Segmenting Bank Customers Based on Their Engagement in Value Co-Creation: A Decision Tree Approach

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ABSTRACT

Understanding and managing customer engagement are crucial in co-creating value and sustaining long-term customer relationships. This study develops a predictive segmentation model tailored to the banking sector, with a specific focus on emerging market contexts. Employing a mixed-methods approach, the research integrates a meta-synthesis of prior studies with a C5.0 decision tree algorithm to identify key engagement drivers. The novelty of the study lies in its integration of Relational Models Theory, Customer Lifecycle stages, and perceived emotional value into a unified predictive framework. A structured survey was administered to Iranian retail banking customers and the model segmented them based on their emotional and functional value perceptions, relational orientations, and lifecycle stages. Findings revealed that emotional value is the most influential predictor of engagement, followed by relationship stage and relational model type. Four distinct customer segments were identified, each with unique engagement profiles. The study offers practical tools for banks to personalize CRM strategies and optimize engagement efforts based on relational and behavioral insights. This research contributes to the literature by combining the relational theory and behavioral prediction within a service-dominant logic, offering actionable insights for banking institutions operating in culturally specific, emerging markets.

KEYWORDS

Customer Participation, Value Co-Creation, Decision Tree Model, Banking Sector, Customer Engagement

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Introduction

Customer segmentation is a critical tool for developing effective marketing strategies and designing customer-centric services. In the banking sector, where services are intangible and competition is intensifying, understanding customer engagement patterns has become essential (Aaker, 2001). Traditional segmentation approaches based on demographic or behavioral variables are increasingly insufficient. The rise of digital platforms and service-dominant logic (Vargo & Lusch, 2004, 2008) has brought the value co-creation to the forefront. Today, firms aim not only to serve but to co-create value with customers—particularly those who actively engage. Customer engagement has been linked to both profitability and innovation. Scholars argue that emotionally engaged customers contribute beyond transactions by providing feedback or referring to others (Kumar & Pansari, 2016). Recent research highlights the role of omnichannel consistency in strengthening this engagement (Kumar & Sharma, 2024). In service contexts, brand value is largely shaped through customer experience and interaction (Berry, 2000). Moreover, customers increasingly seek involvement in shaping the products and services they use. Kotler et al. (2010) note that in today's participatory economy, customers do not merely consume—they influence, co-create, and engage with the brand ecosystem. Customer–bank relationships also evolve across a lifecycle, and the intensity of engagement varies at each stage (Zhang et al., 2016). At the same time, Relational Models Theory (Fiske, 1991) offers insight into how customers perceive and structure interactions, from communal sharing to transactional exchanges. Despite the growing scholarly attention, there remains a significant gap in integrated models that simultaneously account for customers perceived value, relational orientations, and lifecycle stages—especially in emerging markets where cultural dynamics and trust mechanisms differ markedly from Western contexts. Most previous studies either focus on isolated predictors of engagement or are confined to digital-native, developed economies. This gap highlights the need for predictive, data-driven models that reflect the behavioral and emotional patterns of customers in culturally specific banking sectors such as Iran. This study aims to develop a decision tree model for identifying high-engagement customers based on key drivers: perceived value (functional and emotional), relational models, lifecycle stages, and demographic characteristics. The findings offer a segmentation approach aligned with engagement-based value creation.

Literature Review

Customer Engagement

Customer engagement has emerged as a multidimensional construct encompassing emotional, cognitive, and behavioral components. Bowden (2009) defined it as a psychological process by which customers evolve from awareness to loyalty. Van Doorn et al. (2010) emphasized behavioral expressions such as referrals, feedback, and content sharing, while Brodie et al. (2011) highlighted its co-creative and interactive nature. Vivek et al. (2012) underscored the emotional and cognitive depth of engagement, and Kunz et al. (2017) categorized engagement perspectives into psychological, behavioral, and

motivational, offering a more nuanced framework for understanding participation. Pansari and Kumar (2017) presented an integrated view combining behavioral manifestations and affective commitments.

[Recent research also focuses on engagement in digital and AI-driven settings. Li and Zhao (2025) showed that trust in AI-powered services (e.g., banking chatbots) enhances engagement. Kumar and Sharma (2024) emphasized omnichannel consistency as a critical driver of sustained engagement in financial services. In the Iranian context, Kousheshi et al. (2020) highlighted that customer engagement in online platforms is closely linked to relationship quality—particularly trust, satisfaction, and emotional commitment. This underscores the relevance of relational dynamics and cultural expectations in shaping customer–firm interactions.]

The Value of Customer Engagement

Customer engagement generates value for firms in both direct and indirect ways. Kumar et al. (2010) introduced a widely accepted framework that categorizes this value into three dimensions ofCustomer Lifetime Value (CLV), Customer Influence Value (CIV), and Customer Knowledge Value (CKV).

CLV refers to the net present value of all future profits generated by a customer through continued transactions (Kumar & Reinartz, 2016). It captures the economic worth of a loyal customer who consistently engages in repeat purchases or expands their service usage.

CIV reflects the customer's ability to influence potential buyers via word-of-mouth, social sharing, and informal advocacy (Pansari & Kumar, 2017; Verhoef et al., 2009). Customers who voluntarily promote the brand help reduce acquisition costs and enhance brand credibility, especially in service settings.

CKV denotes the knowledge that customers share with the firm—such as feedback, innovative suggestions, or experience-based insights—that can inform product development and process improvements (Hollebeek et al., 2021; Kumar, 2019). Hartono and Wijaya (2023) showed that CKV significantly impacts the customers' intention to reuse mobile banking services.

This tripartite model allows firms to identify customers not solely based on revenue but also on their relational and intellectual contributions. The model's practical relevance has been demonstrated in customer segmentation and resource allocation across multiple industries, including banking and digital services. Overall, recognizing and leveraging engagement value can help firms tailor strategies to cultivate high-potential customers and optimize long-term performance.

Relational Models Theory

Relational Models Theory (RMT), developed by Fiske (1991), provides a comprehensive framework for understanding how individuals construct, interpret, and regulate social relationships. It posits that human interactions are governed by a limited set of relational models that guide expectations and behaviors. While six models were originally proposed, three are particularly relevant in customer–firm contexts: Communal Sharing (CS),

Equality Matching (EM), and Market Pricing (MP) (Kaltcheva et al., 2014).

In the Communal Sharing model, individuals view themselves as members of a shared identity group, emphasizing unity, loyalty, and emotional connection. In business contexts, this model is evident when customers form strong affective bonds with a brand or community and participate in co-creation out of identification rather than calculation (Kaltcheva et al., 2010).

The Equality Matching model is based on balanced reciprocity, where interactions are guided by fairness and equivalence. Customers operating within this model expect mutual consideration; they are more likely to share feedback or participate in service design if their input is acknowledged and reciprocated (Bogodistov et al., 2017).

Market pricing, in contrast, is driven by cost–benefit calculations and the principle of proportionality. Customers engaging in this model evaluate interactions through utility maximization, seeking the highest return for the lowest cost (Giessner et al., 2010). Loyalty is typically contingent on perceived functional value or price advantage.

Understanding these relational orientations enables firms to tailor engagement strategies based on how customers perceive the relationship. For example, CS-oriented customers may be more responsive to emotional appeals, while MP-oriented customers may prioritize efficiency and financial incentives.

Relationship Life Cycle Framework

The relationship life cycle framework conceptualizes the evolving nature of customer–firm interactions over time. Originating from exchange theory and contract law, Dwyer et al. (1987) introduced a five-stage model of relationship development: awareness, exploration, development, maintenance, and termination. Subsequent research adapted this framework to various service contexts, emphasizing the dynamic and bidirectional nature of engagement (Palmatier et al., 2006; Zhang et al., 2016).

In the context of customer engagement, four stages are particularly relevant:

- Exploration: Initial interactions marked by uncertainty and low commitment. Customers evaluate the firm's credibility and potential value.
- Development: Trust and satisfaction begin to form, leading to deeper engagement. Mutual expectations are shaped, and emotional attachment may emerge.
- Maintenance: A mature, stable phase characterized by high trust, relational equity, and consistent value co-creation. Engagement is typically strongest here.
- Decline: Engagement weakens due to changing needs, dissatisfaction, or better alternatives. The risk of defection increases unless proactive interventions occur.

Cambra-Fierro et al. (2018) argue that engagement is not static but fluctuates throughout the lifecycle, with the potential to regenerate or deteriorate depending on contextual and relational factors. Zhang et al. (2016) similarly emphasize that firms must tailor engagement strategies to each stage to sustain customer value and avoid premature disengagement.

In banking, recognizing a customer's position within the relationship lifecycle allows service providers to deliver personalized experiences and optimize timing for interventions, upgrades, or loyalty initiatives.

Customer Perceived Value

Customer Perceived Value (CPV) is a core construct in marketing, defined as the customer's overall evaluation of the trade-off between the perceived benefits of a service and the sacrifices made to obtain it (Zeithaml, 1988). This evaluation influences customer satisfaction, loyalty, and engagement, particularly in intangible service-based settings like banking.

The current study focuses on two primary dimensions of CPV:

- Functional Value: Refers to the utility derived from a service's practical performance, reliability, and effectiveness. Customers assess whether the service fulfills its intended purpose efficiently and meets their expectations regarding convenience and usefulness (Zeithaml et al., 2020).
- Emotional Value: Captures the affective responses generated through the customer's experience, such as feelings of trust, comfort, enjoyment, and psychological security. Emotional value often plays a stronger role than functional value in shaping the customer loyalty and advocacy behaviors (Mohammadi-Far & Poorjamshidi, 2021; Riley et al., 2015).

Research suggests that emotional value has a greater influence on sustained engagement, especially in contexts where trust and relational bonds are essential (Sánchez-Fernández & Iniesta-Bonillo, 2007). In banking, for example, even if functional performance is high, weak emotional resonance may reduce long-term commitment. Recognizing both dimensions enables firms to craft experiences that not only meet functional needs but also foster deep emotional attachment, which in turn supports more active and meaningful customer participation.

Research Gap and Study Contribution

Despite the growing literature on customer engagement, several important gaps remain. First, many studies focus exclusively on transactional metrics or affective dimensions without integrating deeper relational mechanisms such as customers' social orientation or perception of fairness. While concepts like Customer Lifetime Value (CLV) and Customer Influence Value (CIV) have been well-documented (Kumar et al., 2010), fewer empirical models capture engagement as a multidimensional behavioral and psychological construct influenced by relational models and perceived value.

Second, prior research often overlooks the temporal dimension of the customer engagement. Few frameworks explicitly consider how engagement fluctuates across different stages of relationship lifecycle, or how firms can align their strategies accordingly (Cambra-Fierro et al., 2018; Zhang et al., 2016).

Third, although the theoretical underpinnings of customer engagement are robust in Western and digital-native markets, limited empirical evidence exists in emerging economies—particularly within the banking sector of countries like Iran, where the customer behavior is shaped by unique cultural, technological, and institutional factors.

To address these gaps, this study offers a novel, data-driven segmentation approach using a decision tree model that integrates:

- Customers perceived value (emotional and functional),

- Their relational orientation (based on Relational Models Theory),
- Their current stage in the relationship lifecycle,
- And relevant demographic variables. By combining these constructs into a unified predictive model, the study provides practical tools for identifying and prioritizing high-engagement customers, optimizing resource allocation, and designing context-specific engagement strategies.

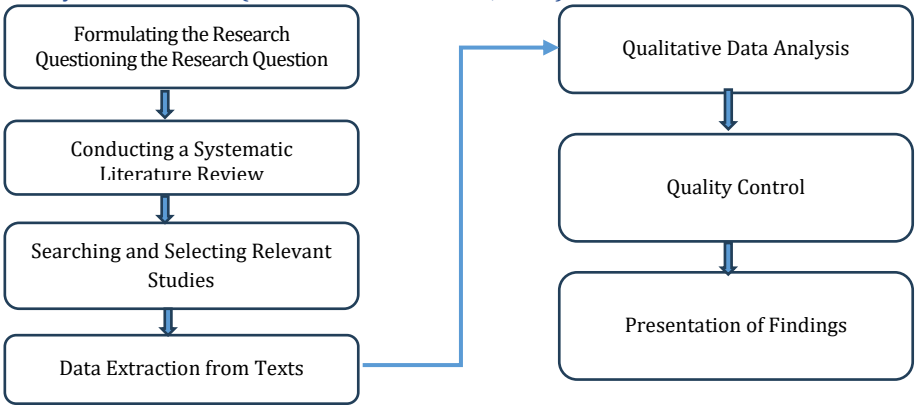
Methodology

This study adopted a mixed-methods design to investigate customer engagement segmentation in the banking sector. A meta-synthesis of prior literature was initially conducted to extract key engagement constructs, followed by a quantitative phase using a C5.0 decision tree model. Data were collected from 880 banking customers in Iran using a structured questionnaire measuring emotional and functional values, relational orientations (based on Relational Models Theory), and stages of relationship lifecycle. Due to operational constraints, convenience sampling was used, which facilitated timely data collection but may introduce selection bias and limit generalizability. The reliability index was confirmed with Cronbach's alpha values exceeding 0.70 for all constructs. To enhance validity, content validity was established through expert judgement by three academic scholars in marketing and services research, while construct validity was verified by Exploratory Factor Analysis (EFA), confirming the distinctiveness of key variables. The cleaned dataset was analyzed using IBM SPSS Modeler, and the C5.0 algorithm generated interpretable rule-based customer segments based on engagement predictors.

Qualitative Phase: Meta-Synthesis

In the first phase, meta-synthesis was employed to extract conceptual factors from previous studies indexed in databases such as Scopus, Emerald, and Science Direct between 2005 and 2023. A total of 33 relevant articles were reviewed and analyzed based on the seven-step framework proposed by Sandelowski and Barroso (2006). The process followed is illustrated in Diagram 1.

Diagram 1.
Stages of the Meta-Synthesis Method (Sandelowski & Barroso, 2007)



(Source: Researcher's Findings)

The guiding research questions for this analysis formulated around what, who, where, and how are briefly described in the text (see summary formerly shown in Table 1).

Table 1.
Research Questions (Meta-Synthesis Analysis)

Dimension	Questions	Answers
What	What are the key factors influencing customer engagement in value co-creation for banks?	Identification of determining factors from prior research on customer engagement in banking value co-creation
Who	What is the study population for identifying these factors?	Valid and credible scientific databases used in this study
When	What is the time range of the reviewed studies?	Research articles published between 2005 and 2023 from selected databases
How	What method was used to collect the relevant studies?	Qualitative data were analyzed using document analysis method

(Source: Researcher's Findings)

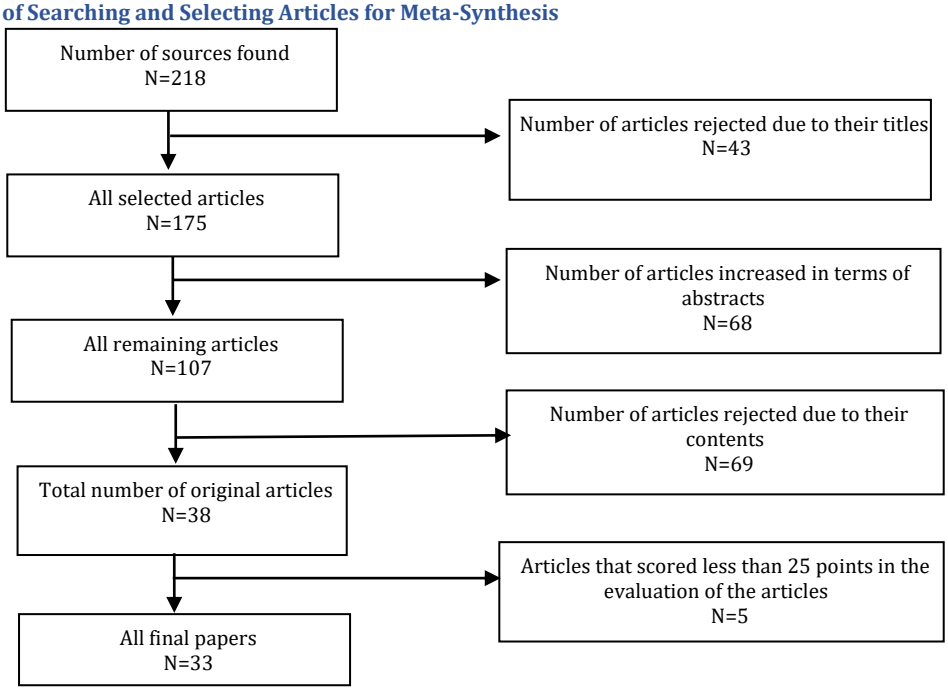
Keywords used for database searches included terms such as "customer engagement", "value co-creation", and "relational orientation" (Table 2 omitted).

Table 2.
The Keywords Searched in Academic Databases

Keywords	Databases
Customer Engagement	Scopus, Emerald, ScienceDirect
Value of Customer Engagement	
Banking Industry	

The process of screening and selecting articles is shown in Diagram 2 (Selection of the Articles for Meta-Synthesis).

Diagram 2.
The Process of Searching and Selecting Articles for Meta-Synthesis



(Source: Researcher's Findings)

Key constructs extracted from the reviewed articles are summarized in Table 3, including the perceived value (emotional and functional), relational models (communal sharing, equality matching, market pricing), stages of relationship lifecycle, and demographic attributes.

These themes served as a theoretical basis for designing the quantitative phase.

Table 3.
The Identified Factors Related to Customer Engagement and Its Value

Identified Factor	Definition	Sources
Functional Value	The value created to fulfill the customer expectations.	Prebensen et al. (2013); Pansari & Kumar (2017); Rahi (2016); Reilly et al. (2015); Naseem et al. (2015); Zeithaml (2020)
Emotional Value	The value arising from the pleasant feelings a product or service creates for the customer.	Prebensen et al. (2013); Pansari & Kumar (2017); James (2002); Choi (2017); Rahi (2016); Reilly et al. (2015); Naseem et al. (2015); Zeithaml (2020)
Communal Sharing Model	What people share and what distinguishes them from those outside their group.	Kaltcheva & Parasuraman (2009); Kaltcheva et al. (2010); Van Doorn et al. (2010); Shi et al. (2016); Carlsson (2018); Zhang (2017)
Equality Matching Model	Involves exchange of resources that are similar in type.	Giessner (2010); Bogodistov et al. (2017); Kaltcheva et al. (2014); Kaltcheva & Parasuraman (2009)
Market Pricing Model	Individuals focus on ratios and rates, calculating costs and benefits.	Giessner (2010); Bougodistou et al. (2017); Kaltcheva et al. (2014); Kaltcheva & Parasuraman (2009)
Customer Lifetime Value	Refers to the repeated selection of firm services and long-term relationship continuation.	Kaltcheva et al. (2014); Pansari & Kumar (2017)
Customer Influence Value	When customers voluntarily and without incentives share their experiences through word-of-mouth.	Verhoef et al. (2009); Kaltcheva et al. (2014); Pansari & Kumar (2017)
Customer Knowledge Value	When customers transfer their knowledge through innovative ideas or suggestions for improvement.	Hoyer et al. (2010); Joshi & Sharma (2004); Fuller et al. (2008); Kumar (2019); Kaltcheva et al. (2014); Pansari & Kumar (2017)
Relationship Life Cycle	A process through which a relationship starts, develops, matures, and eventually ends.	Palmatier (2008); Bleier et al. (2018); Cambra-Fierro (2018); Aali et al. (2019)
Demographic Characteristics	Age, gender, education level, etc.	Aali et al. (2019)

(Source: Researcher's Findings)

Quantitative Phase: Survey and Sampling

Based on the qualitative findings, a structured questionnaire was developed and validated by marketing and banking experts. The statistical population consisted of customers from Iranian commercial bank branches in Tehran. Due to the absence of an accessible sampling frame, convenience sampling was applied. Out of 1,000 questionnaires distributed over one month, 880 valid responses were used for analysis.

Data Mining Approach

Data mining refers to the process of extracting useful patterns and knowledge from large datasets (Huang et al., 2007; Witten & Frank, 2005). It supports decision-making by uncovering hidden relationships in operational data. Common techniques include

decision trees, neural networks, and Bayesian networks (Lee & Tu, 2010). Among them, the C5.0 algorithm, developed by Quinlan, is favored for its high interpretability, ability to handle missing and mixed-type data, and robust classification performance (Gupta et al., 2017; Kumar & Ravi, 2007). In this study, C5.0 was applied as a data mining technique to classify customer engagement patterns based on both demographic and psychological predictors.

Measurement Instruments

Measurement items were drawn from prior studies. Perceived value was assessed with 11 items for functional and 5 for emotional values (Zeithaml et al., 2020). Relational models included 4 items for communal sharing, 3 for equality matching, and 2 for market pricing (Kaltcheva et al., 2014). The customer engagement value was based on Pansari and Kumar's (2016) model, incorporating customer lifetime, influence, and knowledge value. All items were measured on a 5-point Likert scale, except for the stage of relationship, which was assessed using a four-option nominal scale (Jap & Ganesan, 2000).

Data Analysis

Data analysis was conducted in two stages. First, basic descriptive statistics were used to evaluate data distribution. Skewness and kurtosis values were calculated to assess the normality of the data, and all values were within acceptable thresholds. Internal consistency of the constructs was confirmed using Cronbach's alpha, with all values exceeding 0.70 (see Table 6). In the second stage, a data mining technique was applied using the C5.0 decision tree algorithm to identify meaningful classification rules. This model was used to segment customers based on their engagement behavior and related predictor variables, including emotional value, stage of relationship life cycle, and relational orientation.

Findings

Operationalization of Variables

The operational definitions and measurement sources for all key constructs including emotional and functional values, relational models (communal sharing, equality matching, market pricing), stages of relationship life cycle, and customer engagement components are outlined in Table 4. These variables were used as inputs in the decision tree analysis, based on established scales adapted from prior literature.

The segmentation results using the C5.0 decision tree algorithm are illustrated in Figure 1. The model identifies the relationship lifecycle (RLC), emotional perceived value (EPV), relational model (RM), and age as the primary predictors of the customer engagement.

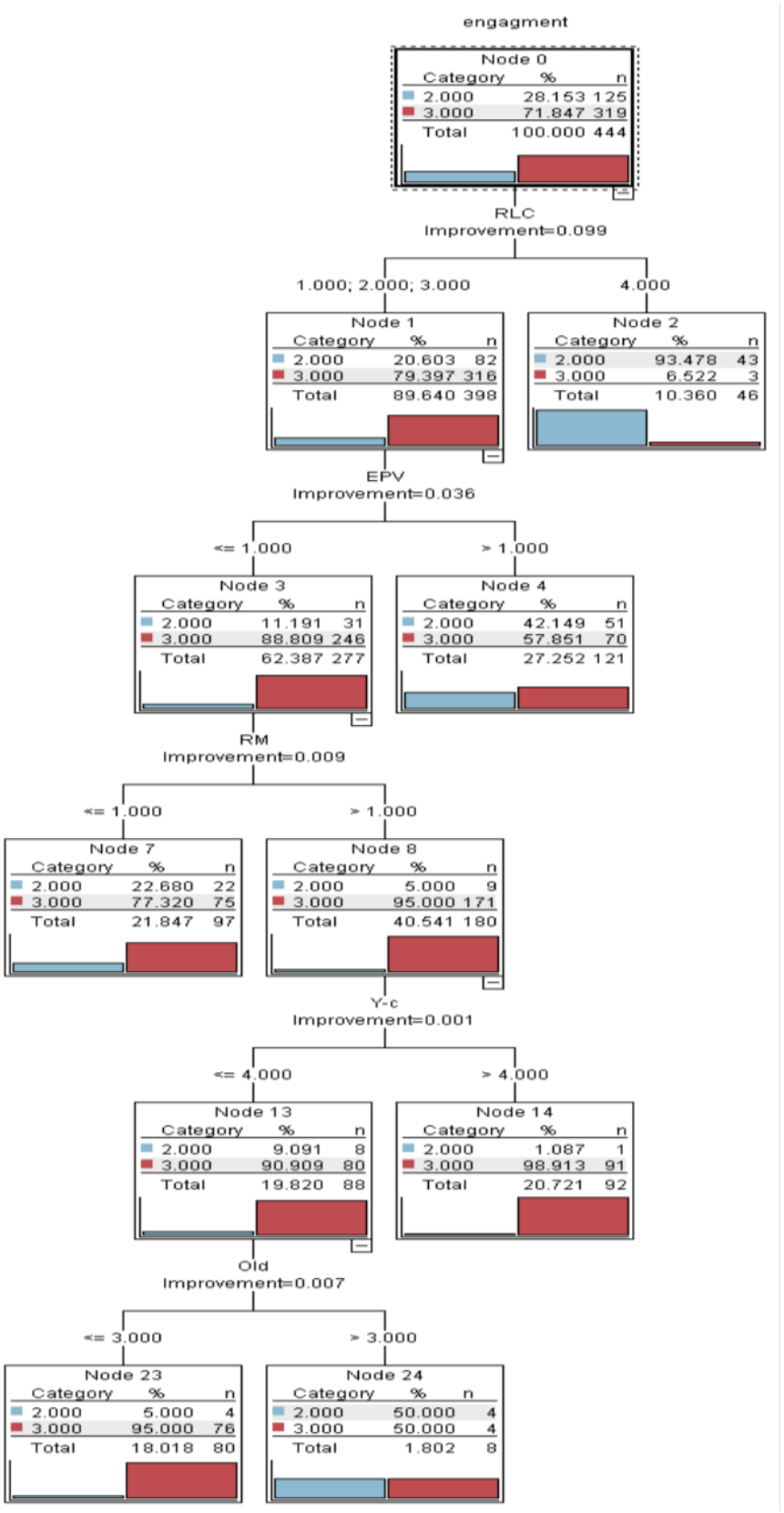
Table 4.
The Operational Definitions of Study Variables

Variable Type	Variable Level / Name	Abbreviation	Operational Definition
Target Variable	Classification of Customers Based on Customer Engagement Value	Engagement	A binary variable operationalized based on the level of customer engagement value (customer lifetime value, customer influence value, and customer knowledge value). Calculated from the average of 9 questions: if the average is less than 3.5 (low engagement), value = 2; if between 3.5 and 5 (high engagement), value = 3.
Predictor Variables	Perceived Value - Emotional Value	EPV	A binary variable indicating the level of emotional value received by the customer from the bank. If the average score ≥ 3.5 (high emotional value), value = 1; otherwise (low emotional value), value = 2.
	Perceived Value - Functional Value	FPV	A binary variable indicating the level of functional value received by the customer from the bank. If the average score ≥ 3.5 (high functional value), value = 1; otherwise (low functional value), value = 2.
	Customer Relational Models - Communal Sharing	RM	A single-level variable corresponding to the communal sharing model. If the mean response score is greater than the average of the equality matching and market pricing models, value = 1.
	Customer Relational Models - Equality Matching		A single-level variable corresponding to the equality matching model. If the mean response score is greater than the averages of the communal sharing and market pricing models, value = 2.
	Customer Relational Models - Market Pricing		A single-level variable corresponding to the market pricing model. If the mean response score is greater than the averages of the equality matching and communal sharing models, value = 3.
	Relationship Life Cycle	RLC	A four-level variable indicating the stage of the relationship between the customer and the bank: identification stage = 1, development stage = 2, maintenance stage = 3, decline stage = 4.
	Demographic - Age	Old	A continuous variable indicating the customer's age at the time of the study.
	Demographic - Education Level	Education	A five-level variable indicating the customer's education level: less than diploma = 1, diploma = 2, associate degree = 3, bachelor's degree = 4, master's degree and above = 5.
	Demographic - Gender	Gender	A binary variable: female = 1, male = 2.
	Demographic - Customer Type	T-C	A binary variable: individual (natural person) customer = 1, corporate (legal entity) customer = 2.
	Demographic - Customer Duration (Years)	Y-C	A five-level variable indicating the number of years the customer has been with the bank: less than 1 year = 1, more than 1 and up to 3 years = 2, more than 3 and up to 6 years = 3, more than 6 and up to 9 years = 4, more than 9 years = 5.
	Demographic - Percentage of Total Banking Activity	TP	A five-level variable indicating the percentage of total banking activities of the customer at Iranian commercial bank: less than 20% = 1, 21%-40% = 2, 41%-60% = 3, 61%-80% = 4, 81%-100% = 5.

(Source: Researcher's Findings)

Figure 1.

The Decision Tree Output for the Customer Engagement Segmentation



(Source: Researcher's Findings)

Demographic Profile

A total of 880 valid responses were retained. Table 5 presents the demographic information of the respondents, including gender, age, education level, and the duration of the relationship with the bank. Most participants were aged between 31 and 50 years, and a significant portion had a university-level education. These attributes provide context for the segmentation results in later stages of the analysis.

Table 5.
Descriptive Characteristics of the Respondents

Demographic Characteristics	Count	Percentage	Demographic Characteristics	Count	Percentage
Gender			Education		
Female	404	45.9%	Below Diploma	80	8%
Male	476	54.1%	Diploma	204	23.2%
Total	880	100%	Associate Degree	194	22%
Age			Bachelor's Degree	244	27.7%
Under 25	92	10.5%	Master's Degree and Above	168	19.1%
26 to 34	186	21.1%	Total	880	100%
35 to 44	206	23.4%	Customer Type		
45 to 54	178	20.2%	Individual (Natural Person)	564	64.1%
55 to 64	154	17.5%	Corporate (Legal Entity)	316	35.9%
Over 65	64	7.3%	Total	880	100%
Total	880	100%			

(Source: Researcher's Findings)

Descriptive Statistics and Reliability of the Instrument

As shown in Table 6, descriptive statistics indicate that the emotional value was higher than the functional value among respondents. Among relational models, communal sharing had the highest average, followed by the equality matching and market pricing. The mean values of all constructs were above the midpoint of the five-point Likert scale, confirming favorable customer perceptions.

Data normality was assessed through skewness and kurtosis values. All values were within acceptable thresholds (±3), suggesting no major deviation from normality. The reliability of the instrument was assessed using Cronbach's alpha. All variables exceeded the 0.70 threshold, indicating high levels of internal consistency. The detailed values are included in Table 6.

Table 6.
Results of the Data Distribution Normality and Reliability of Research Variables

Variable	N	Mean	Standard Deviation	Skewness	Kurtosis	Cronbach's Alpha
Functional Value	880	3.566	0.532	-0.591	0.273	0.870
Emotional Value	880	3.646	0.608	-0.621	0.447	0.795
Communal Sharing	880	3.627	0.593	-0.522	0.149	0.755
Equality Matching	880	3.550	0.661	-0.588	0.778	0.739
Market Pricing	880	3.576	0.746	-0.429	0.364	0.721
Customer Lifetime Value	880	3.601	0.739	-0.482	0.311	0.703
Customer Influence Value	880	3.668	0.689	-0.468	-0.018	0.742
Customer Knowledge Value	880	3.821	0.627	-0.846	0.898	0.734

(Source: Researcher's Findings)

Evaluation of the Decision Tree Model Prediction Accuracy

The accuracy of predicting correct and incorrect classifications of individuals in the training group (620 cases) and the testing group (260 cases) regarding customer engagement in value co-creation was evaluated. The obtained decision tree model was able to correctly predict the occurrence of these phenomena for approximately 91.94% of individuals in the training group (samples used to build the model) and about 83.08% of individuals in the testing group.

Table 7 shows the evaluation results of the correct and incorrect predictions for the decision tree model in the training and testing groups using the C5.0 algorithm.

Table 7.
The Percentage of Correct and Incorrect Predictions of the Decision Tree Model in Training and Testing Groups

'Partition'	1_Training		2_Testing	
Correct	570	91.94%	216	83.08%
Wrong	50	8.06%	44	16.92%
Total	620		260	

(Source: Researcher's Findings)

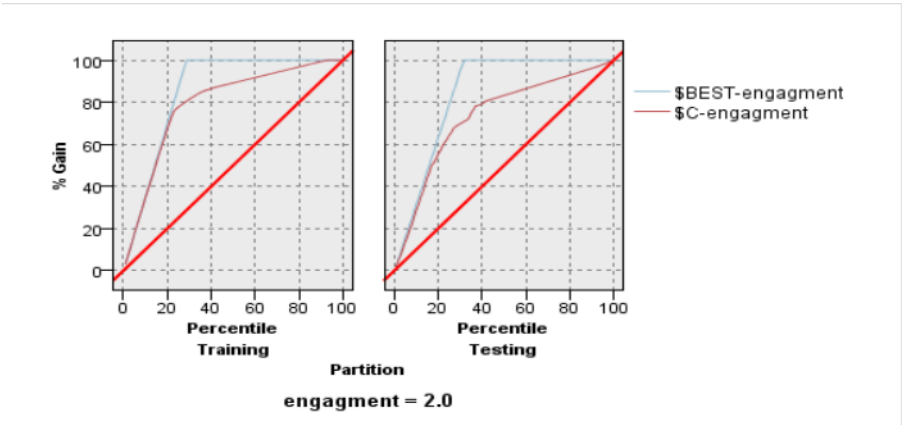
Another important evaluation criterion for decision trees is the Gain chart, which is used to assess one or more models against each other or compare a model with the theoretically best possible model.

Gain is defined as the percentage of total successes occurring within each decile, calculated as:

$$\text{Gain}=\frac{\text{Number of successes in deciles}}{\text{Total number of successes}}\times 100$$

This criterion showed favorable results for the C5.0 algorithm in both the training group (left chart) and the testing group (right chart). Overall, according to Diagram 3, the validity and power of the C5.0 model are very close to the best theoretical model, confirming the suitability of using the C5.0 algorithm in this research.

Diagram 3.
The Gain Chart of the Study Model in Training and Testing Groups under the C5.0 Algorithm



(Source: Researcher's Findings)

The importance coefficients of explanatory variables and components in the decision tree using the C5.0 algorithm are presented in Table 8, ranked from the most to the least important.

Table 8.
The Importance Degrees of the Explanatory Variables Studied

Variable Name	Importance Coefficient
Relationship Life Cycle	0.46
Emotional Value	0.23
Age	0.10
Customer Relational Models	0.08
Customer Duration (Years)	0.06
Gender	0.03
Functional Value	0.03
Percentage of Banking Activity	0.03

(Source: Researcher's Findings)

Rule Extraction: High and Low Engagement Segments

Based on the decision tree structure, conditional rules were generated to classify the customers into segments with high or low engagement in value co-creation.

Table 9.
The Rules Leading to High Engagement

Path	Rule	Engagement
1	Life Cycle: Identification/Development/Maintenance + High Emotional Value + Communal Sharing	High
2	Same Life Cycle + High Emotional Value + Equality Matching or Market Pricing + Duration < 9 years + Age < 45	Very High
3	Same Rule as #2 but Duration > 9 years	Very High
4	Same Life Cycle + Low Emotional Value	Moderate

(Source: Researcher's Findings)

Table 10.
The Rules Leading to Low Engagement

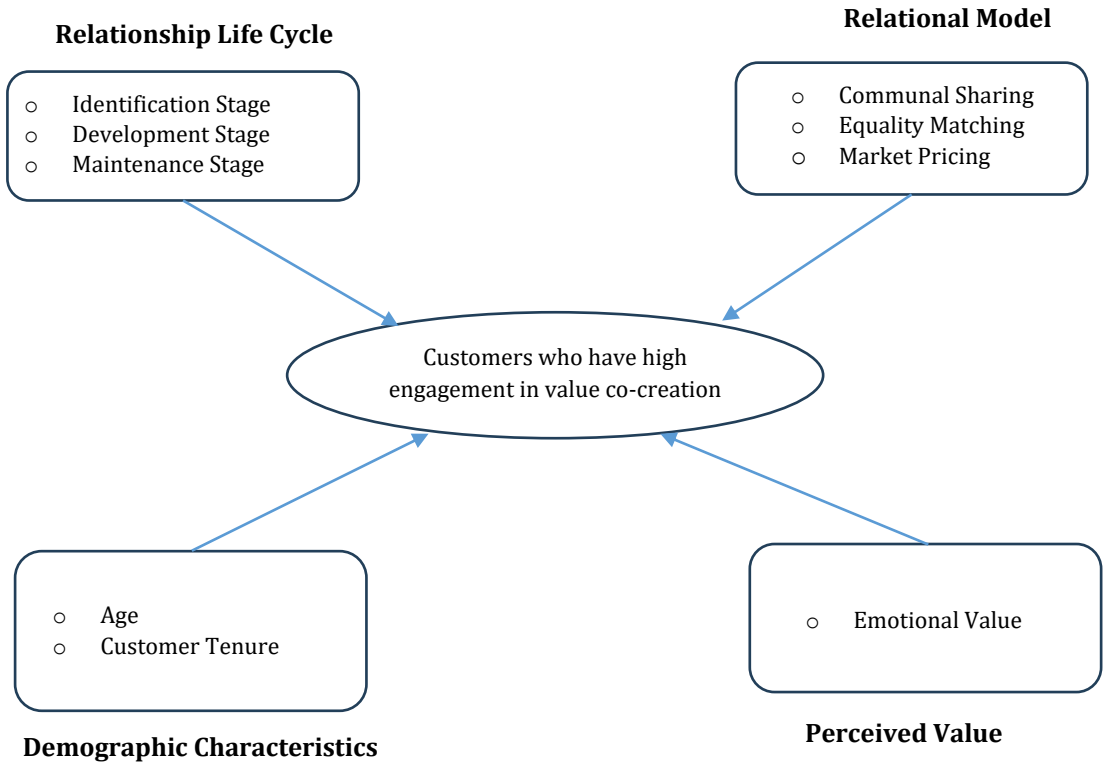
Path	Rule	Engagement
1	Same as Table 9 Rule #2 + Age > 45	Low
2	Life Cycle: Decline stage (regardless of other variables)	Very Low

(Source: Researcher's Findings)

These rules clearly demonstrate the combination of psychological, demographic, and relational factors that differentiate highly engaged customers from less engaged ones. These insights enable the design of more personalized strategies for customer engagement and resource allocation in banking.

Conceptual Model

Figure 2.
The Final Research Model Based on Target Customers in Value Co-Creation for the Bank



(Source: Researcher's Findings)

Discussion and Conclusion

Engagement Patterns and Segmentation Insights

The decision tree analysis revealed four distinct customer engagement segments shaped by emotional value, relational orientation, and stage of relationship lifecycle. The customers in the communal sharing orientation with high emotional value and established relationships demonstrated the highest levels of engagement. In contrast, the customers in the decline stage or those with transactional (market pricing) mindsets and low emotional bonds were less likely to engage deeply. This segmentation highlights that emotional connection, more than demographic or purely functional factors, predicts the customer participation in value co-creation.

The model also uncovered a high-value segment—young customers with long tenure and strong emotional ties—suggesting that emotional loyalty may develop even in early adulthood, provided the relationship continuity is sustained. Segment D, representing low-engagement customers in decline, offers a clear target for retention and win-back efforts.

Dominance of Emotional Value in Driving Engagement

Emotional value emerged as the most influential predictor of engagement, surpassing functional utility. This confirms prior findings (Mohammadi-Far & Poorjamshidi, 2021;

Sánchez-Fernández & Iniesta-Bonillo, 2007) that emotional and psychological factors such as trust, comfort, and belongingness drive sustained participation in service contexts.

In Iran's banking environment—marked by high interpersonal expectations and relational norms—emotional resonance appears even more critical. Unlike Western contexts emphasizing efficiency and speed (Li & Zhao, 2025), Iranian customers respond more to loyalty-based and trust-centered strategies. This cultural sensitivity reinforces the need to embed emotional cues into service experiences.

Strategic Implications for Customer Relationship Management

The findings offer actionable guidance for relationship marketing and CRM implementation:

- Communal Sharing customers benefit from emotionally driven strategies such as loyalty programs, appreciation gestures, and co-creation events.
- Equality Matching customers respond to fairness-based initiatives, transparent communication, and reciprocal recognition.
- Market Pricing customers value cost-efficiency, promotional clarity, and service performance.

Mapping customers by their lifecycle stage enables banks to time interventions—e.g., onboarding support, maintenance engagement, or win-back offers—with greater precision. Embedding emotional and relational logic into CRM systems can enhance the targeting accuracy and deepen the customer ties.

Theoretical and Practical Contributions

This study makes a theoretical contribution by integrating relational models, lifecycle stages, and perceived value into a unified, empirically validated segmentation framework. Unlike prior models that examine engagement in isolation, this framework reveals how relational schemas and emotional value jointly shape participation.

Practically, the study equips service firms—particularly in emerging markets—with tools to personalize engagement strategies using psychological and behavioral variables. The model's interpretability (via decision tree logic) also facilitates its operational use by managers.

Limitations and future research directions

Like all empirical studies, this research has limitations. The use of convenience sampling may introduce selection bias, and cultural context limits the generalizability beyond Iranian banking. Future studies should test this framework across industries and geographies to establish its external validity. Cross-cultural replication and longitudinal tracking of customer engagement over time would strengthen the model's robustness. Further research might also explore the integration with AI-driven CRM tools or examine how regulatory differences affect the relational dynamics.

This study demonstrates that customer engagement is best predicted through a multidimensional lens—capturing the emotional value, relational orientation, and lifecycle status. The decision tree segmentation provides both theoretical clarity and practical utility. By recognizing customers not just as buyers but as co-creators of value, firms can

craft culturally informed, emotionally resonant, and lifecycle-aligned engagement strategies that enhance satisfaction and long-term loyalty. Ultimately, this research offers a replicable, analytics-based approach to engagement segmentation in emerging service markets, contributing to both marketing scholarship and strategic practice.

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