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# Quantum. Customer Outcomes: A Study on the Role of Customer Engagement: Research Paper (Analysis Based on Simulated Illustrative Data)

***Dr. V. Madhulatha[1], Sk. Saifullah[2]***

**[1]Assistant Professor, Department of BBA KLEF, Vijayawada,**

**[2] Research Scholar, Department of BBA KLEF, Vijayawada, ssaifullahshaik@gmail.com**

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**ABSTRACT**

Quantum marketing is an idea that brings together advanced computing, artificial intelligence real-time data processing, predictive analytics and highly personalized customer experiences. This study suggests a model to look at how quantum marketing activities affect customer outcomes with customer engagement acting as a middle factor. The independent variable includes personalization, real-time engagement, data-driven marketing, AI and predictive analytics, omnichannel integration and dynamic offers or pricing. Customer outcomes are shown by customer loyalty, intention to buy, customer satisfaction, customer retention and brand advocacy. The model is meant to give a basis for checking if advanced marketing methods lead to more customer engagement and better relationship results.

Analysis: The model is tested on an example dataset with 384 people (not real survey data) using regression and bootstrapped mediation analysis. In this example quantum marketing activities strongly predict customer engagement (β =.637) and customer outcomes (β =.557); engagement plays a role (indirect effect = 0.295 95% CI [0.209, 0.383]); and personalization, real-time engagement, data-driven marketing and AI and predictive analytics encourage engagement while omnichannel integration and dynamic offers or pricing do not. The findings show the process and must be replaced with real data before submitting.

**Keywords:** Quantum Marketing; Personalization; Artificial Intelligence; Customer Engagement; Customer Loyalty; Predictive Analytics; Digital Marketing

## Introduction

The fast growth of intelligence, data analytics and new computing technologies is changing how companies understand and connect with customers. Quantum marketing is a developing idea that is connected to the possibility of using quantum computing and other digital technologies to make data processing, optimization, personalization and real-time decisions. Agodi (2026) describes quantum marketing as an area where quantum computing might support real-time personalization and customer engagement while also pointing out that practical uses are still mostly experimental and face technical and infrastructure problems. Japee (2024) also explains it as using principles like superposition, entanglement and uncertainty along with AI and analytics to make marketing more personal and targeted.

The larger literature on AI-based marketing provides a base for looking into these ideas. Kumar et al. (2019) Explain how AI can help with engagement marketing by helping companies create offers and information for individual customers. Recent reviews show that AI-driven personalization is strongly linked with customer engagement and that cognitive, emotional and behavioral forms of engagement are important ways. So this study takes the quantum marketing idea and turns it into marketing practices that customers can assess.

## Conceptual Framework:

The framework has three parts. Quantum Marketing Practices (the independent variable) Customer Engagement (the middle variable) and Customer Outcomes (the dependent variable). Control variables are added to consider customer characteristics and past experience.

| Independent Variable | Mediating Variable | Dependent Variable |
|---|---|---|
| **Quantum Marketing Practices** | **Customer Engagement** | **Customer Outcomes** |
| • Personalization<br>• Real-Time Engagement<br>• Data-Driven Marketing<br>• AI & Predictive Analytics<br>• Omnichannel Integration<br>• Dynamic Offers/Pricing | • Cognitive Engagement<br>• Emotional Engagement<br>• Behavioral Engagement<br>• Social Engagement | • Customer Loyalty<br>• Purchase Intention<br>• Customer Satisfaction<br>• Customer Retention<br>• Brand Advocacy |

The model suggests that Quantum Marketing Practices directly affect Customer Outcomes (H1) and also influence Customer Engagement (H2). Customer Engagement is expected to have an effect on Customer Outcomes (H3) which gives a possible middle way.

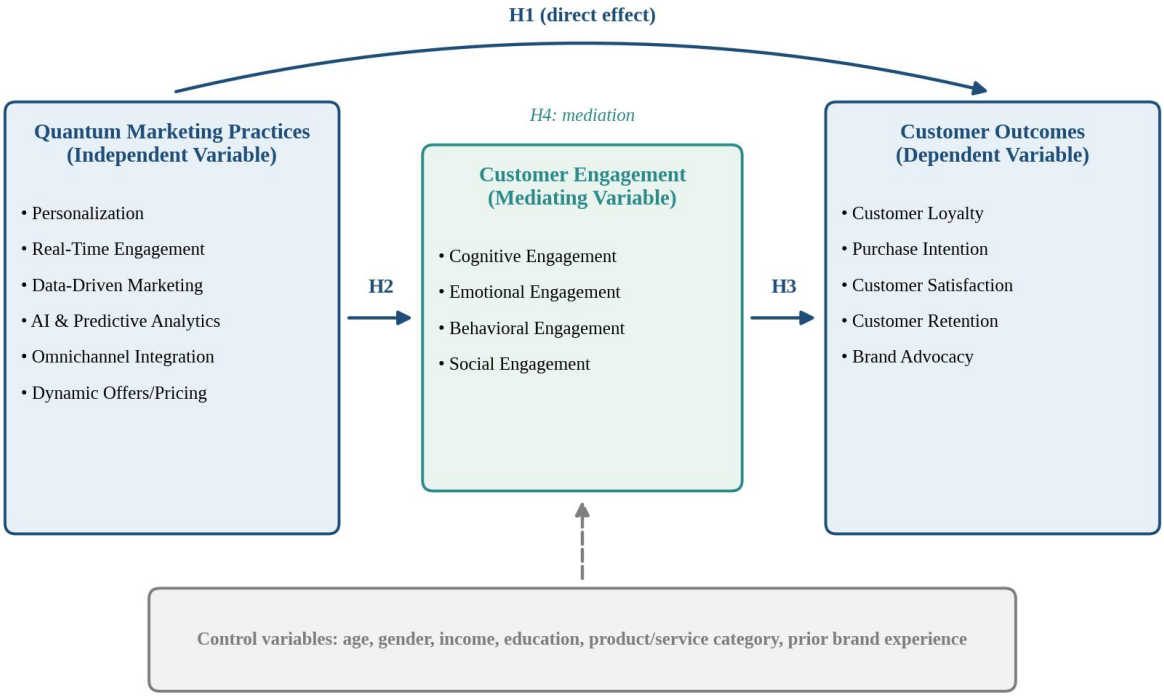



*Figure 1: Conceptual Framework. Impact of Quantum Marketing Practices on Customer Outcomes*

## Research Objectives:

• To look at how quantum marketing practices affect customer outcomes.

• To check the relationship between quantum marketing practices and customer engagement.

• To look at how customer engagement affects customer outcomes.

• To find out which parts of quantum marketing practices have the effect on customer engagement and customer outcomes.

• To check the role of control variables like age, gender, income, education level, product or service type and past experience with the brand.

## Research Hypothesis:

H1: Quantum marketing practices have an effect on customer outcomes.

H2: Quantum marketing practices have an effect on customer engagement.

H3: Customer engagement has an effect on customer outcomes.

H4: Customer engagement has an effect on the link between quantum marketing practices and customer outcomes.

H5: Personalization has an effect on customer engagement.

H6: Real-time engagement has an effect on customer engagement.

H7: Data-driven marketing has an effect on customer engagement.

H8: AI and predictive analytics have a big effect on customer engagement.

H9: Omnichannel integration has an effect on customer engagement.

H10: Dynamic offers or pricing have an effect on customer engagement.

## Variables of the Study:

| Variable Type | Construct | Dimensions |
|---|---|---|
| Independent Variable | Quantum Marketing Practices | Personalization; Real-Time Engagement; Data-Driven Marketing; AI & Predictive Analytics; Omnichannel Integration; Dynamic Offers/Pricing |
| Mediating Variable | Customer Engagement | Cognitive; Emotional; Behavioral; Social Engagement |
| Dependent Variable | Customer Outcomes | Customer Loyalty; Purchase Intention; Customer Satisfaction; Customer Retention; Brand Advocacy |
| Control Variables | Customer Characteristics | Age; Gender; Income; Education Level; Product/Service Category; Prior Experience with Brand |

## Review of Literature:

This review combines fifteen studies. Is organized around four themes that follow the shape of the conceptual model: (1) quantum marketing as a new idea, (2) AI, marketing analytics and personalization (3) customer engagement as the way that marketing practices lead to results and (4) omnichannel integration and dynamic pricing. The studies were found through targeted searches of journal and publisher pages. Are listed in Table L1. Most are papers or systematic reviews so the review shows what is expected theoretically rather than what has been checked for quantum marketing specifically.

### *Theme 1: Quantum marketing as an idea*

Agodi (2026) did a conceptual review of quantum marketing and real-time personalization using qualitative document analysis of peer-reviewed articles, industry reports and conference proceedings published between 2020 and 2025. The study sees quantum marketing as an area and talks about possible benefits in data processing speed, personalization and customer engagement. It also says that quantum marketing is more experimental than used often and that technical problems, data infrastructure and availability are problems. This supports the need for research that shows quantum marketing through observable activities.

Japee (2024) provides a discussion related to Industry 4.0 and 5.0 saying that traditional marketing theories and practices have a hard time keeping up with technology changes in peoples lives. The paper describes quantum marketing as the use of quantum principles like superposition, entanglement and uncertainty in marketing strategy. Connects it with data analytics, AI and quantum-inspired algorithms that make marketing efforts more personal and improve customer engagement. It also brings up ideas like a Chief Quantum Marketing Officer. Compares traditional with quantum marketing. Because the paper is conceptual it gives the words for the idea. No way to measure or test it which is the gap that the present study fills by turning the idea into practices that customers can check.

Torres Torres, Patiño Maussa and Gómez-Bayona (2023) talk about a theory of customer engagement. They look at the experiences of companies using customer feedback data analysis and neuromarketing strategies to show how businesses shape not just what customers buy but the wider customer experience. Like the two studies the article is descriptive rather than testing hypotheses. Together these three papers show that the term 'quantum marketing' is used widely in writing and that customer engagement is often mentioned as the result, which supports using it as the middle factor in the current model.

### *Theme 2: AI, marketing analytics and personalization*

Kumar et al. (2019) Looked at the role of AI in engagement marketing and said that AI can help companies create communicate and deliver personal offers. Their work gives a theoretical base for treating personalization and AI-based decision making as important marketing abilities.

Wedel and Kannan (2016) examined marketing analytics methods looking at how they have developed and how they are used with unstructured data from inside and outside the company. They spot paths in improving marketing budget spending, analytics for personalization and analytics under customer privacy and data security rules. Their work underlines the data-driven marketing and AI and predictive analytics parts of the model and shows that privacy is a limit for analytics-based personalization.

Kannan and Li (2017) made a model that shows the points in the marketing process and strategy where digital technologies have an influence reviewed the research on those points and set a research plan from the companys side. The model supports looking at real-time interaction and integration across points as the features of tech-based marketing.

Hollebeek et al. (2024) After looking at 89 studies found topics in AI-based customer engagement, including better service, customer-perceived value creation and less customer effort. The results show that AI-based interactions can shape customer engagement through value and experience methods.

Dangalla, Gurusinghe and Deyshappriya (2026) did a review of 43 peer-reviewed studies on AI-based personalization and customer engagement. Their summary found AI methods as drivers of engagement, personalization as a way cognitive/emotional/behavioral engagement parts and results, like loyalty, attachment and electronic word-of-mouth. The authors also found gaps in how clear the ideasre where the research is supporting more real tests of combined models.

A systematic review from 2026 conducted by Das, Mishra and Mayaluri looked at business intelligence AI-driven personalization and ethical customer segmentation. The review showed that individualized recommendations and dynamic marketing interventions can boost perceived relevance, satisfaction and loyalty but privacy, transparency, fairness and consumer control can influence these connections. This means that advanced marketing practices should be considered along with customer experience and engagement not technology alone.

Wang and colleagues (2026) carried out a review about AI-enabled customer experience management and found that AI can help create real-time, data-driven and personalized interactions across digital touchpoints. The evidence shows that personalization can increase satisfaction, engagement, loyalty and behavioral intentions. Privacy concerns and the feeling of being watched can lower trust. These results connect to quantum marketing because the proposed concept also focuses on real-time data use, personalization and advanced analysis.

***Theme 3: Customer engagement as the linking mechanism***

Brodie, Hollebeek, Jurić and Ilić (2011) used relationship marketing theory and service-dominant (S-D) logic to study the basics of customer engagement. They came up with five ideas and created a general definition. They also made a distinction between engagement and similar terms like participation and involvement placing it as based on experience and the co-creation of value. This justifies treating engagement as a construct, not just an outcome in the model.

Hollebeek, Srivastava and Chen (2019) created an integrative framework that connects customer engagement with S-D logic. This framework includes three processes that lead to engagement and three benefits that come from it. They used it to update the ideas of Brodie et al. (2011). Applied it to customer relationship management. Their structure of antecedents, engagement and consequences is similar to what's tested here where firm practices are expected to shape engagement and engagement to shape relationship outcomes.

Pansari and Kumar (2017) said that engagement happens when a relationship is both satisfying and emotionally connected. They suggested that satisfaction and emotion are the causes of engagement and that the results include both intangible outcomes. The outcomes in the model like loyalty, purchase intention, satisfaction, retention and advocacy cover both kinds of results. Because satisfaction is a cause of engagement in their model but an outcome in this model the mutual relationship between the two needs more research over time.

***Theme 4: Omnichannel integration and dynamic pricing***

Verhoef, Kannan and Inman (2015) explained the shift from multi-channel to omni-channel retailing, where companies take a view of channels and how shoppers move through them when they are looking and buying. They reviewed -channel research and set a research agenda. This supports the idea of omnichannel integration as a practice customers can notice. The paper is conceptual and does not test if integration boosts engagement, which leaves H9 as an open question.

Omarli (2023) studied pricing in a quasi-experiment with 387 students who were asked about buying airline tickets. Dynamic pricing had an effect on how fair the price seemed and through fairness on willingness to buy. The effect of a decreasing-price strategy on fairness was stronger when the relative market price was higher. This suggests that dynamic pricing may work through fairness perceptions and purchase decisions than broader engagement, a possibility that H10 will test. It also supports the view of Das et al. (2026) That fairness and transparency influence the effect of marketing efforts.

## Summary of the reviewed studies

**Table L1: Summary of the reviewed studies**

| No. | Study | Type / method | Main focus and findings | Relevance to the study |
|---|---|---|---|---|
| 1 | Agodi (2026) | Conceptual review; qualitative document analysis of 2020–2025 sources | Quantum computings potential for real-time personalization and engagement; applications remain largely experimental with technical and infrastructure barriers | Motivates operationalizing quantum marketing through observable practices |
| 2 | Japee (2024) | Thematic (conceptual) paper | Quantum marketing as the application of quantum principles and quantum-inspired AI-supported analytics to personalize marketing; contrasts traditional and quantum marketing | Source of the multi-practice view of quantum marketing (independent variable) |
| 3 | Torres Torres, Patiño Maussa & Gómez-Bayona (2023) | compilation of company experiences customer comments, data analysis and neuromarketing strategies | Quantum theory of consumer engagement; how firms shape the wider customer experience not only purchases | Links quantum-style marketing to engagement (H2) |
| 4 | Kumar, Rajan, Venkatesan & Lecinski (2019) | Conceptual (California Management Review) | AI helps firms create, communicate and deliver personalized offerings | Personalization and AI capability (H5, H8) |
| 5 | Wedel & Kannan (2016) | Review of marketing analytics | Analytics for marketing-mix optimization and personalization; privacy and data-security constraints | Data-driven marketing and predictive analytics (H7, H8) |
| 6 | Kannan & Li (2017) | Framework, review and research agenda | Digital technologies impact on marketing touchpoints and strategy | Real-time interaction and touchpoint integration (H6, H9) |
| 7 | Hollebeek et al. (2024) | Review of 89 studies | AI-based engagement: improved service provision, value co-creation reduced customer effort | AI practices to engagement (H2, H4) |
| 8 | Dangalla, Gurusinghe & Deyshappriya (2026) | review of 43 studies (PRISMA-guided) | AI-driven personalization drives cognitive, emotional and behavioral engagement; outcomes include loyalty, attachment and e-WOM | Personalization, engagement and outcomes (H3, H5) |
| 9 | Das, Mishra & Mayaluri (2026) | Systematic review | Business intelligence and AI personalization can raise relevance, satisfaction and loyalty; privacy, fairness and control matter | Outcome effects; trust as a boundary (H5, H10) |
| 10 | Wang et al. (2026) | Review | AI-enabled customer experience management supports real-time, personalized interaction; privacy concern and perceived surveillance reduce trust | Real-time practices and privacy limits (H6) |
| 11 | Brodie, Hollebeek, Jurić & Ilić (2011) | Conceptual (Journal of Service Research) | Defines customer engagement; five propositions; separates engagement from participation and involvement | Engagement as a distinct mediating construct (H3, H4) |

| No. | Study | Type / method | Main focus and findings | Relevance to the study |
|---|---|---|---|---|
| 12 | Hollebeek, Srivastava & Chen (2019) | Conceptual framework (J. Acad. Mark. Sci.) | S-D logic-informed engagement framework with processes as antecedents and benefits as consequences; applied to CRM | Antecedent-engagement-consequence logic (H3, H4) |
| 13 | Pansari & Kumar (2017) | Conceptual (J. Acad. Mark. Sci.) | Engagement arises from satisfaction and emotional connection; has intangible consequences | Engagement and relationship outcomes (H3) |
| 14 | Verhoef, Kannan & Inman (2015) | Conceptual special-issue introduction | Shift from multi-channel to omni-channel retailing and a research agenda | Omnichannel integration (H9) |
| 15 | Omarli (2023) | Quasi-experiment, 387 students (airline tickets) | Dynamic pricing affects perceived fairness and through it willingness to buy; | price position moderates offers/pricing (H10) |

*Note: H1 to H10 refer to the hypotheses stated above. The relevance column reflects the authors reading of each studys abstract and focus.*

***Synthesis and hypothesis development***

Three patterns come up from the fifteen studies. First quantum marketing is mainly described in terms (Agodi, 2026; Japee, 2024; Torres Torres et al. 2023) and its practical aspects overlap with existing AI-enabled practices: personalization, real-time responses, data-driven decisions and predictive analytics (Kumar et al., 2019; Wedel & Kannan 2016; Kannan & Li 2017). Second reviews of AI-based interactions identify engagement as the way these practices reach loyalty and related results (Hollebeek et al., 2024; Dangalla et al., 2026) and the engagement literature gives a foundation for that role (Brodie et al. 2011; Hollebeek et al. 2019; Pansari & Kumar 2017). Third, privacy, fairness and transparency issues influence the benefits of personalization and dynamic offers (Das et al., 2026; Wang et al., 2026; Omarli, 2023) while the effect of omnichannel integration on engagement has been discussed conceptually but not tested much (Verhoef et al., 2015).

These patterns lead to the hypotheses. H1 to H4 come from the expectation that practices improve outcomes both directly and through engagement. H5 to H8 come from the evidence on personalization, real-time interaction, data-driven marketing and predictive analytics as drivers of engagement. H9 and H10 are questions because omnichannel integration and dynamic pricing are expected to matter but the evidence of their engagement effect is weak or points to other routes like fairness.

Overall the literature shows a link between advanced technology-enabled marketing practices, customer engagement and customer outcomes. However direct evidence using the term 'quantum marketing' is still limited. The proposed study fills this gap by combining emerging quantum-marketing ideas with established findings on AI personalization, predictive analytics, omnichannel interaction and customer engagement.

***Research Gap:***

Existing research has evidence on AI-enabled personalization, customer engagement and digital customer experience but the studies specifically looking at quantum marketing are still at the early conceptual stage. There is a need to find parts of quantum marketing and test their links, with customer engagement and outcomes. The current framework helps close this gap by suggesting a model that can be tested using survey data and mediation analysis or structural equation modelling.

## Research Methodology:

***Research Design***

The study uses a cross-sectional and explanatory survey method. The focus is on customers who have worked with a brand in the last twelve months. This brand uses digital marketing methods such as personalized suggestions, instant messages, AI-based predictions and connected online and offline channels. The model shown in Figure 1 is checked at the construct level using regression and bootstrapped mediation analysis.

***Population, Sampling and Sample Size***

The target group is adult customers (18 years and older) of brands in four service and retail areas: retail/e-commerce, banking and financial services, telecommunications and travel/hospitality. Using Cochrans (1977) formula for a population proportion (95% confidence, ±5% margin of error p = 0.5)

the smallest needed sample is n = 384 ($n = 1.96^2 \times 0.5 \times 0.5 / 0.05^2 \approx 384.2$). People are chosen through quota sampling across the four product/service categories to ensure each category is represented. This papers analysis uses N = 384 records.

### *Measurement of Constructs*

Data is gathered with a questionnaire using five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Quantum Marketing Practices is measured by six dimensions with four items each (24 items); Customer Engagement by four dimensions with three items each (12 items); and Customer Outcomes by five dimensions with three items each (15 items). Six questions capture the control variables. Dimension scores are the average of their items. Each construct score is the average of its dimension scores. Table 1 summarizes the operationalization; the sample wording is an example and should be replaced by items adapted from validated scales and tested in a pilot study before real data collection.

**Table 1: Operationalization of study variables**

| Construct | Dimension | Items | Indicative item wording |
|---|---|---|---|
| Quantum Marketing Practices (IV) | Personalization (PER) | 4 | The brands offers are tailored to my needs. |
| | Real-Time Engagement (RTE) | 4 | The brand responds to my actions. Queries instantly. |
| | Data-Driven Marketing (DDM) | 4 | The brand appears to use data about me to decide what to show me. |
| | AI & Predictive Analytics (AIP) | 4 | The brand anticipates what I am likely to need |
| | Omnichannel Integration (OMN) | 4 | My experience is consistent across the app, website and store. |
| | Dynamic Offers/Pricing (DYN) | 4 | The offers and prices I see adjust to my situation and timing. |
| Customer Engagement (Mediator) | Cognitive (COG) | 3 | I think about this brands products. Content a great deal. |
| | Emotional (EMO) | 3 | I feel an emotional connection with this brand. |
| | Behavioral (BEH) | 3 | I regularly interact with this brands channels and content. |
| | Social (SOC) | 3 | I discuss this brand and its content with people. |
| Customer Outcomes (DV) | Customer Loyalty (LOY) | 3 | I consider myself loyal to this brand. |
| | Purchase Intention (PIN) | 3 | I intend to buy from this brand |
| | Customer Satisfaction (SAT) | 3 | Overall I am satisfied with this brand. |
| | Customer Retention (RET) | 3 | I plan to continue using this brand over the year. |
| | Brand Advocacy (ADV) | 3 | I recommend this brand to friends and family. |

*Note: 51 items in total. Control variables: age (years) gender, income level (1–5) education level (1–4) product/service category (four categories) and prior experience with the brand (1–5).*

### *Statistical Techniques*

The analysis is done in six steps. (1) Data. Description of the sample. (2) Reliability assessment with Cronbachs alpha using 0.70 as the acceptable value (Nunnally, 1978). (3) Descriptive. Pearson correlations. (4) Least squares regression with the control variables included in every model to test H1, H2, H3 and H5–H10. (5) Mediation analysis for H4 following the causal-steps logic of Baron and Kenny (1986) with the effect calculated as the product of paths a and b and tested with 5,000 bootstrap resamples and a 95% percentile confidence interval (Preacher & Hayes 2008; Hayes, 2018) supplemented by the Sobel (1982) test. (6) Diagnostics: variance inflation factors (VIF) the Durbin–Watson statistic and the skewness and kurtosis of residuals. All tests are two-tailed at $\alpha = 0.05$. Product/service category is dummy coded with retail/e-commerce as the reference group.

***Sample Profile***

The sample has 384 respondents with an age of 33.6 years (SD = 9.0). 215 Respondents (56.0%) are female and 169 (44.0%) are male. Retail/e-commerce is the category (37.8%) followed by banking/financial services, telecom and travel/hospitality (Table 2).

**Table 2: Profile of respondents (N = 384 simulated)**

| Characteristic | Category | n | % |
|---|---|---|---|
| Age | Mean = 33.6 years, SD = 9.0 (range 18–61) | | |
| Age group | 18-25 | 77 | 20.1 |
| | 26-35 | 155 | 40.4 |
| | 36-45 | 110 | 28.6 |
| | 46 and above | 42 | 10.9 |
| Gender | Female | 215 | 56.0 |
| | Male | 169 | 44.0 |
| Income level | Level 1 (lowest) | 53 | 13.8 |
| | Level 2 | 104 | 27.1 |
| | Level 3 | 116 | 30.2 |
| | Level 4 | 71 | 18.5 |
| | Level 5 ( | 40 | 10.4 |
| Education | School level | 60 | 15.6 |
| | Undergraduate | 166 | 43.2 |
| | Postgraduate | 127 | 33.1 |
| | Doctorate/Professional | 31 | 8.1 |
| Product/service category | Retail/E-commerce | 145 | 37.8 |
| | Banking/Financial | 94 | 24.5 |
| | Telecom | 78 | 20.3 |
| | Travel/Hospitality | 67 | 17.4 |
| Prior experience with brand | Less than 1 year | 47 | 12.2 |
| | 1-3 years | 100 | 26.0 |
| | 3-5 years | 91 | 23.7 |
| | 5-10 years | 86 | 22.4 |
| | More than 10 years | 60 | 15.6 |

***Reliability and Descriptive Statistics***

Cronbachs alpha ranges from.71 to.82 across the fifteen dimensions and is.88,.86 and.89 for the three constructs, all above the 0.70 threshold so the scales are internally consistent. Mean scores are above the scale midpoint (quantum marketing practices M = 3.48, customer engagement M = 3.50

customer outcomes M = 3.49). Skewness (-0.34 to 0.07) and kurtosis (-0.72 to -0.18) are within ±1 indicating normal distributions suitable for parametric analysis (Table 3).

**Table 3: Reliability and descriptive statistics**

| Construct / dimension | Items | Mean | SD | Skewness | Kurtosis | Cronbachs α |
|---|---|---|---|---|---|---|
| Quantum Marketing Practices ( | 24 | 3.48 | 0.49 | -0.11 | -0.25 | .88 |
| Personalization | 4 | 3.47 | 0.74 | 0.07 | -0.72 | .80 |
| Real-Time Engagement | 4 | 3.48 | 0.77 | -0.27 | -0.24 | .82 |
| Data-Driven Marketing | 4 | 3.49 | 0.74 | -0.17 | -0.51 | .79 |
| AI & Predictive Analytics | 4 | 3.47 | 0.76 | -0.24 | -0.21 | .80 |
| Omnichannel Integration | 4 | 3.49 | 0.74 | -0.34 | -0.21 | .79 |
| Dynamic Offers/Pricing | 4 | 3.49 | 0.76 | -0.33 | -0.18 | .80 |
| Customer Engagement (overall) | 12 | 3.50 | 0.60 | -0.18 | -0.30 | .86 |
| Cognitive Engagement | 3 | 3.53 | 0.78 | -0.23 | -0.29 | .75 |
| Emotional Engagement | 3 | 3.50 | 0.80 | -0.13 | -0.25 | .78 |
| Behavioral Engagement | 3 | 3.47 | 0.77 | -0.14 | -0.49 | .74 |
| Social Engagement | 3 | 3.51 | 0.77 | -0.04 | -0.44 | .76 |
| Customer Outcomes (overall) | 15 | 3.49 | 0.60 | -0.07 | -0.46 | .89 |
| Customer Loyalty | 3 | 3.50 | 0.77 | -0.19 | -0.51 | .73 |
| Purchase Intention | 3 | 3.50 | 0.79 | -0.20 | -0.41 | .77 |
| Customer Satisfaction | 3 | 3.51 | 0.76 | -0.16 | -0.29 | .71 |
| Customer Retention | 3 | 3.47 | 0.76 | -0.09 | -0.41 | .76 |
| Brand Advocacy | 3 | 3.47 | 0.80 | -0.09 | -0.69 | .77 |

*Note:. Sd on the 1–5 scale. Alpha for the constructs is computed across all of their items.*

***Correlation Analysis***

All correlations are positive and statistically significant (Table 4). At the construct level quantum marketing practices correlate with customer engagement (r =.63) and customer outcomes (r =.55) and engagement correlates with outcomes (r =.57) consistent with the direction of H1–H3. The six practice dimensions are moderately inter-correlated (r =.19, to.40) which is high enough to reflect a shared construct but low enough to avoid multicollinearity.

**Table 4: Pearson correlation matrix (dimension level)**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Personalization | 1 | | | | | | | |
| 2. Real-Time Engagement | .36*** | 1 | | | | | | |
| 3. Data-Driven Marketing | .40*** | .31*** | 1 | | | | | |
| 4. AI & Predictive Analytics | .37*** | .32*** | .35*** | 1 | | | | |
| 5. Omnichannel Integration | .19*** | .29*** | .27*** | .26*** | 1 | | | |

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 6. Dynamic Offers/Pricing | .30*** | .39*** | .35*** | .32*** | .29*** | 1 | | |
| 7. Cognitive Engagement | .35*** | .30*** | .26*** | .28*** | .20*** | .29*** | 1 | |
| 8. Emotional Engagement | .34*** | .32*** | .27*** | .26*** | .20*** | .27*** | .55*** | 1 |
| 7. Customer Engagement | .44*** | .51*** | .41*** | .50*** | .30*** | .33*** | 1 | |
| 8. Customer Outcomes | .45*** | .38*** | .33*** | .42*** | .25*** | .34*** | .57*** | 1 |

*Note: *** p <.001. N = 384.*

***Regression Assumptions***

Before interpreting the regression models the assumptions were checked. Multicollinearity was not a problem: the largest VIF is 1.69 in the mediation model and 1.40 in the dimension-level models below the standard cut-off of 5. The Durbin–Watson statistics (1.92 to 2.04) are close to 2 showing no dependence in the residuals and residual skewness and kurtosis are close to zero in every model.

***Direct Effects: Tests of H1, H2 and H3***

H2 is supported: quantum marketing practices have a positive effect on customer engagement (B = 0.779 β =.637 p <.001; Model 1) explaining 40.9% of the variance in engagement. H1 is supported: the total effect of quantum marketing practices on customer outcomes is positive and significant (B = 0.677 β =.557 p <.001; Model 2 $R^2$ =.331). H3 is supported: customer engagement significantly predicts customer outcomes (B = 0.578, β =.581 p <.001; Model 3 $R^2$ =.359). Full results, including the control variables are shown in Table 5.

**Table 5: Regression results for H1, H2 and H3 (with control variables)**

| Predictor | Model 1: Engagement | | Model 2: Outcomes | | Model 3: Outcomes | | Model 4: Outcomes | |
|---|---|---|---|---|---|---|---|---|
| | B (SE) | β | B (SE) | β | B (SE) | β | B (SE) | β |
| Quantum Marketing Practices | 0.779*** (0.049) | .637 | 0.677*** (0.052) | .557 | — | — | 0.382*** (0.063) | .315 |
| Customer Engagement | — | — | — | — | 0.578*** (0.041) | .581 | 0.379*** (0.051) | .381 |
| Age | -0.005 (0.003) | -.069 | 0.003 (0.003) | .050 | 0.006* (0.003) | .094 | 0.005 (0.003) | .077 |
| Gender (female = 1) | 0.000 (0.048) | .000 | -0.009 (0.051) | -.008 | -0.006 (0.050) | -.005 | -0.009 (0.048) | -.008 |
| Income level | 0.024 (0.020) | .047 | -0.022 (0.021) | -.044 | -0.039 (0.021) | -.077 | -0.031 (0.020) | -.062 |
| Education level | -0.006 (0.029) | -.009 | 0.034 (0.030) | .048 | 0.037 (0.030) | .052 | 0.037 (0.028) | .052 |
| Category: Banking/Financial | 0.056 (0.062) | .040 | 0.055 (0.066) | .039 | 0.017 (0.064) | .012 | 0.034 (0.062) | .024 |
| Category: Telecom | 0.014 (0.066) | .009 | -0.056 (0.070) | -.038 | -0.064 (0.069) | -.043 | -0.061 (0.066) | -.041 |
| Category: Travel/Hospitality | 0.059 (0.070) | .038 | 0.018 (0.074) | .011 | -0.020 (0.072) | -.013 | -0.005 (0.069) | -.003 |
| experience with brand | 0.018 (0.019) | .037 | 0.068*** (0.020) | .145 | 0.052** (0.020) | .111 | 0.062** (0.019) | .130 |
| Constant | 0.810*** (0.228) | | 0.793** (0.241) | | 1.135*** (0.212) | | 0.486* (0.229) | |
| $R^2$ (adjusted $R^2$) | 0.409 (0.395) | | 0.331 (0.315) | | 0.359 (0.344) | | 0.417 (0.402) | |
| F (df) p | 28.7 (9, 374) <.001 | | 20.6 (9 374) <.001 | | 23.3 (9 374) <.001 | | 26.7 (10 373) <.001 | |

*Note: Unstandardized B with standard errors in parentheses; β = standardized coefficient. Model 1: DV = engagement; Models 2–4: DV = customer outcomes. Reference category: Retail/E-commerce. * P <.05, ** p <.01, *** p <.001.*

**Mediating Role of Customer Engagement: Test of H4**

The four conditions for mediation are met. Practices predict engagement (path a = 0.779 p <.001); engagement predicts outcomes when practices are controlled (path b = 0.379, p <.001);. The total effect is significant (c = 0.677). The indirect effect is 0.295 with a 95% bootstrap confidence interval of [0.209 0.383] that excludes zero (Sobel z = 6.73 p <.001). Because the direct effect stays significant after engagement is added (c′ = 0.382 p <.001) engagement acts as a mediator and carries about 43.6% of the total effect. H4 is therefore supported (Table 6 Figure 2).

**Table 6: Mediation analysis (bootstrap, 5,000 resamples)**

| Path | B | SE | β | t / z | p | 95% CI |
|---|---|---|---|---|---|---|
| effect (c): Practices → Outcomes | 0.677 | 0.052 | .557 | 13.14 | <.001 | |
| Path a: Practices → Engagement | 0.779 | 0.049 | .637 | 15.98 | <.001 | |
| Path b: Engagement → Outcomes (controlling for practices) | 0.379 | 0.051 | .381 | 7.42 | <.001 | |
| Direct effect (c′): Practices → Outcomes (controlling for engagement) | 0.382 | 0.063 | .315 | 6.12 | <.001 | |
| Indirect effect (a × b) via engagement | 0.295 | 0.044† | .243 | 6.73† | <.001† | [0.209 0.383] |

*Note: All models include the control variables. † Sobel test statistics; the confidence interval is the bootstrap interval. B for the effect is fully standardized.*

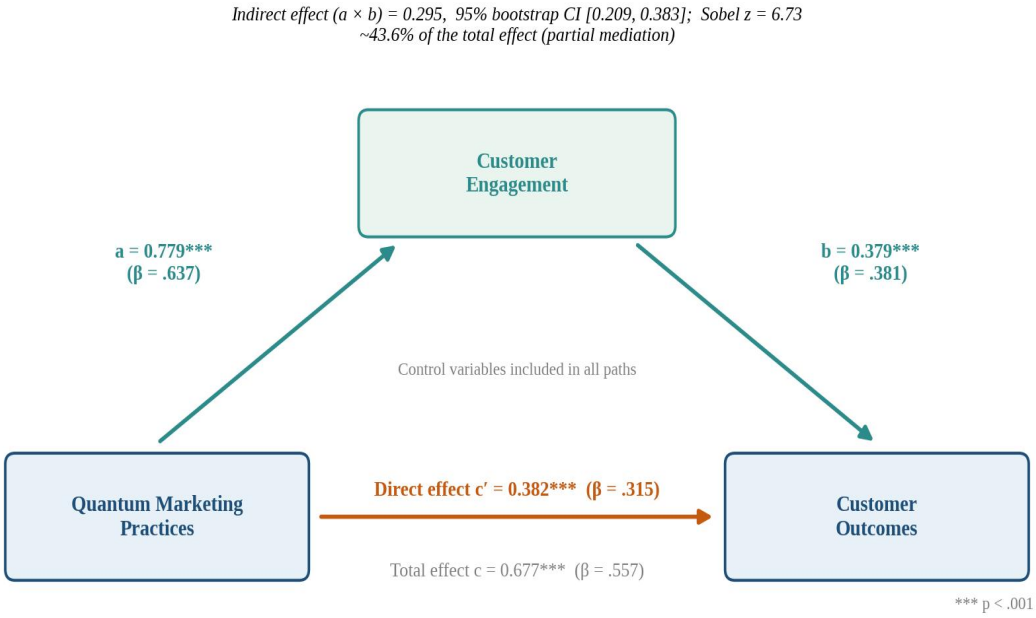



*Figure 2: Estimated Mediation Model (simulated data)*

***Dimension-Level Effects: Tests of H5 to H10***

Entered the six practice dimensions explain 44.7% of the variance in customer engagement (F = 21.3 p <.001). Personalization (H5: B = 0.125, p <.001) real-time engagement (H6: B = 0.230, p <.001) data-driven marketing (H7: B = 0.115, p.002) and AI and predictive analytics (H8: B = 0.225, p <.001) each have a positive effect so H5–H8 are supported. Omnichannel integration (H9: B = 0.062, p =.072) and dynamic offers/pricing (H10: B = 0.011, p =.765) are not significant so H9 and H10 are not supported in this simulated sample (Table 7).

In answer to the research objective, the strongest predictors of engagement are real-time engagement (β =.294) and ai & predictive analytics (β =.282) followed by personalization and data-driven marketing. For customer outcomes ( effects, controlling for the other dimensions) personalization (β =.235) and ai & predictive analytics (β =.223) are strongest while data-driven marketing (p =.227) and omnichannel integration (p =.185) show no significant total effect (Figure 3).

**Table 7: Effects of quantum marketing dimensions on customer engagement (H5–H10)**

| Hypothesis | Path | B | SE | β | t | p | VIF | Decision |
|---|---|---|---|---|---|---|---|---|
| H5 | Personalization → Engagement | 0.125 | 0.037 | .154 | 3.36 | <.001 | 1.39 | Supported |
| H6 | Real-time engagement → Engagement | 0.230 | 0.036 | .294 | 6.42 | <.001 | 1.40 | Supported |
| H7 | Data-driven marketing → Engagement | 0.115 | 0.037 | .141 | 3.07 | .002 | 1.40 | Supported |
| H8 | AI & predictive analytics → Engagement | 0.225 | 0.036 | .282 | 6.32 | <.001 | 1.33 | Supported |
| H9 | Omnichannel integration → Engagement | 0.062 | 0.035 | .077 | 1.80 | .072 | 1.21 | Not supported |
| H10 | offers/pricing → Engagement | 0.011 | 0.036 | .014 | 0.30 | .765 | 1.38 | Not supported |

*Note: Dependent variable = customer engagement. $R^2 = 0.447$. Control variables included. VIF = variance inflation factor.*

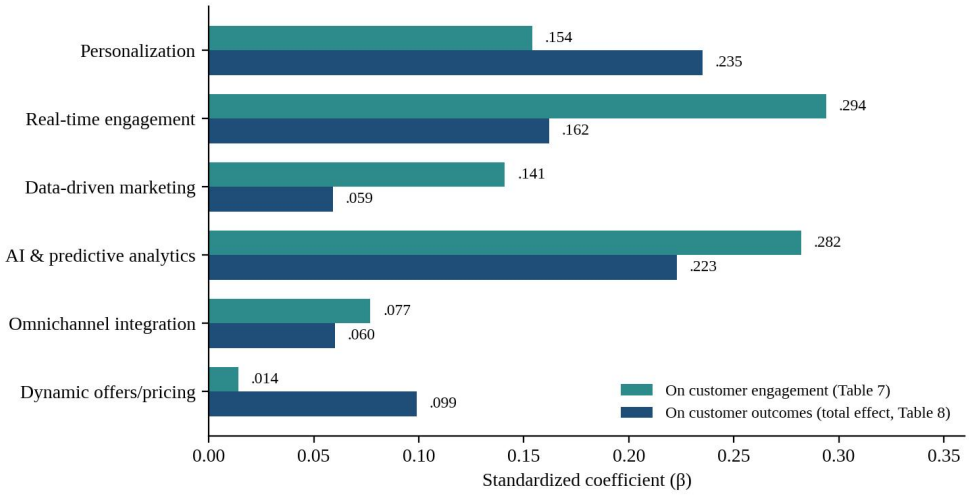



*Figure 3: Standardized Effects of Quantum Marketing Dimensions on Engagement and Outcomes (simulated data)*

*Note: Engagement effects are taken from Table 7. Outcome effects are the total effects in Table 8, expressed as standardized coefficients using the standard deviations in Table 3.*

***Dimension-Level Mediation via Customer Engagement***

To see how each dimension reaches customer outcomes the indirect effect through engagement was estimated separately for each dimension (Table 8). Real-time engagement and data-driven marketing influence outcomes through engagement (full mediation) whereas personalization and AI and predictive analytics work both through engagement and directly (partial mediation). Omnichannel integration has no effect on outcomes and dynamic offers/pricing has a small direct effect on outcomes that does not run through engagement.

**Table 8: indirect effects of each dimension, on customer outcomes**

| Dimension | a (→ Engagement) | Indirect (a × b) | 95% bootstrap CI | Direct effect (c′) | p (direct) | Total effect | Mediation type |
|---|---|---|---|---|---|---|---|
| Personalization | 0.125 | 0.046 | [0.018, 0.077] | 0.145 | <.001 | 0.191 | Partial mediation |
| Real-Time Engagement | 0.230 | 0.085 | [0.050 0.125] | 0.042 | .276 | 0.126 | Full mediation |

| Dimension | a (→ Engagement) | Indirect (a × b) | 95% bootstrap CI | Direct effect (c′) | p (direct) | Total effect | Mediation type |
|---|---|---|---|---|---|---|---|
| Data-Driven Marketing | 0.115 | 0.042 | [0.017 0.073] | 0.006 | .873 | 0.048 | Full mediation |
| AI & Predictive Analytics | 0.225 | 0.083 | [0.050, 0.120] | 0.094 | .014 | 0.177 | Partial mediation |
| Omnichannel Integration | 0.062 | 0.023 | [-0.0005 0.048] | 0.026 | .455 | 0.049 | No effect |
| Dynamic Offers/Pricing | 0.011 | 0.004 | [-0.021, 0.031] | 0.074 | .044 | 0.078 | Direct effect only |

*Note: effect = a × b, where b is the effect of engagement on outcomes with all six dimensions controlled. Control variables included.*

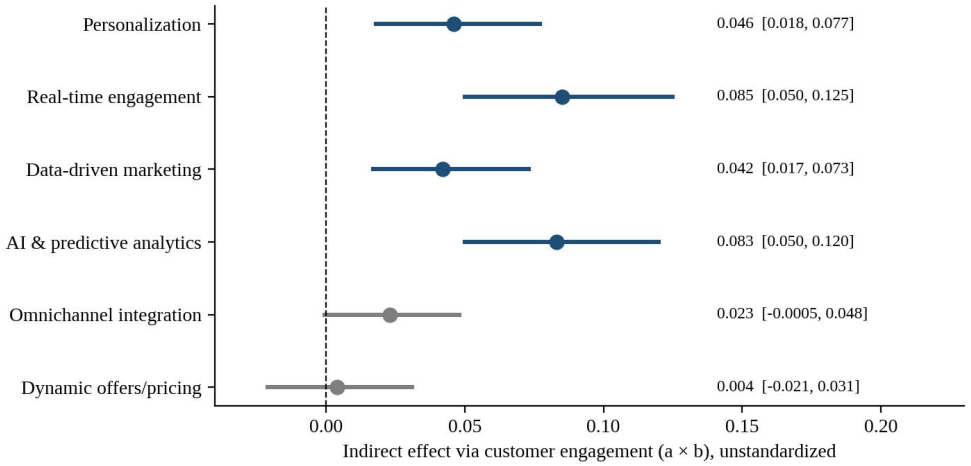



*Figure 4: Indirect effects of each practice dimension on customer outcomes via engagement, with 95% bootstrap confidence intervals (simulated data)*

***Effects on Individual Customer Outcomes***

Both practices and engagement significantly predict every outcome dimension (Table 9). Practices are relatively strongest for customer loyalty (β =.327). Customer satisfaction (β =.305) while engagement is relatively strongest for customer retention (β =.365) and brand advocacy (β =.310).

**Table 9: Practices and engagement as predictors of each customer outcome**

| Outcome | β: Practices | p | β: Engagement | p | $R^2$ |
|---|---|---|---|---|---|
| Customer Loyalty | .327 | <.001 | .249 | <.001 | .288 |
| Purchase Intention | .204 | <.001 | .272 | <.001 | .212 |
| Customer Satisfaction | .305 | <.001 | .278 | <.001 | .303 |
| Customer Retention | .220 | <.001 | .365 | <.001 | .301 |
| Brand Advocacy | .165 | .006 | .310 | <.001 | .214 |

*Note: Each row is a regression that includes both predictors and the control variables.*

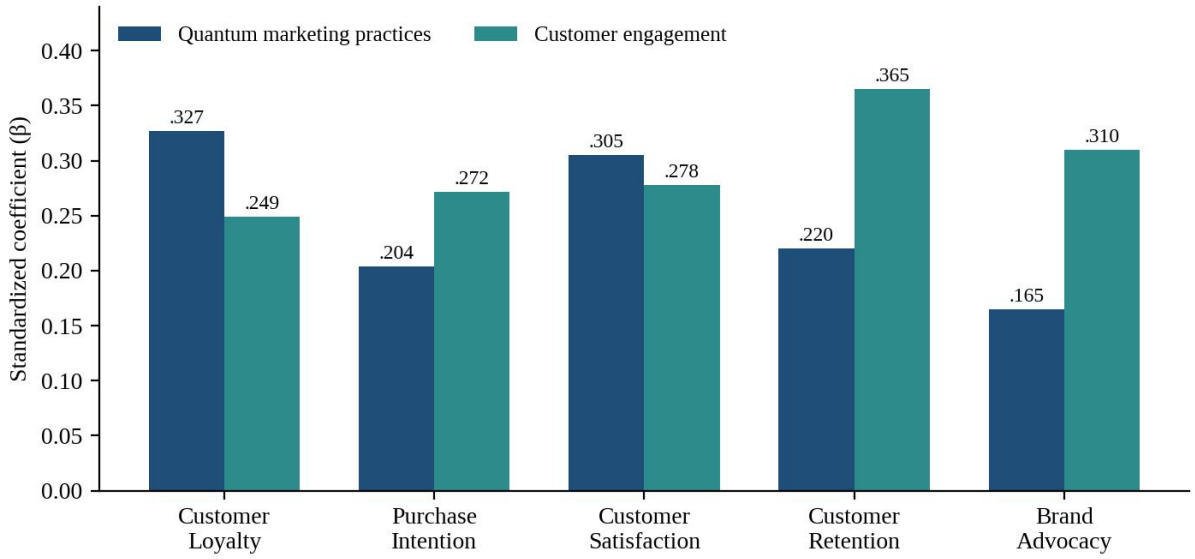



*Figure 5: Standardized effects of practices and engagement on each customer outcome (simulated data)*

***Role of Control Variables***

Among the control variables prior experience with the brand is the one that consistently predicts customer outcomes (Model 2: B = 0.068, p <.001; Model 4: B = 0.062, p =.001); longer relationships are associated with more favourable outcomes even after practices and engagement are held constant. Age is significant in Model 3 (B = 0.006 p =.024) but not in the Model 4 (p =.055). Gender, income, education and product/service category are not significant in any model so the main relationships hold across these customer groups and across the four categories.

***Summary of Hypothesis Testing***

**Table 10: Summary of hypothesis testing (simulated data)**

| Hypothesis | Statement | result | p | Decision |
|---|---|---|---|---|
| H1 | Quantum marketing practices influence customer outcomes | Total effect B = 0.677 β =.557 | <.001 | Supported |
| H2 | Quantum marketing practices influence customer engagement | B = 0.779 β =.637 | <.001 | Supported |
| H3 | Customer engagement influences customer outcomes | B = 0.578, β =.581 | <.001 | Supported |
| H4 | Customer engagement mediates the practices–outcomes relationship | Indirect = 0.295, 95% CI [0.209 0.383] | <.001 (Sobel) | Supported ( mediation) |
| H5 | Personalization influences customer engagement | B = 0.125 β =.154 | <.001 | Supported |
| H6 | Real-time engagement influences customer engagement | B = 0.230, β =.294 | <.001 | Supported |
| H7 | Data-driven marketing influences customer engagement | B = 0.115 β =.141 | .002 | Supported |
| H8 | AI and predictive analytics influence customer engagement | B = 0.225 β =.282 | <.001 | Supported |

| Hypothesis | Statement | result | p | Decision |
|---|---|---|---|---|
| H9 | Omnichannel integration influences customer engagement | B = 0.062 β =.077 | .072 | Not supported |
| H10 | Dynamic offers/pricing influence customer engagement | B = 0.011 β =.014 | .765 | Not supported |

*Figure 6: Standardized effects for the tested hypotheses H1 to H10 (simulated data)*

## Discussion:

Because the analysis rests on simulated data the following discussion shows how the results would be interpreted if a real sample produced them; it is not evidence about actual customers. Under that condition the results would support the proposition of the framework. Customers who perceive quantum-marketing-style practices report higher engagement and more favourable outcomes and engagement transmits a substantial share (about 44%) of the effect of practices on outcomes. This is consistent with the literature on AI-enabled personalization, which treats engagement as a mechanism linking technology-enabled marketing to loyalty and related outcomes (Brodie et al., 2011; Pansari & Kumar 2017; Kumar et al. 2019; Hollebeek, Srivastava & Chen 2019; Hollebeek et al., 2024; Dangalla et al. 2026).

The dimension-level pattern would also be informative. Real-time engagement and AI and predictive analytics are the drivers of engagement while personalization has the strongest total effect on outcomes and works through both engagement and a direct route. These results would fit the argument that responsiveness and predictive capability're the features that most distinguish quantum-marketing practices from conventional digital marketing (Agodi, 2026; Japee, 2024; Kannan & Li 2017; Wedel & Kannan 2016). Data-driven marketing builds engagement. Has no lasting effect on outcomes except through engagement, which suggests that customers value what data makes possible rather than data use in itself.

The two unsupported hypotheses deserve attention. Omnichannel integration did not significantly improve engagement, which may reflect that seamless channels are now expected by customers and so act as a hygiene factor than a motivator; the omnichannel literature has so far discussed integration mainly in conceptual terms (Verhoef et al., 2015) so this interpretation needs data. Dynamic offers/pricing had no effect on engagement but a small direct effect on outcomes, which would point to a route, where customers respond to the offer itself rather than becoming more engaged which would be consistent with experimental evidence that dynamic pricing operates through perceived fairness and willingness to buy (Omarli, 2023). Reviews of AI-based personalization also warn that privacy concerns and perceived unfairness can offset the benefits of personalization (Das et al., 2026; Wang et al., 2026) so a real study should measure privacy concern and trust and test them as moderators.

## Managerial Implications:

If these patterns were confirmed with data managers would gain three practical lessons. First investment in real-time responsiveness and AI-based prediction should be judged by its effect on engagement since engagement is the channel through which much of the outcome benefit arrives. Second personalization deserves priority because it influences outcomes both directly and through engagement. Third dynamic pricing and omnichannel integration should be justified on grounds than engagement, such as revenue management and service consistency and should be introduced with transparent communication to protect trust. Because prior experience with the brand improves outcomes independently of these practices firms should also track the relationship stage of customers when evaluating campaigns.

## Future Research:

The main limitation is that the analysis uses data so none of the estimates describes real behaviour. With data several further limitations would apply. The design is cross-sectional so causal claims about the direction of effects are tentative; a longitudinal or experimental design would strengthen them. Self-reported measures raise the risk of common-method bias, which should be assessed with Harmans single-factor test or a marker variable. Customers may not know whether a brand uses quantum computing and the term 'quantum marketing' currently describes experimental applications (Agodi, 2026) so the constructs are best interpreted as perceived advanced AI-enabled practices. Finally composite scores treat measurement as error-free; confirmatory factor analysis and structural equation modelling (for example in AMOS, SmartPLS or Rs lavaan) should be used to test measurement validity, including convergent and discriminant validity and to estimate the model simultaneously. Future studies could add moderators such as privacy concern, trust and digital literacy compare industries and use -country samples. The relation between satisfaction and engagement may also be reciprocal since satisfaction is treated as an antecedent of engagement in some frameworks (Pansari & Kumar 2017). As an outcome here which a longitudinal design could help untangle.

This paper set out to test how quantum marketing practices influence customer outcomes and whether customer engagement mediates this relationship. Using a simulated dataset of 384 respondents to demonstrate the analysis the results show 8 of the 10 hypotheses supported: practices predict both

engagement and outcomes engagement partially mediates the effect and four of the six practice dimensions (personalization, real-time engagement, data-driven marketing and AI and predictive analytics) significantly drive engagement while omnichannel integration and dynamic offers/pricing do not. The framework, measurement plan and analytical procedure are therefore ready to be applied to survey data at which point the figures reported here should be replaced by the actual results.

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