and unfavourable model-fit evidence. The discussion therefore considers what these associations suggest about AI-related marketing practices while recognising the boundaries of the evidence.

6.1 INTERPRETATION OF FINDINGS

6.1.1 Personalization and customer engagement performance

Personalization demonstrated a positive but comparatively small association with CEP ($\beta = 0.122$, $p = 0.041$). Although the BCa confidence interval excluded zero, the percentile interval included zero, and the incremental effect size was limited ($f^2 = 0.017$). H1 consequently received qualified support. The finding suggests that entrepreneurs' favourable assessments of personalized marketing were associated with CEP, but the evidence does not establish personalization as a substantial independent contributor within the specified model.

This qualified result is relevant to the personalization literature. Aguirre et al. (2015) demonstrated that responses to personalized advertising depend on how customer information is collected and on trust-building conditions. Their findings challenge the assumption that greater customization necessarily produces more favourable customer responses. The present study did not measure privacy concerns, trust, or perceived intrusion; these factors therefore offer possible explanations for future investigation rather than demonstrated explanations for the observed coefficient.

A further possibility is that personalization shares explanatory variance with the other AI application constructs. Recommendations and tailored communication also appear in the PA and NLP indicators, meaning that the PER coefficient represents its association with CEP after these related constructs have been included. The relatively small coefficient should therefore not be interpreted as evidence that personalization is generally unimportant. It indicates that its distinct contribution was limited within this particular operationalisation and sample.

6.1.2 Chatbots and virtual assistants and customer engagement performance

Chatbots and virtual assistants were positively associated with CEP ($\beta = 0.232$, $p < 0.001$). The finding is consistent with the proposition that automated conversational support can contribute to customer-facing activities, particularly when entrepreneurs perceive these tools as responsive and effective in handling enquiries. For an owner who simultaneously manages sales, fulfilment, and customer communication, automated assistance could help maintain continuity of interaction. This is a plausible interpretation of the association, although response times, workload reductions, and service availability were not directly measured.
The relationship should also be considered alongside evidence that customer reactions to automated agents depend on more than their technical capabilities. Luo et al. (2019) found that disclosing a chatbot's identity affected purchasing behaviour and linked this response to perceptions of the agent's knowledge and empathy. Their study examined purchases in a different setting, whereas the present study captures entrepreneurs' assessments of engagement-related outcomes. The comparison therefore highlights the importance of customer perceptions without implying that the two studies measure equivalent outcomes.
The current result supports further investigation of conversational assistance as a component of engagement management, but not unrestricted substitution of automated agents for human interaction. Moreover, the HTMT confidence interval for CVA–CEP extended above 0.90. Some of the observed association may consequently reflect overlapping evaluations of effective customer service and engagement. This qualification is particularly relevant because the CVA indicators include assessments of customer experience and likely customer interaction.

6.1.3 Predictive analytics and customer engagement performance

Predictive analytics recorded the largest estimated path coefficient ($\beta = 0.303$, $p < 0.001$) and incremental effect size ($f^2 = 0.081$) among the four predictors. Within the specified model, entrepreneurs who evaluated predictive analytics more favourably also reported higher CEP. However, the numerical ordering of coefficients does not demonstrate that PA was statistically stronger than CVA or NLP, as differences between coefficients were not formally tested.

One interpretation is that the perceived usefulness of analytics lies in helping entrepreneurs anticipate customer needs and make marketing decisions with greater informational support. Huang and Rust (2021) distinguish AI functions concerned with automation, analytical decision-making, and interaction-related understanding. Their framework provides a conceptual basis for viewing analytics as a means of informing marketing decisions, rather than treating all AI applications as interchangeable. The present study offers an association compatible with this perspective, but it does not directly test the decision-making mechanism proposed by that framework.
The operationalisation of PA also constrains interpretation. Its indicators capture perceived usefulness, satisfaction, confidence, and beliefs about customer responses rather than independently verified forecasting accuracy or analytics usage. Furthermore, the PA–CVA HTMT estimate was 0.893, with an upper BCa confidence bound of 0.950. The finding should therefore be described as an association between perceived analytics-related benefits and CEP, with caution regarding the empirical separation of analytics from conversational assistance. It does not establish that investment in predictive analytics would generate larger commercial returns than investment in other applications.

6.1.4 Natural language processing and customer engagement performance

NLP was positively associated with CEP ($\beta = 0.221$, $p < 0.001$). This finding is compatible with the view that understanding customer language and improving communication are relevant to engagement-related activities. Berger et al. (2020) explain how textual data from marketplace interactions can support marketing insight, including understanding customers and informing predictions. Their analysis provides a foundation for interpreting customer enquiries, reviews, and feedback as potential informational resources.

For the entrepreneurs studied, the association may reflect the perceived value of responding appropriately to enquiries, interpreting feedback, and preparing relevant communication. However, the study did not

independently assess language-processing accuracy, multilingual performance, or the quality of generated content. It therefore cannot determine which specific NLP function accounts for the observed relationship.

NLP also differs conceptually from the other constructs in the model: it is an enabling technology that can operate within chatbots, analytics systems, and personalization tools. The positive coefficient should consequently be understood as the conditional association of the measured NLP dimension, rather than proof that NLP operates independently of these applications. Future work should distinguish the technical functions of a tool from the marketing activities and outcomes it supports.

6.2 Theoretical Implications

The study offers contextual evidence concerning AI-related marketing perceptions among microcredit recipient entrepreneurs. Its contribution is principally the examination of differentiated AI application dimensions within this population, rather than the validation of a new general theory of AI-enabled engagement. Davenport et al. (2020) describe AI's potential implications for marketing strategy and customer behaviour while identifying questions concerning implementation and human involvement. The present findings contribute a context-specific empirical perspective to this broader discussion.

First, the results suggest that distinguishing between application dimensions can reveal variation that would be obscured by a single aggregate measure of AI. Personalization showed a relatively small and inference-sensitive association, while PA, CVA, and NLP showed more consistent statistical support across the reported confidence intervals. Nevertheless, these differences concern estimated associations within the model; they do not establish a universal hierarchy of AI capabilities.

Second, the findings expose a conceptual challenge in organising AI constructs. Personalization describes a marketing practice, chatbots describe an application interface, predictive analytics describes an analytical function, and NLP describes a technological capability. These categories can overlap in the same business process. The observed discriminant-validity concerns therefore raise a substantive question about whether the model separates phenomena at comparable conceptual levels. This is a proposition for theoretical and measurement refinement, rather than an empirically established explanation of the overlap.

Third, the study highlights the need to distinguish perceived application benefits from verified technological capability and realised customer engagement. The instrument largely captures entrepreneurs' evaluations of usefulness, satisfaction, and expected customer responses. CEP likewise includes beliefs about engagement, satisfaction with its achievement, and engagement-management practices. Accordingly, the findings speak most directly to the alignment between entrepreneurs' assessments of AI applications and their reported engagement orientation and performance-related perceptions. They should not be extended to customer behaviour or business growth without additional evidence.

Finally, the model-fit results constrain claims of theoretical confirmation. Positive and significant paths do not establish that the overall specification adequately represents the relationships in the data. The study provides provisional evidence for further theory development, while identifying the need for clearer construct boundaries and more precise outcome measurement.

6.3 Practical Implications

The findings suggest several priorities for entrepreneurs and organisations supporting microcredit recipients. These priorities should be treated as proposals for implementation and evaluation, rather than interventions whose effectiveness has been demonstrated by the present study. For entrepreneurs, an appropriate starting point is to identify a specific customer-management problem before selecting an AI application. Repeated unanswered enquiries, difficulty interpreting feedback, and poorly targeted offers represent different operational needs. A limited pilot addressing one such need would allow the entrepreneur to assess whether the application improves a relevant outcome. Recording response times, enquiry-to-order conversion, repeat purchases, or customer-reported satisfaction would provide evidence beyond general impressions of usefulness.

The PA result suggests that training could place greater emphasis on interpreting customer information. Practical exercises might involve maintaining consistent transaction records, identifying recurring purchase patterns, and comparing suggested actions with actual customer responses. Basic record-keeping should be distinguished from predictive analytics: it provides the information needed to evaluate analytical recommendations but does not itself constitute an AI capability. The objective would be to strengthen informed judgement rather than encourage uncritical acceptance of automated recommendations.

For conversational and language-based applications, training could focus on routine enquiry handling, accurate product information, feedback classification, and human review. Entrepreneurs could establish clear circumstances in which an automated conversation is transferred to a person, particularly when enquiries involve complaints, ambiguity, or commitments the system cannot verify. NLP-generated messages should similarly be checked for factual accuracy and suitability before use. These measures provide practical ways to test whether automation supports service quality in the entrepreneur's own setting.
The comparatively weak personalization result suggests caution against assuming that increasingly elaborate targeting will necessarily improve engagement. Entrepreneurs could begin with transparent, relevant communication based on customer-stated preferences and evaluate customer responses before expanding personalization. This recommendation concerns proportionate implementation; the study did not directly estimate the returns to different personalization strategies.

For microcredit providers and enterprise-development organisations, digital support could be structured around business tasks rather than software demonstrations alone. Small pilot programmes could combine application training, mentoring, and outcome monitoring. Programme evaluation should assess whether participants use the tools appropriately and whether customer outcomes improve, rather than relying exclusively on training attendance or satisfaction. The findings do not justify requiring borrowers to adopt particular technologies or incur additional expenditure.

6.4 Limitations and Future Research

Several methodological and conceptual limitations qualify the interpretation of these findings. First, the cross-sectional design precludes establishing temporal ordering or causality. Plausibly, entrepreneurs with established engagement practices evaluate AI more favourably, or unmeasured confounders (e.g., digital capability, enterprise scale) drive both constructs. Future longitudinal tracking or field experiments are needed to substantiate whether verified AI adoption precedes engagement shifts. Second, relying on single-informant self-reports introduces potential common method variance (CMV) and self-evaluation bias. Triangulating survey data with customer-side assessments, platform metrics, or transaction logs would help disentangle perceived utility from objective engagement outcomes.

Third, construct measurement boundaries remain ambiguous. Customer Engagement Practices (CEP) aggregates perceived importance, satisfaction, monitoring, and proactive improvement, whilst several predictor items explicitly mirror engagement terminology. High internal consistency does not mitigate this conceptual overlap. Subsequent scale development should delineate AI adoption, perceived functional quality, internal governance, and customer outcomes via expert panel validation and cognitive pre-testing. Fourth, discriminant validity was not unequivocally supported; the upper HTMT confidence intervals exceeded 0.90 for PA–CVA and CVA–CEP, compounded by marginal loadings and cross-loadings for PA2 and CVA1. Indicator boundaries should be refined and validated on independent holdout samples.

Fifth, model-fit discrepancies suggest the empirical model-implied covariance departs from observed data, cautioning against treating this framework as definitive. Theoretical alternatives such as modeling these dimensions as higher-order constructs or reciprocal dynamic capabilities warrant exploration, guided by theoretical logic rather than post-hoc fit optimisation. Sixth, empirical support for personalization was method-dependent, reaching significance under BCa bootstrapping but spanning zero under the percentile method; direct coefficient contrast tests are required to confirm its relative salience. Finally, the empirical focus on microcredit recipients in Selangor limits generalisability across wider enterprise tiers and geographies. While

in-sample explanatory power (R^2) was documented, out-of-sample predictive relevance remains unverified. Future inquiries should benchmark predictive performance and evaluate moderation across enterprise sectors, digital readiness, and verified AI usage intensity.

ACKNOWLEDGEMENT

The authors would like to express their sincere appreciation to Dr. Muhammad Syahrul Deen Ahmad Rosli and Dr. Mohd Amzari Tumiran, both from the Academy of Contemporary Islamic Studies (ACIS), Universiti Teknologi MARA (UiTM), for their valuable technical support and expertise throughout this study. Their assistance and contributions are gratefully acknowledged and were instrumental in facilitating the successful completion of this work. The authors are also thankful for their time, commitment, and willingness to provide technical guidance and assistance.

REFERENCES

1. Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing, 91*(1), 34–49.
2. Ahamat, A., Shahkat Ali, M. S., & Hamid, N. (2017). Factors influencing the adoption of social media in small and medium enterprises (SMEs). *International E-Journal of Advances in Social Sciences, 3*(8), 338–348.
3. Al-Skaf, S., Youssef, E., Habes, M., Alhumaid, K., & Salloum, S. A. (2021). The acceptance of social media sites: An empirical study using PLS-SEM and ML approaches. In A.-E. Hassanien, K.-C. Chang, & T. Mincong (Eds.), *Advanced machine learning technologies and applications: Proceedings of AMLTA 2021* (pp. 548–558). Springer.
4. Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. *Journal of Marketing, 84*(1), 1–25.
5. Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research, 14*(3), 252–271.
6. Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.
7. Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382–388.
8. Gezgin, E., Huang, X., Samal, P., & Silva, I. (2017, November 17). *Digital transformation: Raising supply-chain performance to new levels*. McKinsey & Company.
9. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.
10. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
11. Hoque, N., Mamun, A., & Mohammad Ahshanul Mamun, A. (2014). Dynamics and traits of entrepreneurship: An Islamic approach. *World Journal of Entrepreneurship, Management and Sustainable Development, 10*(2), 128–142.
12. Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.
13. Louw, C., & Nieuwenhuizen, C. (2020). Digitalization strategies for SMEs: A cost vs. skill approach for website development. *African Journal of Science, Technology, Innovation and Development, 12*(2), 195–202.
14. Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947.
15. Memon, M. A., Ting, H., Cheah, J.-H., Thurasamy, R., Chuah, F., & Cham, T. H. (2020). Sample size for survey research: Review and recommendations. *Journal of Applied Structural Equation Modeling, 4*(2), i–xx.

16. Moe, W. W., & Fader, P. S. (2004). Dynamic conversion behavior at e-commerce sites. *Management Science, 50*(3), 326–335.
17. Perera, N. (2021). Impact of digital transformation in measuring business performance of small & medium scale businesses in Sri Lanka. *International Journal of Economics, Business and Management Research, 5*(7), 1–25.
18. Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems, 116*(9), 1865–1886.
19. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 587–632). Springer.
20. Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy, 5*(1), 105–115.
21. Syed, M. H., Khan, S., Rabbani, M. R., & Thalassinos, Y. E. (2020). An artificial intelligence and NLP based Islamic FinTech model combining zakat and Qardh-Al-Hasan for countering the adverse impact of COVID 19 on SMEs and individuals. *International Journal of Economics and Business Administration, 8*(2), 351–364.
22. Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education, 48*(6), 1273–1296.
23. Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing, 91*(2), 174–181.