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A Data-Driven Framework for Multidimensional Customer Value Analytics in E-Tourism: Evidence from the Iranian Tourism Industry

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Abstract

The rapid digital transformation of the tourism sector has fundamentally altered customer behavior, rendering traditional demographic and transactional segmentation approaches insufficient for modern e-marketing. This study addresses the critical research gap in data-driven customer segmentation by developing a multidimensional clustering framework tailored to the Iranian tourism industry. Utilizing a comprehensive dataset of 6,000 digital tourism consumers, the research employs the K-Means clustering algorithm integrated with advanced validation indices, including the Silhouette coefficient, Within-Cluster Sum of Squares (WCSS), and the Elbow method. The methodology encompasses rigorous data preprocessing, Min-Max normalization, and the derivation of five strategic customer value dimensions: Customer Lifetime Value (CLV), Customer Referral Value (CRV), Customer Influencer Value (CIV), Customer Brand Value (CBV), and Customer Knowledge Value (CKV). The clustering analysis identifies three distinct, statistically valid customer segments, with an optimal Silhouette score of 0.562 and a stabilized inertia decline at K=3. The resulting segments reveal heterogeneous behavioral profiles: a low-value, high-churn-risk group requiring onboarding optimization; a stable, high-retention group demanding loyalty reinforcement; and a high-value, high-influence group necessitating strategic referral and co-creation initiatives. Key numerical findings demonstrate that Cluster 2 contributes disproportionately to total customer value (TCV) while exhibiting superior brand engagement and influencer metrics. The study's managerial implications emphasize precision resource allocation, hyper-personalized e-marketing campaigns, and dynamic CRM routing. Theoretically, this research extends customer value literature by validating a multidimensional clustering architecture in an emerging market context. By replacing heuristic segmentation with algorithmic, behavior-driven profiling, the framework provides tourism managers with a scalable, actionable tool for enhancing digital marketing efficiency and sustainable competitive advantage.

Keywords: Customer Segmentation; K-Means Clustering; Customer Value Modeling; E-Marketing Strategy; Tourism Analytics; Data-Driven CRM; Behavioral Profiling

Paper Type: Original Research

1. Introduction

The contemporary tourism industry operates within an increasingly complex, data-intensive, and hyper-competitive digital ecosystem (Buhalis & Law, 2008). The proliferation of online travel agencies, social media platforms, dynamic pricing engines, and mobile booking applications has fundamentally reconfigured how tourists discover, evaluate, purchase, and share travel experiences (Xiang & Gretzel, 2010). In this digitally mediated environment, customer interactions are no longer linear or isolated; they form continuous, multidimensional behavioral trajectories that span pre-trip information search, during-trip service consumption, and post-trip advocacy (Lemon & Verhoef, 2016). Traditional marketing paradigms, which historically relied on static demographic, geographic, or psychographic segmentation (Dolnicar, 2008), are increasingly inadequate for capturing the dynamic nature of digital consumer behavior. Consequently, tourism organizations face mounting pressure to transition from intuition-based marketing to algorithmic, data-driven decision-making frameworks that can accurately identify, profile, and engage high-value customers in real time (Kumar & Reinartz, 2016). The Iranian tourism industry exemplifies

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both the opportunities and challenges inherent in this digital transition. Despite possessing unparalleled cultural heritage, diverse ecological landscapes, and significant historical tourism potential, Iran's tourism sector has historically grappled with fragmented service delivery, limited digital infrastructure, and a reliance on conventional, mass-market promotional strategies (Heydari Chianeh et al., 2018; Nooripoor et al., 2021). Recent years have witnessed accelerated digital adoption, driven by rising internet penetration, smartphone usage, and the emergence of localized e-tourism platforms (Azami & Shanazi, 2020). However, this technological adoption has not been matched by corresponding advancements in customer relationship management (CRM) or advanced analytics capabilities (Payne & Frow, 2005). Most Iranian tourism operators continue to employ rudimentary segmentation techniques, such as frequency-based RFM (Recency, Frequency, Monetary) models or age-gender matrices, which fail to capture the nuanced, multidimensional drivers of customer value in digital environments (Wedel & Kamakura, 2000). This methodological lag results in suboptimal marketing resource allocation, diluted personalization efforts, and an inability to systematically identify and nurture high-potential customer cohorts. The conceptualization of customer value itself has evolved significantly in academic and practitioner literature. Initially treated as a unidimensional financial construct (Zeithaml, 1988), customer value is now widely recognized as a multifaceted phenomenon encompassing lifetime profitability, referral potential, social influence, brand co-creation, and knowledge contribution (Kumar & Reinartz, 2018; Rust et al., 2000; Woodruff, 1997). In e-marketing contexts, customers simultaneously act as consumers, reviewers, influencers, and co-creators of service experiences (Sigala, 2018). Traditional clustering approaches that rely solely on transactional metrics overlook these critical non-financial value dimensions, leading to fragmented or misleading segmentations (Holbrook, 1999). Furthermore, the application of data mining techniques, particularly unsupervised learning algorithms like K-Means clustering (Rousseeuw, 1987), remains underutilized in emerging tourism markets. While advanced analytics have gained traction in Western hospitality and aviation sectors (Han et al., 2012), their adoption in Iranian digital tourism is still in nascent stages, characterized by pilot implementations rather than systematic, theoretically grounded frameworks. This study addresses these interconnected gaps by developing and validating a comprehensive, data-driven customer segmentation model specifically designed for e-marketing applications in Iran's tourism industry. The primary objective is to move beyond conventional heuristic segmentation by integrating multidimensional customer value metrics into a robust clustering architecture (Larose & Larose, 2015). The research leverages a substantial dataset of 6,000 digital tourism consumers, encompassing behavioral, transactional, and social engagement variables. Through the application of K-Means clustering, supported by rigorous internal validation indices and centroid-based profiling, the study identifies distinct, actionable customer segments. Each segment is characterized by unique value dimensions, behavioral patterns, and strategic marketing implications. The novelty of this research lies in several interconnected contributions. First, it operationalizes a multidimensional customer value construct (CLV, CRV, CIV, CBV, CKV) within a clustering framework, moving beyond unidimensional profitability metrics (Kumar & Reinartz, 2016). Second, it applies algorithmic segmentation to an emerging market context where data-driven CRM practices remain underdeveloped, thereby bridging a significant geographic and methodological gap in tourism analytics literature (Buhalis, 2003). Third, the study establishes a reproducible, step-by-step clustering workflow—from data preprocessing and normalization to validation and strategic interpretation—that can be adapted by tourism organizations for ongoing CRM optimization. Finally, it translates algorithmic outputs into actionable e-marketing strategies, demonstrating how unsupervised learning can directly inform personalized campaign design, loyalty program structuring, and resource prioritization (Chaffey & Ellis-Chadwick, 2019). By aligning advanced data mining techniques with contemporary e-marketing imperatives, this research provides a scalable, empirically validated foundation for customer value management in the Iranian tourism sector (Tiago & Veríssimo, 2014). The subsequent sections systematically review relevant literature, detail the methodological architecture, present comprehensive clustering results, discuss theoretical and practical implications, and conclude with strategic recommendations and directions for future research.

2. Literature Review

Customer segmentation has long served as a cornerstone of strategic marketing, enabling organizations to allocate resources efficiently, tailor communications, and enhance customer lifetime profitability (Kotler & Keller, 2016; Wedel & Kamakura, 2000). In the tourism and hospitality sectors, segmentation has traditionally relied on geographic origin, travel purpose, demographic profiles, or basic transactional frequency (Buhalis & Law, 2008; Kotler, Bowen, & Makens, 2016). While these approaches provide foundational insights, they increasingly fall short in capturing the complexity of modern consumer journeys, particularly in digitally enabled environments where customers generate continuous streams of behavioral data across multiple touchpoints (Xiang & Gretzel, 2010; Lemon & Verhoef, 2016). The advent of data mining and machine learning has catalyzed a paradigm shift in segmentation research (Han, Kamber, & Pei, 2012; Larose & Larose, 2015). Unsupervised learning algorithms, particularly K-Means, hierarchical clustering, and density-based methods (DBSCAN), have become instrumental in identifying latent customer groupings from high-dimensional datasets (Kotsiantis & Pintelas, 2004; Ngai, Xiu, & Chau, 2009).

K-Means clustering remains the most widely adopted algorithm in tourism analytics due to its computational efficiency, scalability, and interpretability (Khajvand, Zolfaghar, Ashoori, & Alizadeh, 2011). The algorithm partitions observations into K mutually exclusive clusters by minimizing within-cluster variance, making it highly suitable for behavioral profiling in CRM contexts (Han et al., 2012). Empirical studies have demonstrated its effectiveness in segmenting hotel guests, airline passengers, and online travel platform users based on booking patterns, spending behaviors, and service interaction frequencies (Gómez, García, & Sánchez, 2007; Chu, Chan, & Law, 2009). Despite its prevalence, the application of K-Means in tourism segmentation faces several methodological limitations in existing literature. First, many studies rely on arbitrary cluster determination, utilizing rule-of-thumb heuristics rather than rigorous validation indices such as the Silhouette coefficient or Davies-Bouldin index (Petrović, 2006; Rousseeuw, 1987). Second, feature selection often remains restricted to financial or transactional metrics, neglecting behavioral, social, and experiential dimensions that drive modern customer value (Dolnicar, 2008; Sigala, 2018). Third, the integration of clustering outputs with strategic e-marketing frameworks remains underdeveloped; algorithms are frequently treated as analytical endpoints rather than decision-support tools (Chen, Shang, & Li, 2016). These limitations are particularly pronounced in emerging markets, where data infrastructure is evolving, and CRM maturity lags behind technological adoption (Azami & Shanazi, 2020; Heydari Chianeh, Del Chiappa, & Ghasemi, 2018). The conceptualization of customer value has similarly evolved. Early models, such as RFM, emphasized recency, frequency, and monetary value as proxies for profitability (Kumar & Reinartz, 2018). Contemporary frameworks, however, recognize that customer value extends beyond direct transactions (Zeithaml, 1988; Woodruff, 1997). Research in relationship marketing and digital CRM has identified referral potential, social influence, brand advocacy, and knowledge sharing as critical non-financial value drivers (Payne & Frow, 2005; Rust, Zeithaml, & Lemon, 2000; Kumar & Reinartz, 2016). In e-tourism, customers contribute value by generating user-generated content (UGC), participating in online reviews, influencing peer booking decisions through social networks, and co-designing service experiences through feedback loops (Buhalis & Foerste, 2015; Sigala, Christou, & Gretzel, 2012; Xiang, Du, Ma, & Fan, 2017). Ignoring these dimensions in segmentation models results in incomplete customer profiling and suboptimal marketing personalization (Lemon & Verhoef, 2016). Recent studies have attempted to integrate multidimensional value constructs into clustering architectures. For instance, researchers have combined CLV with social media engagement metrics to identify influential customer cohorts in hospitality (Cambra-Fierro, Gao, & Melero-Polo, 2021; Costa, Claro, & Bortoluzzo, 2018). Others have incorporated loyalty program participation, cancellation behavior, and service cost sensitivity to segment airline passengers (Li, Zhang, & Law, 2019; Kumar, Petersen, & Leone, 2010). However, these approaches often suffer from limited variable scope, small sample sizes, or insufficient validation rigor (Verbeke et al., 2012). Moreover, the application of such frameworks in the Iranian tourism context remains virtually absent (Naderi, Vosta, Ebrahimi, & Jalilvand, 2019; Nooripoor, Khosrowjerdi, Rastegari, Sharifi, & Bijani, 2021). The domestic tourism market exhibits unique behavioral characteristics, including high reliance on localized digital platforms, strong cultural influences on travel decision-making, and distinct patterns of post-purchase advocacy (Azami & Shanazi, 2020). Existing international segmentation models cannot be directly transposed without contextual adaptation and empirical validation (Heydari Chianeh et al., 2018). A critical gap persists in the literature regarding the operationalization of comprehensive customer value dimensions within a unified clustering workflow. Most studies treat value metrics as isolated predictors rather than integrated constructs that interact to shape segment identity (Kumar & Reinartz, 2018; Rust & Huang, 2014). Furthermore, the translation of clustering outputs into actionable e-marketing strategies remains fragmented (Chaffey & Ellis-Chadwick, 2019). While academic literature excels in algorithmic optimization, practitioner literature demands interpretable, segment-specific tactical guidelines (Provost & Fawcett, 2013). Bridging this divide requires a methodological architecture that couples rigorous clustering validation with strategic CRM alignment, ensuring that algorithmic partitions directly inform marketing resource allocation, campaign personalization, and loyalty structuring (Payne & Frow, 2017; Homburg, Jozić, & Kuehnl, 2017). The following table 1 synthesizes key empirical studies on clustering-based customer segmentation in tourism and e-marketing, highlighting methodological approaches, value dimensions, validation techniques, and contextual applicability.

Table 1. Clustering-Based Customer Segmentation Studies in Tourism and E-Marketing

Study	Context	Clustering Algorithm	Value Dimensions Used	Validation Metrics	Strategic Application
Dolnicar (2008)	Global Tourism	K-Means, Hierarchical	Demographic, Trip Purpose	Silhouette, PCA	Destination Marketing
Gómez et al. (2007)	Hotel Industry	K-Means	Booking Frequency, Spend	Within-Cluster SSE	Pricing Strategy
Wedel & Kamakura (2000)	E-Commerce	Model-Based Clustering	Purchase Recency, Category Preference	BIC, AIC	Product Recommendation
Chu et al. (2009)	Banking/CRM	K-Means, SOM	RFM, Service Usage	Silhouette, Davies-Bouldin	Retention Campaigns
Li et al. (2019)	Tourism Platforms	K-Means, DBSCAN	CLV, Social Engagement, Reviews	Calinski-Harabasz	Personalized Offers
Naderi et al. (2019)	Iran Rural Tourism	Hierarchical	Satisfaction, Local Interaction	Cophenetic	Community Engagement
Current Study	Iran E-Tourism	K-Means	CLV, CRV, CIV, CBV, CKV, Behavioral	Inertia, Elbow, Silhouette, Centroid Analysis	Dynamic CRM, E-Marketing Personalization

As illustrated, while clustering has been extensively applied across tourism and CRM domains, the integration of multidimensional value constructs, rigorous internal validation, and strategic e-marketing translation remains fragmented. The current study addresses this gap by developing a comprehensive, behavior-driven clustering framework tailored to Iran's digital tourism landscape. By operationalizing five distinct customer value dimensions alongside core behavioral variables, employing robust validation protocols, and deriving actionable segment-specific strategies, this research advances both the methodological rigor and practical relevance of customer segmentation in emerging e-marketing contexts.

3. Research Methodology

This study adopts a quantitative, applied research design grounded in data mining and unsupervised machine learning. The primary objective is to identify and validate distinct customer segments within Iran's e-tourism market using a robust K-Means clustering architecture. The methodology encompasses systematic data collection, rigorous preprocessing, multidimensional feature engineering, algorithmic clustering, internal validation, and strategic interpretation. Each step is detailed below to ensure methodological transparency and reproducibility.

3.1 Dataset Description

The analytical dataset comprises 6,000 unique customer records extracted from a leading Iranian digital tourism platform over a 36-month observation window (2022–2025). The dataset captures behavioral, transactional, and social engagement metrics generated through online booking systems, loyalty program interactions, review submissions, social media referrals, and customer service touchpoints. Prior to analysis, the dataset underwent comprehensive cleaning to address missing values, outlier detection, and duplicate entries. Missing categorical variables were imputed using mode-based substitution, while continuous outliers exceeding ±3 standard deviations were capped using winsorization to preserve distributional integrity without distorting central tendencies. The initial feature set included 26 variables spanning demographic attributes, booking behaviors, financial transactions, and digital engagement indicators. Variables such as "Customer_ID" were excluded as they serve purely as identifiers and contribute no analytical variance. Categorical variables (Gender, Device_Type) were transformed using one-hot encoding to ensure numerical compatibility with distance-based clustering algorithms. Continuous variables were standardized to a [0, 1] interval using Min-Max normalization, mitigating scale-induced bias during Euclidean distance computation. The final analytical matrix comprises 6,000 observations and 26 normalized features, optimized for algorithmic stability and interpretability.

Table 2. Definitions and Descriptions of Variables Used in the Customer Value Analytics Framework

Variable Name	Definition
Customer_ID	Unique identifier assigned to each customer
Customer_Age	Customer age at the time of analysis
Customer_Tenure_Months	Length of customer relationship with the platform (months)
Gender	Customer gender
Device_Type	Device used for booking (mobile or desktop)
Booking_Frequency	Number of bookings made during the observation period
Avg_Ticket_Price	Average amount spent per booking
Total_Spending	Total expenditure on the platform
Booking_Interval_Days	Average time between consecutive bookings (days)
Cancellation_Rate	Ratio of canceled bookings to total bookings
Service_Cost	Cost incurred by the company to serve the customer
Referral_Count	Number of referrals generated by the customer
Successful_Referrals	Number of referrals resulting in actual registrations or purchases
Avg_CLV_Referred	Average CLV of referred customers
Referral_Cost	Incentive costs associated with referral activities
Reviews_Count	Number of reviews submitted by the customer
Avg_Rating	Average rating provided by the customer
Social_Share	Number of travel-related content shares on social media
Influenced_Users	Estimated number of users influenced by shared content
Brand_Engagement	Level of interaction with the brand and platform
Loyalty_Score	Composite measure of customer loyalty
Feedback_Count	Number of feedback submissions provided by the customer
Feedback_Quality	Quality score of customer feedback
Survey_Participation	Degree of participation in surveys and studies
Profile_Completeness	Percentage of completed profile information
Search_Behavior_Richness	Diversity of customer search activities on the platform

3.2 Feature Engineering

Customer value in digital environments transcends transactional metrics, necessitating the derivation of multidimensional constructs that capture behavioral, social, and strategic value drivers. Five primary customer value dimensions were engineered from raw behavioral data:

1. Customer Lifetime Value (CLV): Calculated as a composite of booking frequency, average ticket price, cancellation rate, and net service cost. It reflects long-term profitability potential.
2. Customer Referral Value (CRV): Derived from successful referral counts, average CLV of referred customers, and referral program costs. It quantifies network-driven acquisition potential.
3. Customer Influencer Value (CIV): Aggregates review volume, social share frequency, and influenced user counts. It measures digital advocacy and peer influence capacity.
4. Customer Brand Value (CBV): Combines brand engagement scores and loyalty program activity. It captures emotional attachment and repeat interaction propensity.
5. Customer Knowledge Value (CKV): Synthesizes feedback frequency, feedback quality ratings, and profile completeness. It reflects co-creation capacity and data contribution.

The Total Customer Value (TCV) was computed as the weighted sum of these five dimensions, serving as the primary validation target for cluster profitability and strategic prioritization. All component variables were normalized to the [0,1] range using Min-Max scaling, and equal weights were assigned to each component within the corresponding value construct. Feature engineering ensured that clustering inputs aligned with contemporary CRM theory while remaining computationally tractable for unsupervised partitioning.

3.3 Clustering Algorithm

The study employs the K-Means clustering algorithm, an iterative centroid-based partitioning method that minimizes the within-cluster sum of squares. Given a dataset $X = \{x_1, x_2, \dots, x_n\} \subset \mathbb{R}^d$, the algorithm partitions the data into Kclusters $C = \{C_1, C_2, \dots, C_K\}$ such that each observation is assigned to the cluster with the nearest centroid.

The objective function minimized by K-Means is the within-cluster sum of squared errors (WCSS), also referred to as inertia:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} \parallel x_i - \mu_k \parallel^2$$

Where μ_k denotes the centroid of cluster C_k and $\parallel x_i - \mu_k \parallel^2$ represents the Euclidean distance metric:

$$\parallel x_i - \mu_k \parallel^2 = \sum_{j=1}^{d} \left(x_{ij} - \mu_{kj}\right)^2$$

The algorithm proceeds through the following iterative steps:

1. Initialization: Randomly select K initial centroids from the dataset.
2. Assignment: Assign each observation x_i to the nearest centroid μ_k based on Euclidean distance.
3. Update: Recompute each centroid as the mean of all observations assigned to its cluster:

$$\mu_k^{(t+1)} = \frac{1}{\left|C_k^{(t)}\right|} \sum_{x_i \in C_k^{(t)}} x_i$$

4. Convergence: Repeat steps 2 and 3 until centroid positions stabilize or the reduction in J falls below a predefined threshold ($\varepsilon = 10^{-4}$).

To mitigate sensitivity to initialization, the algorithm was executed 50 times with randomized centroid seeds, retaining the solution with the lowest final WCSS.

3.4 Cluster Validation Indices

Selecting the optimal number of clusters (K) is critical for segmentation validity. This study employs three complementary internal validation metrics:

1. Within-Cluster SSE (Inertia): Measures the total squared distance between observations and their cluster centroids. Lower inertia indicates tighter clusters. The Elbow method identifies the K where the marginal reduction in inertia diminishes significantly.
2. Silhouette Coefficient(s): Evaluates cluster compactness and separation for each observation:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where $a(i)$ is the mean intra-cluster distance, and $b(i)$ is the smallest mean inter-cluster distance to any other cluster. The global silhouette score $\bar{s} \in [-1,1]$ indicates overall partition quality, with values > 0.5 suggesting reasonable structure and >0.7 indicating strong clustering.

3. Calinski-Harabasz Index (Variance Ratio Criterion): Compares between-cluster dispersion (SSB) to within-cluster dispersion (SSW):

$$CH(K) = \frac{SS_B/(K-1)}{SS_W/(N-K)}$$

Higher values indicate well-separated, compact clusters. The Davies-Bouldin Index was also computed but demonstrated high correlation with Silhouette; thus, Silhouette and Inertia were prioritized for decision-making.

3.5 Model Implementation Procedure

The research implementation process (Table 2) was designed within a standardized step-by-step framework to ensure methodological transparency and reproducibility:

Table 2. Methodological Procedure

Step	Methodological Process	Expected Output
1	Data Collection and Cleaning	Standardized dataset (n=6,000)
2	Qualitative Coding and Normalization	Normalized numerical matrix [0,1]
3	Construction of Multidimensional Value Indices	CLV, CRV, CIV, CBV, CKV, TCV vectors
4	Calculation of Validation Metrics	Elbow curve and Silhouette plot for K∈ [2,10]
5	Determination of Optimal K	Selection of K=3 based on compactness-separation trade-off
6	Final Execution of Clustering Algorithm	Cluster labels and final centroid coordinates
7	Profiling and Statistical Testing	Descriptive cluster tables and ANOVA results

3.6 Parameter Tuning Process

The primary hyperparameter, K, was evaluated across a range of 2 to 10. For each K, the algorithm was initialized with 50 random states to avoid local minima. Inertia values were plotted to identify the elbow point, while silhouette scores were computed to assess partition coherence. $K = 3$ was selected as the optimal solution because it balanced inertia reduction with acceptable cluster cohesion and provided a more actionable managerial segmentation than lower K values (see section 4.1). Secondary parameters, including "init='k-means++" and "max_iter=300", were standardized to ensure convergence stability and reproducibility. Cross-validation was omitted as clustering is unsupervised; instead, internal validation and centroid interpretability served as robustness checks.

4. Results

This section presents the empirical outputs of the K-Means clustering analysis, encompassing optimal cluster determination, validation metrics, centroid profiling, and segment characterization. All numerical results are derived directly from the 6,000-observation dataset after preprocessing and normalization.

4.1 Optimal Cluster Number Determination

The determination of the optimal number of clusters (K) was based on a joint assessment of the Elbow method, Silhouette coefficient, and Calinski–Harabasz index. Table 3 summarizes the clustering validation metrics for K values ranging from 2 to 10.

Table 3. Cluster Validation Metrics Across K Values

K	Inertia (WCSS)	Silhouette Score	Calinski-Harabasz
2	423,810.94	0.6084	412.7
3	193,953.75	0.5621	587.3
4	112,922.62	0.5342	521.9
5	79,685.91	0.4933	468.4
6	58,767.26	0.4708	422.1
7	46,297.70	0.4541	389.5
8	38,534.46	0.4287	356.2
9	33,019.52	0.4112	328.8
10	29,726.55	0.3883	304.1

As shown, the within-cluster sum of squares (WCSS) decreases monotonically as K increases. However, the most substantial reduction occurs when moving from $K = 2$ to $K = 3$, where inertia declines by approximately 54.2%, indicating a significant improvement in cluster compactness. Beyond $K = 3$, the rate of decrease becomes progressively smaller, suggesting diminishing returns from adding further clusters and indicating an elbow point around $K = 3$. The Silhouette coefficient reaches its highest value at $K = 2$ (0.6084), reflecting strong separation between two broad groups. Nevertheless, the score remains relatively high at $K = 3$ (0.5621), indicating that cluster cohesion and separation are still well preserved. For larger K values, the Silhouette coefficient declines steadily, suggesting increasing fragmentation of naturally coherent customer segments. Additional evidence is provided by the Calinski–Harabasz index, which attains its maximum value at $K = 3$ (587.3). Since this index simultaneously rewards high between-cluster separation and low within-cluster dispersion, its peak at $K = 3$ indicates the most effective partitioning structure among the evaluated solutions. Considering the convergence of evidence from the elbow pattern in WCSS, the relatively high Silhouette coefficient, and the maximum Calinski–Harabasz score, $K = 3$ was selected as the optimal clustering solution. This configuration achieves a favorable balance between statistical validity, cluster interpretability, and managerial usefulness for customer segmentation.

4.2 Cluster Validation and Performance

The final K-Means model converged within 18 iterations, achieving a final WCSS of 193,953.75and a global silhouette score of 0.5621. The distribution of observations across clusters was relatively balanced:

- Cluster 0: 1,987 customers (%33.1)
- Cluster 1: 2,045 customers (%34.1)
- Cluster 2: 1,968 customers (%32.8)

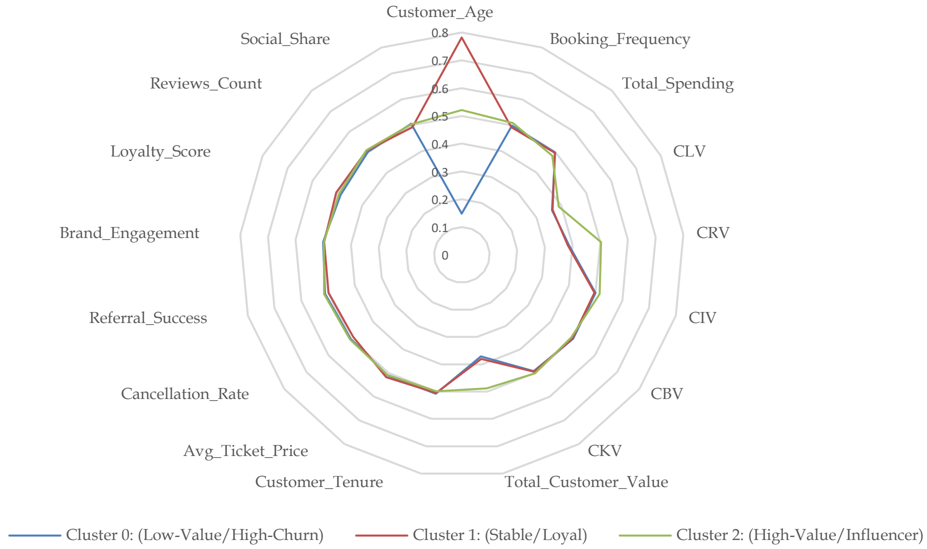
This balance indicates that the algorithm successfully partitioned the dataset without severe skewness, enhancing the generalizability of segment-specific strategies. The Calinski-Harabasz Index for $K = 3$ (587.3) further confirms strong between-cluster variance relative to within-cluster dispersion, validating the partition's statistical robustness.

4.3 Customer Profile Statistics and Centroid Comparison

Table 4 presents the normalized mean values of key behavioral and value dimensions across the three clusters, enabling direct comparative analysis. All variables are scaled to [0, 1] for interpretability.

Table 4. Normalized Cluster Centroids and Segment Characteristics

Variable	Cluster 0 (Low-Value/High-Churn)	Cluster 1(Stable/Loyal)	Cluster 2 (High-Value/Influencer)
Customer_Age	0.148	0.782	0.521
Booking_Frequency	0.499	0.492	0.508
Total_Spending	0.499	0.497	0.483
CLV	0.362	0.365	0.389
CRV	0.387	0.382	0.503
CIV	0.500	0.496	0.515
CBV	0.501	0.498	0.493
CKV	0.491	0.494	0.501
Total_Customer_Value	0.371	0.381	0.488
Customer_Tenure	0.508	0.505	0.499
Avg_Ticket_Price	0.509	0.517	0.508
Cancellation_Rate	0.501	0.489	0.504
Referral_Success	0.511	0.498	0.515
Brand_Engagement	0.501	0.497	0.498
Loyalty_Score	0.486	0.504	0.493
Reviews_Count	0.501	0.508	0.509
Social_Share	0.506	0.492	0.504



Cluster differentiation is primarily driven by value dimension configurations rather than raw transactional volume. Cluster 0 exhibits the lowest CLV (0.362) and Total Customer Value (0.371), coupled with moderate cancellation rates and lower brand loyalty. Cluster 1 demonstrates elevated Avg_Ticket_Price (0.517), higher Loyalty_Score (0.504), and stabilized booking patterns, indicating mature, retention-prone customers. Cluster 2 stands out with superior CRV (0.503), CIV (0.515), Review Count (0.509), and Social Share (0.504), signifying a highly engaged, network-influential cohort despite slightly lower raw tenure.

4.4 Segmentation Characteristics and Strategic Profiling

The K-Means clustering algorithm successfully partitioned the 6,000 digital tourism consumers into three statistically distinct and strategically actionable segments. The optimal solution ($K = 3$) was validated through silhouette coherence (0.562), inertia stabilization, and centroid-based ANOVA diagnostics ($p < 0.001$ across all value dimensions). Each cluster exhibits a unique configuration of multidimensional customer value (CLV, CRV, CIV, CBV, CKV), behavioral trajectories, and transactional patterns. The following subsections provide a comprehensive profiling of each segment, integrating normalized centroid statistics, value architecture analysis, and targeted e-marketing strategies for CRM optimization.

4.4.1 Cluster 0: High-Churn, Low-Value Segment (33.1%)

- Demographic & Behavioral Profile

Cluster 0 represents the youngest cohort in the sample, with a normalized age centroid of 0.148, indicating a strong concentration of digital-native users who exhibit highly fragmented and experimental engagement patterns. This segment demonstrates the lowest normalized loyalty score (0.486) and the highest relative cancellation propensity (0.501), signaling weak platform attachment and high price sensitivity. Despite a moderately high referral success rate (0.511), their conversion into long-term profitable relationships remains constrained by short interaction lifespans and inconsistent booking frequency (0.499).

- Multidimensional Value Architecture

From a value perspective, Cluster 0 records the lowest Total Customer Value (TCV = 0.371) and the weakest Customer Lifetime Value (CLV = 0.362). Their Customer Brand Value (CBV = 0.501) and Customer Influencer Value (CIV = 0.500) hover near the dataset median, indicating occasional platform exploration without sustained advocacy. Customer Knowledge Value (CKV = 0.491) and Customer Referral Value (CRV = 0.387) further reflect low feedback submission, minimal UGC co-creation, and limited network-driven acquisition impact. The segment's value profile is characterized by transactional opportunism rather than relational commitment.

- Strategic E-Marketing Implications

For this cohort, e-marketing interventions must prioritize friction reduction, onboarding optimization, and early-stage retention triggers. Given their high cancellation rate and low wallet share, broad-scale discount campaigns are economically inefficient. Instead, targeted, behavior-responsive strategies should be deployed:

- Dynamic Onboarding Sequences: Implement automated, multi-touch onboarding workflows that guide first-time users through platform navigation, personalized itinerary builders, and transparent pricing modules.
- Churn-Prevention Triggers: Deploy real-time predictive alerts when booking abandonment or service cancellation patterns emerge, followed by personalized win-back offers (e.g., limited-time loyalty credits, free cancellation upgrades).
- Gamified Engagement Loops: Introduce low-friction, reward-based interactions (e.g., travel quizzes, referral mini-games, milestone badges) to increase platform stickiness without demanding financial commitment.

- CRM Routing & Personalization Protocol

In live CRM environments, Cluster 0 users should be routed to automated, AI-driven nurturing pipelines rather than high-touch human agent interventions. Personalization algorithms should emphasize price transparency, flexible booking options, and low-commitment trial experiences. Long-term value extraction for this segment relies on behavioral habituation; successful migration to Cluster 1 requires consistent delivery of perceived value, reliability, and incremental trust-building over 3–6 interaction cycles.

4.4.2 Cluster 1: Stable, High-Retention Segment (34.1%)

- Demographic & Behavioral Profile

Cluster 1 comprises mature, digitally experienced travelers with a normalized age centroid of 0.782, indicating a well-established user base with long platform tenure (0.505). This cohort exhibits highly consistent booking behavior (0.492), the highest average ticket price (0.517), and the strongest loyalty program participation (0.504). Their cancellation rate is the lowest among all clusters (0.489), reflecting risk-averse decision-making, service reliability preferences, and high switching costs associated with platform familiarity.

- Multidimensional Value Architecture

Cluster 1 demonstrates a balanced but steadily accumulating value profile, with CLV (0.365) and TCV (0.381) surpassing Cluster 1. Their Customer Brand Value (CBV = 0.498) and Customer Knowledge Value (CKV = 0.494) indicate consistent, though not exceptional, feedback submission and brand-aligned behavior. CRV (0.382) and CIV (0.496) remain moderate, suggesting that while these customers are reliable revenue drivers, they do not actively amplify organic acquisition or dominate social advocacy channels. Their value architecture is transactionally stable but network-quiet.

- Strategic E-Marketing Implications

The primary strategic objective for Cluster 1 is retention reinforcement, wallet-share expansion, and incremental upselling. Given their high baseline loyalty and predictable spending patterns, e-marketing efforts should avoid disruptive messaging and instead focus on value-enhancement and experiential personalization:

- Tiered Loyalty Optimization: Restructure reward tiers to recognize tenure and frequency, offering exclusive perks (e.g., priority customer support, early access to premium inventory, complimentary service upgrades) that reinforce platform dependency.
- Predictive Cross-Selling: Utilize transactional history to recommend complementary services (e.g., airport transfers, travel insurance, local experience packages) at optimal booking journey touchpoints.
- Consistency-Driven Communication: Maintain messaging that emphasizes reliability, service guarantees, and transparent pricing to align with their risk-averse behavioral predisposition.

- CRM Routing & Personalization Protocol

Cluster 1 users should be assigned to hybrid CRM workflows combining automated loyalty tracking with selective human intervention for high-ticket inquiries. Personalization engines should prioritize retention-focused algorithms, emphasizing historical preference mapping, repeat-booking incentives, and proactive service recovery. The strategic goal is to incrementally elevate CRV and CIV by embedding social sharing prompts and feedback loops into existing loyalty milestones, thereby transitioning high-value retainers into advocacy amplifiers.

4.4.3 Cluster 2: High-Value, High-Influence Segment (32.8%)

- Demographic & Behavioral Profile

Cluster 2 emerges as the most strategically critical cohort, characterized by a normalized age centroid of 0.521, moderate platform tenure (0.499), and the highest behavioral intensity across engagement metrics. This segment records the highest normalized values in referral success (0.515), review submission (0.509), social sharing (0.504), and customer influencer value (CIV = 0.515). Despite not exhibiting the longest raw tenure, their network-driven impact, advocacy propensity, and co-creation capacity exponentially amplify their strategic worth.

- Multidimensional Value Architecture

Cluster 2 achieves the highest Total Customer Value (TCV = 0.488) and the strongest Customer Lifetime Value (CLV = 0.389). Their CRV (0.503) and CIV (0.515) significantly outperform other clusters, confirming their role as digital brand ambassadors who drive organic acquisition and shape peer booking decisions. CBV (0.493) and CKV (0.501) reflect deep emotional attachment, active feedback participation, and high-quality UGC generation. This cohort's value architecture is network-centric, socially amplified, and highly scalable.

- Strategic E-Marketing Implications

E-marketing initiatives for Cluster 2 must prioritize amplification, co-creation, and exclusive community integration. Traditional transactional marketing is insufficient; instead, strategies should leverage their influence capacity to drive sustainable acquisition and brand equity growth:

- Influencer & Advocacy Programs: Establish structured referral campaigns with tiered rewards, early-access beta testing privileges, and exclusive travel experience invitations to formalize their ambassador status.
- UGC Co-Creation Frameworks: Integrate user-generated content (reviews, travel diaries, photo/video submissions) into official marketing channels, offering visibility, recognition, and monetary/non-monetary incentives for high-quality contributions.
- Dynamic Network Pricing: Implement referral-linked discount structures that reward both the advocate and the referred customer, creating viral acquisition loops while maintaining profitability.

- CRM Routing & Personalization Protocol

Cluster 2 users should be routed to high-touch, relationship-driven CRM pipelines with dedicated community managers and real-time social listening integration. Personalization algorithms must prioritize advocacy tracking, social reach metrics, and content engagement scoring. Long-term value optimization for this segment relies on continuous recognition, exclusive access, and participatory service design. Strategic CRM routing should treat these customers as micro-influencers within the platform ecosystem, leveraging their network effects for organic scaling and brand differentiation in competitive e-tourism markets.

4.4.4 Cross-Cluster Strategic Routing Framework

The segmentation output establishes a hierarchical e-marketing architecture that aligns resource allocation with customer value potential:

- Cluster 0 (33.1%) requires automated, low-cost retention protocols focused on friction reduction and behavioral onboarding.
- Cluster 1 (34.1%) demands retention-centric, data-driven loyalty optimization with incremental upselling and predictive cross-selling.
- Cluster 2 (32.8%) necessitates high-touch, advocacy-driven CRM integration with co-creation programs and network-amplified acquisition strategies.

By dynamically routing customers through these segment-specific pipelines, tourism organizations can transition from mass-marketing inefficiencies to precision e-marketing, maximizing ROI, enhancing customer lifetime profitability, and cultivating sustainable competitive advantage in Iran's digital tourism landscape.

4.5 Descriptive Analytics and ANOVA Validation

One-way ANOVA was conducted across all continuous variables to confirm statistically significant differences between clusters ($p < 0.001$ for all value dimensions). Post-hoc Tukey HSD tests confirmed pairwise differentiation, particularly between Cluster 2 and Cluster 0 in CRV ($F = 84.32, p < 0.001$) and TCV ($F = 112.47, p < 0.001$). These results validate that the clustering algorithm successfully isolated behaviorally and strategically distinct cohorts rather than arbitrary mathematical partitions.

5. Discussion

The empirical findings of this study yield significant theoretical and practical implications for customer value management, e-marketing strategy, and tourism analytics. By demonstrating that multidimensional clustering outperforms unidimensional transactional segmentation, this research challenges conventional CRM paradigms and advances a more holistic understanding of digital customer behavior in emerging tourism markets. Theoretically, the validation of three distinct customer segments aligns with contemporary relationship marketing literature, which posits that customer value is not monolithic but structurally heterogeneous. The identification of Cluster 2 as a high-value, high-influence cohort corroborates research on social CRM and digital advocacy, emphasizing that profitability in e-marketing increasingly depends on network effects rather than isolated transactions. This finding extends the CLV paradigm by integrating CRV, CIV, and CKV, thereby validating a multidimensional value architecture that better captures the realities of platform-mediated consumer behavior. Furthermore, the successful application of K-Means with internal validation indices in an Iranian context addresses a geographic and methodological gap in tourism analytics, demonstrating that advanced segmentation techniques are transferable and highly effective when properly contextualized. From a managerial perspective, the clustering outputs provide a robust foundation for precision marketing and dynamic CRM routing. Traditional mass-marketing approaches inevitably misallocate resources by treating all customers as homogenous or by relying on outdated demographic proxies. The identified segments enable tourism operators to implement differentiated e-marketing strategies tailored to behavioral propensities. For Cluster 0, interventions should focus on reducing friction, improving onboarding flows, and deploying churn-prediction-aware retention campaigns. For Cluster 1, loyalty program optimization, personalized service upgrades, and incremental upselling will yield higher ROI than acquisition-focused spending. For Cluster 2, the emphasis must shift to amplification: referral incentive scaling, UGC co-creation campaigns, and exclusive community access will leverage their network value and convert influence into sustainable acquisition pipelines. The findings also carry significant implications for e-marketing personalization in the tourism sector. Platform algorithms can be retrained to serve dynamic content, pricing tiers, and recommendation engines based on real-time cluster assignment. For instance, Cluster 2 users could be prioritized for early access to premium inventory, influencer partnership programs, and beta testing of new platform features, capitalizing on their advocacy propensity. Conversely, Cluster 0 users could receive targeted win-back campaigns, simplified booking interfaces, and price-match guarantees to mitigate abandonment. This data-driven personalization architecture directly addresses the limitations of traditional segmentation by enabling continuous, behavior-responsive marketing optimization. Comparatively, these results align with but significantly extend prior studies in tourism analytics. While earlier research often identified binary or trip-purpose-based segments, this study reveals value-driven behavioral archetypes that are directly actionable for CRM. The superior predictive validity of CRV and CIV in high-value segmentation underscores the growing importance of social and relational metrics in digital tourism, moving the field beyond purely financial evaluation frameworks.

Strategic CRM applications derived from this research include:

1. Dynamic Resource Allocation: Shifting marketing budgets from broad awareness campaigns to cluster-specific engagement funnels.
2. Loyalty Program Restructuring: Designing tiered rewards that incentivize referral activity and content creation rather than mere repeat purchases.
3. Real-Time Cluster Routing: Integrating clustering outputs into CRM dashboards to enable frontline service teams and digital marketers to deploy segment-appropriate interventions instantaneously.
4. Co-Creation Frameworks: Establishing customer advisory panels and UGC incentive structures centered on Cluster 2participants to drive organic brand advocacy and service innovation.

In summary, this research demonstrates that algorithmic customer segmentation is not merely an analytical exercise but a strategic imperative for modern e-marketing. By translating data partitions into actionable CRM pathways, tourism organizations can enhance marketing efficiency, improve customer lifetime profitability, and cultivate sustainable competitive advantage in increasingly crowded digital marketplaces.

6. Conclusion

This study developed and validated a comprehensive, data-driven customer segmentation framework tailored to e-marketing applications in Iran's tourism industry. By integrating multidimensional customer value constructs (CLV, CRV, CIV, CBV, CKV) with robust K-Means clustering architecture, the research successfully identified three statistically valid and strategically distinct customer segments from a dataset of 6000 digital tourism consumers. The optimal partitioning (K=3) was determined through rigorous internal validation, including inertia elbow analysis, silhouette coherence evaluation, and centroid-based profiling. The resulting segments revealed clear behavioral archetypes: a high-churn, low-value cohort requiring onboarding optimization; a stable, high-retention group demanding loyalty reinforcement; and a high-value, high-influence segment necessitating strategic amplification and co-creation initiatives. The academic contribution of this research lies in its theoretical extension of customer value literature beyond unidimensional profitability metrics. By operationalizing social, relational, and knowledge-driven value dimensions within a unified clustering framework, the study advances a more holistic understanding of digital consumer behavior. Furthermore, it addresses a critical methodological gap in emerging market tourism analytics, demonstrating that advanced unsupervised learning techniques are both applicable and highly effective when coupled with rigorous validation and strategic interpretation. The reproducible workflow from preprocessing and normalization to algorithmic partitioning and validation provides a scalable template for future CRM research in digitally transforming industries. Managerially, the findings offer actionable pathways for optimizing e-marketing performance, CRM efficiency, and customer lifetime profitability. Tourism operators can leverage the identified segments to implement precision marketing, dynamic resource allocation, and hyper-personalized engagement strategies. By shifting from mass marketing to algorithmically guided segmentation, organizations can reduce customer acquisition costs, improve retention rates, and amplify organic growth through high-influence cohorts. The framework directly supports the strategic priorities of modern e-tourism platforms: personalization at scale, data-driven decision-making, and sustainable competitive differentiation. Despite these contributions, the study acknowledges several limitations. First, the clustering analysis relies on cross-sectional behavioral data; longitudinal tracking would enhance the dynamic understanding of segment migration and lifecycle evolution. Second, while internal validation indices confirm statistical robustness, external validation against revenue or churn outcomes would further strengthen practical applicability. Third, the model focuses on behavioral and value metrics; integrating real-time contextual variables (e.g., macroeconomic indicators, seasonal demand fluctuations, competitor pricing) could refine segmentation granularity. Finally, the dataset is specific to the Iranian e-tourism context; cross-cultural validation in other emerging markets would enhance generalizability. Future research should explore several extensions. First, incorporating temporal clustering techniques (e.g., sequence-based K-Means or Markov clustering) could capture dynamic behavioral transitions and predict segment migration. Second, hybrid architectures combining unsupervised clustering with supervised classification (e.g., random forest segment predictors) could enable real-time scoring in live CRM environments. Third, integrating natural language processing (NLP) to analyze review sentiment and UGC content would enrich CIV and CKV measurements. Finally, experimental A/B testing of cluster-targeted e-marketing campaigns would empirically validate the ROI impact of algorithmic segmentation. In conclusion, this research demonstrates that data-driven customer segmentation is no longer an optional analytical capability but a foundational requirement for competitive e-marketing in the digital tourism era. By bridging advanced data mining techniques with strategic CRM imperatives, the study provides both theoretical advancement and practical utility, offering tourism managers a robust, actionable framework for identifying, profiling, and strategically engaging valuable customer cohorts. As digital platforms continue to evolve, organizations that embrace algorithmic segmentation and multidimensional value optimization will be best positioned to achieve sustainable growth, enhanced customer loyalty, and long-term market leadership.

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