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A Localized Model for New Product Development in Electronic Banking Based on a Business Intelligence Approach

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Abstract

Amid rapid technological advancements and rising customer expectations in the banking industry, the development of data-driven banking products tailored to customer needs and feedback has become a strategic imperative. This study presents a localized model for the development of electronic banking products through the integration of Business Intelligence (BI) and the Quality Function Deployment (QFD) methodology. In the first phase, customer needs were identified via a comprehensive literature review and classified into nine key dimensions: speed, accuracy, security, user interface, cost, advanced features, financial consulting, accessibility, and responsiveness. Customer segmentation was conducted using the K-means clustering algorithm based on Customer Lifetime Value (CLV). The clustering validity was confirmed using the silhouette coefficient (0.63), and the target cluster—representing the highest average CLV—was selected for further analysis. Subsequently, text mining techniques were employed to analyze customer feedback within the selected cluster, and their needs were categorized using the Kano model. A QFD House of Quality matrix was then constructed to derive the corresponding technical requirements, which were prioritized using the eigenvector method. The findings revealed that responsiveness, security, accessibility, accuracy, and user interface are fundamental needs; speed represents a performance need; while cost, advanced features, and financial consulting fall under attractive needs. The top technical priorities identified include the "design of artificial intelligence algorithms," "implementation of business intelligence solutions (integration and data analytics)," and "development of control and compliance processes." This model represents the first localized framework that combines QFD and business intelligence in the context of Iran's banking industry.

Keywords: Electronic Banking, Customer Clustering, QFD, Business Intelligence, Data Analysis

1 Introduction and Problem Statement

In recent decades, the banking industry has undergone significant transformation due to rapid technological advancements and the growing expectations of customers. Electronic banking, as a digital paradigm, has facilitated swift

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access to financial services and intensified market competition. Consequently, banks are confronted with numerous challenges, including escalating customer demands, increasing competition, and the continuous need for innovation. Banks collect vast volumes of transactional and behavioral data from diverse sources such as customer loyalty programs and transactional databases. Proper analysis of this data can provide valuable insights for improving services and developing new products. However, many banks continue to rely on traditional product development methods, which often fail to align with the actual needs of customers. This gap between evolving customer expectations and banks' ability to meet them underscores the urgent need for an innovative approach. Addressing this need requires the adoption of powerful tools. Quality Function Deployment (QFD) is recognized as a key methodology in product development that can translate customer needs into technical specifications. Additionally, the Kano model can be employed to categorize customer requirements into three main groups: basic, performance, and attractive needs. Simultaneously, Business Intelligence (BI), supported by data mining techniques, enables analytical processing of large-scale data. Previous studies in the fields of electronic banking, business intelligence, and quality improvement methods have primarily focused on identifying customer needs and the factors influencing customer satisfaction. The present study aims to introduce the first localized framework for integrating Business Intelligence (BI) and Quality Function Deployment (QFD) within the context of Iranian banking. Adopting a mixed-method and exploratory approach, this research seeks to provide a comprehensive framework to assist banks in becoming more efficient and customer-centric.

2 Theoretical Foundations and Literature Review

Numerous studies in the domains of electronic banking, business intelligence, and service quality improvement have been conducted in Iran, with a focus on understanding customer needs. These studies primarily concentrate on identifying the factors influencing customer satisfaction, designing management frameworks, and integrating modern technologies into banking systems. The key contributions are summarized as follows:

Adeniran et al. (2024) [1] in their article titled "Integrating Business Intelligence and Predictive Analytics in Banking" propose a framework for combining BI with predictive analytics in banking, emphasizing BI's role in optimizing financial decision-making, risk management, and personalized customer engagement. The study demonstrates that BI tools can assist banks in establishing integrated data architectures and strategic decision-making processes. Pratap et al. (2024) [14], in "Customer Segmentation Using RFM Model and K-means Technique", focus on customer clustering based on Customer Lifetime Value (CLV), aiming to improve CRM by categorizing clients more accurately according to consumption behavior and annual income. Their results highlight the potential of clustering techniques in enabling personalized banking services.

A 2024 article in Banker Journal [11] titled "Digital Banking: What Do Customers Really Want?" identifies top customer expectations, including the use of AI for account management, financial advisors, communication, and personalized services. Ramirez and Gomez (2023) [13], in their study "Big Data Analytics in QFD for Banking Innovation: A Latin American Case Study", apply big data—drawn from transactions and social media comments—as input for QFD to drive innovation. Their focus is on using unstructured external data (e.g., in Colombia) to guide product development.

Feizollahi and Heidari (2022) [7], in "Identifying Customer Needs in Electronic Banking Services Using a Hybrid Approach", utilized interviews and surveys to categorize customer needs into five dimensions: reliability and security, access time, understanding and awareness, service features, and value/cost. Their findings showed significant influence of these factors on customer expectations. Khosravi et al. (2022) [8], in "A Model for Customer Retention in Electronic Banking", identified elements such as information security, ease of use, and time saving as key drivers of customer loyalty. The study stresses the necessity of data-driven systems to enhance customer service. Glance (2023) [3], in "The Importance of Customer-Centric Design in Digital Banking", highlights the top customer needs, including attractive visual layouts, personalized services, interactive UI design, speed, content-driven recommendations, targeted product suggestions, and proactive financial insights.

Rahman et al. (2023) [12] explore the application of QFD in Islamic banking product development in Indonesia. Their study exclusively addresses Shariah compliance and the alignment of products with Islamic banking principles using QFD to assess the degree of halal certification and avoidance of interest (riba). Dhoke (2023) [4] conducted a study to evaluate customer attitudes toward e-banking services and their satisfaction levels. Key customer needs identified included security, communication, ease of use, user interface, efficiency, and personalized services. Nithya and Kiruthika (2021) [9] proposed a conceptual framework for customer relationships in e-banking, emphasizing the integration of BI systems with CRM. They found that analyzing historical and real-time behavioral data can reduce risk, identify high-value customers, and help develop targeted strategies. Asayesh and Safabakhsh (2022) [15], in "Customer Segmentation Based on Lifetime Value and Profitability", showed the value of using CLV to segment profitable banking clients. Nouri and Motadel (2022) [10] developed a design framework for managerial dashboards using QFD in intelligent business systems. Their results suggest that integrating QFD with smart technologies—such as real-time analytics and machine learning—enables translation of stakeholder needs into technical specifications and helps prioritize dashboard features. The researchers emphasize that this alignment improves strategic consistency and data-driven decision-making. Vakil et al. (2022) [16], in "A Conceptual Framework for CRM in E-Banking with Emphasis on Business Intelligence Tools", designed a framework to integrate BI into CRM systems. Their findings indicate that combining BI with CRM allows analysis of customer behavior using both historical and real-time data, thereby aiding in identifying purchase patterns, preferences, and risks. The proposed framework emphasizes the importance of integrating BI platforms with e-banking systems and training staff to maximize value extraction.

Although various studies have explored these domains, the literature reveals a notable gap regarding the integration of Business Intelligence (BI) and Quality Function Deployment (QFD) for new product development. The present study aims to address and bridge this specific gap.

3 Research Methodology

From the perspective of research purpose, the present study is applied-developmental. The main objective is to propose a model for new product development in electronic banking and to present the first native framework for integrating Business Intelligence (BI) and Quality Function Deployment (QFD) in Iranian banking. Regarding data collection and the nature of the research, this study is descriptive-analytical (based on data gathering and analysis processes) and follows a mixed-method approach. The research began by identifying customer needs through a literature review and extracting customer opinions from the bank's customer club database. Subsequently, an extensive analysis of these data was conducted.

This analysis included:

1. Classification of customer needs using the Kano model,
2. Customer clustering based on the Customer Lifetime Value (CLV) index employing the K-means technique,
3. Data mining and text analysis of customer feedback using Artificial Intelligence tools,
4. Application of software such as Orange, and databases like Farsnet [6] and Virastaran [5],
5. Finally, utilizing the QFD model to translate customer needs into technical requirements.

It is worth noting that the use of the K-means algorithm, as a data mining technique within the BI framework, enabled the discovery of hidden customer segments based on banking transaction patterns, allowing managerial strategies to be targeted with the help of QFD.

The nature of the study aligns with an exploratory mixed-methods approach. This compatibility arises from the combination of quantitative and qualitative methods (congruent with data analysis approaches) and the use of various data types on one hand, and on the other, from the goal of developing a novel native framework to fill existing research gaps and explore effective integration of BI and QFD in the context of Iranian banking. The research implementation steps are illustrated in Figure 1.

In this study, customer needs were first identified through a literature review. These needs included speed, accuracy, security, user interface, cost, advanced features, financial consulting, accessibility, and responsiveness. Next, leveraging Business Intelligence and data mining, customers of a specific bank were clustered into value groups based on the Customer Lifetime Value (CLV) index using the K-means technique. The K-means clustering method was chosen due to its simplicity, high efficiency, and good separability in large datasets. This method divides customers into homogeneous clusters, enabling better analysis of behavioral patterns based on CLV. Parameters used to calculate CLV included "average customer lifetime," "average number of transactions," and "average transaction amount." In this research, 11,279 customer samples from one bank were categorized into three main groups according to the CLV index. To evaluate cluster quality, the Silhouette statistical analysis method was used. The Silhouette index is a key criterion for assessing clustering quality and is an effective tool to evaluate data partitioning in clustering. The Silhouette validation index ranges between +1 and -1. The highest Silhouette value indicates the optimal number of clusters because it shows that points are well matched to their own clusters and well separated from other clusters. After clustering customers, text mining techniques using Artificial Intelligence tools in the Orange software environment were applied to analyze the feedback of the selected cluster's customers. By extracting key concepts and hidden patterns in textual data, their perspectives on the 9 customer need indicators were identified. The key steps in this process included data selection, preprocessing, processing, data analysis, and interpretation and application of the results. Orange is a component-based data mining software with a wide range of techniques based on the Python language.

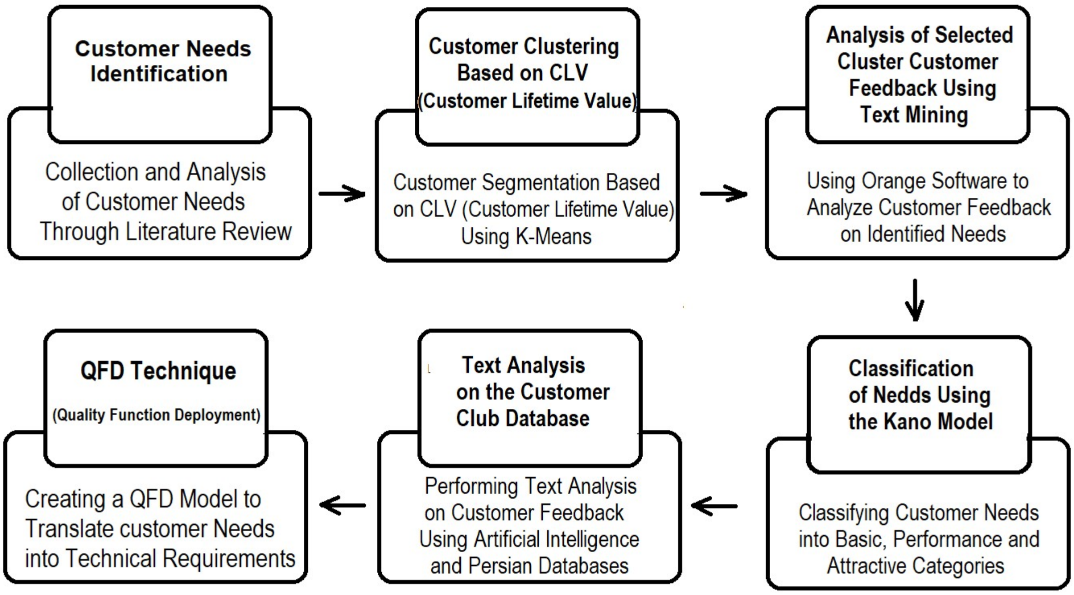


Figure 1: Implementation Steps of the New Product Development Model in Electronic Banking.

This text mining was conducted using Persian databases such as Farsnet (the first, most accurate, and largest Persian WordNet with more than 130,000 lexical entries) and Virastaran (a comprehensive Persian synonym and antonym vocabulary). During analysis, non-important words known as ”stop words” were identified and removed. The Persian stop word list used in this research, as introduced by [2] (Ziaa, 2018), is shown in Table 1. This stop word list, licensed under MIT, was loaded into Orange software before starting the text mining process.

Table 1: Persian Stopword List

Source (author)	Text File	Stopword Count	License
Jacques Savoy	PersianST.txt	332	BSD
Kazem.Taghva et al.	non-verbal_stopwords.txt	155	?
Kazem.Taghva et al.	verbal_stopwords.txt	33	?
Nima Mazdak	Persian_StopList.txt	149	?
Mohammad	PersianSopWords.txt	796	?
Kharazi	Persian_Stop_Words_List.txt	778	?
Shokri	stop-words	2435	MIT

For each of the customer need indicators, a set of keywords and their synonyms were identified and extracted using artificial intelligence and Persian language databases. Additionally, corresponding keywords related to the three Kano classification categories (basic, performance, and attractive) were similarly applied in the text mining process. A pilot sample of 53 customer reviews was initially input into the Orange software for preliminary validation, and the results confirmed the accuracy of the analysis with an error rate of less than 5%. Subsequently, this analysis was extended to the entire dataset of customer reviews. The text mining and Kano classification process in the Orange software included data input, conversion to textual documents, processing steps (such as tokenization and stop word removal), and filtering based on the keywords related to the customer need indicators and Kano categories, as illustrated in Figure 2.

The first step involves importing customer needs data into Orange software via the File widget. Next, the Corpus widget is used to convert the data into textual documents. Then, the Corpus Viewer widget filters the customer feedback based on keywords representing each customer need indicator. In the preprocessing stage, the Preprocess Text widget is applied, which processes the text by tokenizing it into smaller units, filtering tokens, performing normalization (stemming), generating n-grams, and tagging tokens with parts of speech. These preprocessing steps are repeated for all customer need indicators. Finally, the Quality Function Deployment (QFD) technique is employed as a powerful tool for product development. QFD facilitates the translation of customer language into technical requirements during product development.

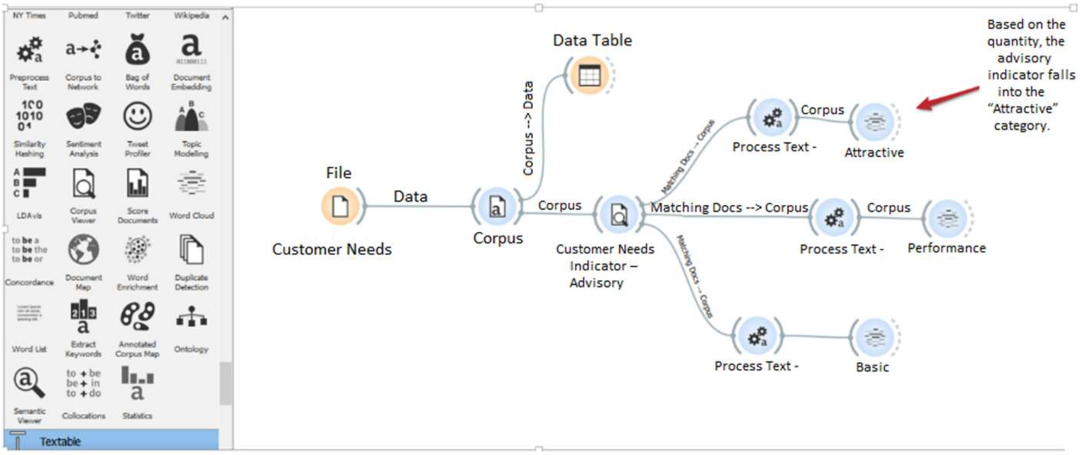


Figure 2: Text Mining and Classification Process in Orange Software.

4 Research Findings

Based on the analysis conducted in this study, nine key customer needs in electronic banking were identified, including the indicators of speed, accuracy, security, user interface, cost, advanced features, financial consultation, accessibility, and responsiveness. These needs were classified according to the Kano model, as presented in Table 2.

Table 2: Kano Classification Based on Text Mining

Database Output	Attractive	Performance	Basic	Category Kano Model Indicator
Analysis Using Orange Software and Text Mining	10	**106**	76	Speed
	12	82	**96**	Responsiveness
	6	29	**38**	Security
	17	92	**157**	Accessibility
	2	29	**34**	Accuracy
	15	7	7	Cost
	61	31	38	Advanced Features
	35	**112**	**112**	User Interface
	23	21	20	Advisory

The overall classification of all indicators based on text mining using Orange software was performed as shown in Figure 3.

The findings indicate that responsiveness, security, accessibility, accuracy, and user interface are essential needs. Speed was identified as a performance need. Cost, advanced features, and financial consulting were recognized as attractive needs. Kano analysis through text mining helps us gain a deeper understanding of customer needs. Additionally, this study employed customer clustering techniques using the K-means method based on the Customer Lifetime Value (CLV) index. The clustering was performed using SPSS Modeler software, enabling precise clustering execution, result evaluation with the silhouette criterion, and dividing customers into value-based groups. For a specific bank, 11,279 customer samples were classified into three main categories according to CLV, as shown in Table 3.

Table 3: Results of Clustering Using the K-means Method

		Number of Cases in each Cluster
Cluster	1	5122.000
	2	3723.000
	3	2434.000
Valid		11279.000
Missing		3.000

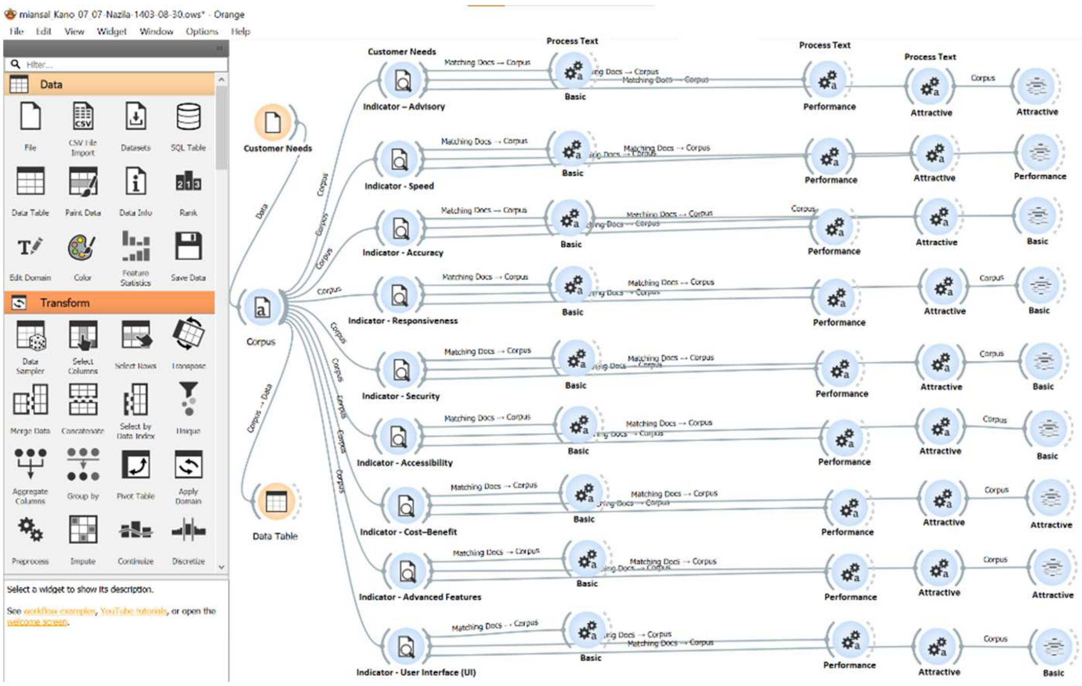


Figure 3: Text Mining and Kano Classification Process for All Indicators in Orange Software.

The Table 3 shows that customers were divided into three main clusters. The distance between clusters indicates a significant difference among them. Out of a total of 11,279 customer data entries included in this analysis, only three samples were excluded from the main dataset due to data deficiencies. To evaluate the quality of the clusters, the silhouette analysis method was used. The results obtained by inputting different numbers of clusters into the K-means algorithm for clustering are presented in Table 4

Table 4: Silhouette Index Values Based on Number of Clusters

Number of Clusters	2	**3**	4	5	6	7	8
Silhouette Value	0.559	**0.673**	0.571	0.561	0.554	0.553	-0.184

From the analysis of this table, it can be concluded that the silhouette index reaches its highest value, 0.673, when clustering into three clusters. This value indicates that the best separation of clusters is achieved by dividing customers into three main groups. Table 5 provides information about the customer clustering of the bank, based on the analysis of Customer Lifetime Value (CLV), average number of transactions, customer lifetime, and transaction values within each cluster.

Table 5: Cluster Information

Cluster Selection Criteria		Average			Cluster#
Number per Cluster	CLV	Transaction	Lifetime	Number of Transactions	
5,122.00	300.00	69,000.00	7.56	5.41	1
3,723.00	2,200.00	65,000.00	7.58	4.70	2
2,434.00	**10,000.00**	**202,000.00**	**7.63**	**5.13**	**3**

The aim of this clustering is to identify key differences between various customer groups based on behavioral patterns and revenue generation for the bank. The results of each cluster's information are as follows:

1. Cluster 1: With 5,122 samples, it includes the largest number of customers, about 45% of the total. The average Customer Lifetime Value (CLV) rate for this cluster is 300 billion rials, approximately 3% of the total. The profitability of customers in this cluster is 3%.
2. Cluster 2: Contains 3,723 samples, representing a medium-sized group, about 33% of the total data. The average CLV rate for this cluster is 2,200 billion rials, about 18% of the total. The profitability of customers in this cluster is 18%.

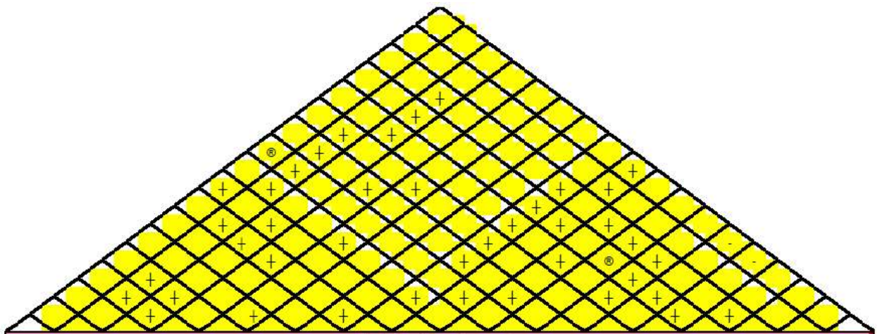
3. Cluster 3: With 2,434 samples, it is the smallest group, including about 22% of the customers. However, it has the highest average CLV rate of 10,000 billion rials, representing 79% of the total. The profitability of customers in this cluster is 79%.

Findings showed that Cluster 3 was identified as the selected cluster with the highest profitability. Despite being the smallest customer group, making up about 22% of the total customers, it has the highest average CLV rate, accounting for 79% of the total. This indicates the high profit potential of this group for the bank, making this category valuable and strategic customers. Customers in this cluster, besides a high CLV, have a longer lifetime (7.63 years) and regularly use the bank's services. These frequent interactions and a high number of transactions indicate that customers in Cluster 3 are more loyal to the bank and play a key role in its sustainable profitability.

Selecting Cluster 3 as the target group allows the bank to optimize resource management by focusing on high-value customers and to implement marketing and service strategies more accurately. Ultimately, the bank can execute related strategies focused on meeting the needs of these customers.

For this purpose, the translation of customer needs into technical requirements was performed using the QFD technique. The QFD process involved building the House of Quality (HOQ) to convert customer needs into technical and operational requirements. Through meetings and interviews with the bank's technical experts, technical requirements related to customer needs were extracted and recorded in the columns of the House of Quality, as shown in Figure 4.

The findings of this process specify the relationship between customer needs and technical requirements that can address them. The degree of correlation between each technical requirement and customer need, according to experts' opinions, is rated as 3, 6, or 9 in Figure 4, where 9 indicates the highest level of correlation.



		Technical Requirements																		
		Design of Engaging and Brand Aligned UI	UX Design Based on Customer Behavioral Analysis	Data and IT Infrastructure Security	Strong Authentication Penetration Testing, and Continuous Security Assessment	Design of Artificial Intelligence Algorithms	Design of Control and Compliance Processes	Business Intelligence (Data Integration and Analytics (Solutions	Development of a Multi Channel (Omni Channel) Platform	Design of an Assistive User Interface for People with Disabilities	Intelligent Advisory System Alongside Interactive Channels	Customization and Personalization	Optimization of IT Infrastructure	Reliability, Transparency, and Service Speed	Personalization and Interaction Capabilities with FinTechs	System Accessibility and Response Speed	Ability to Track and Access Records	Cost Management and Optimization (Operational (Marketing, etc	Offering Reduced Pricing and Cost Effective Facilities	
	C	D	H	L	P	T	X	AB	AF	AJ	AN	AR	AV	AZ	BD	BH	BL	BP	BT	
Customer Needs	Weight	Matrix of Relationships Between Technical Requirements and Customer Needs																		
User Interface	0.091	9.00	9.00							9.00		9.00				9.00				
Transaction Security	0.089			9.00	9.00	3.00	3.00		3.00				3.00							
Transaction Accuracy	0.246	-			3.00	9.00	9.00	9.00		-				3.00						
Fast Accessibility	0.091	9.00							9.00	6.00						3.00				
Financial Advisory	0.109					3.00		3.00			9.00	9.00					3.00			
Speed	0.090												9.00	3.00						
Service Features	0.057													9.00	9.00					
Customer Responsiveness	0.100	3.00							3.00							9.00	9.00			
Price and Cost	0.128											3.00						9.00	9.00	
Weight and Priority of Technical Requirements		1.94	0.82	0.80	1.54	2.81	2.48	2.54	1.39	1.37	0.98	2.18	1.08	1.52	0.51	1.99	1.23	1.15	1.15	27.48
Normalized Weight and Priority		0.07	0.03	0.03	0.06	0.10	0.09	0.09	0.05	0.05	0.04	0.08	0.04	0.06	0.02	0.07	0.04	0.04	0.04	1.00
Implementation Sequence of Technical Requirements		6				1	3	2				4				5				

Figure 4: QFD Technique – Technical Requirements Aligned with Customer Needs.

To determine the weights of the indicators (customer needs) from the perspectives of three experts, the eigenvector technique was used. The inconsistency coefficients obtained were 0.07, 0.02, and 0.08, respectively. Since all values are less than 0.1, this indicates the judgments are consistent and valid. Therefore, their average weights were calculated as shown in Table 6.

Table 6: Weights of Indicators (Customer Needs)

	Expert Opinion Weight			Indicator Weights
	One	Two	Three	Average
User Interface (UI)	0.062	0.102	0.108	0.091
Security	0.025	0.053	0.188	0.089
Accuracy	0.291	0.203	0.243	0.246
Accessibility	0.041	0.086	0.146	0.091
Financial Advisory	0.146	0.141	0.041	0.109
Speed	0.072	0.088	0.110	0.090
Service Features	0.049	0.075	0.046	0.057
Responsiveness	0.145	0.087	0.067	0.100
Price and Cost	0.167	0.165	0.052	0.128

To extract the weight and priority of the technical requirements, the weight of each technical requirement was calculated by multiplying the relationship score (ranging from 3 to 9) by the weight of the customer need and then summing the results according to the following formula. This formula was repeated for all technical requirements.

$$\begin{aligned} D60 = {} & (D51 * \$C\$51) + (D52 * \$C\$52) + (D53 * \$C\$53) + (D54 * \$C\$54) + (D55 * \$C\$55) \\ & + (D56 * \$C\$56) + (D57 * \$C\$57) + (D58 * \$C\$58) + (D59 * \$C\$59) = 1.94 \end{aligned}$$

For normalizing the weights, the following formula was used:

$$D61 = D60/SUM(D60 : BT60) = 0.071$$

This formula was applied to all technical requirements repeatedly, and ultimately, the weight and priority for implementing each technical requirement were calculated according to Table 7.

Table 7: Description of Technical Quality Requirements and Their Corresponding Weights

Row	**Description of Technical Quality Requirement**	**Weight**	**Normalized Weight**
1	Design of Artificial Intelligence Algorithms (Prediction and Decision-Making)	2.808	0.102
2	Business Intelligence with Design of Data Integration and Analytics Solutions	2.541	0.092
3	Design of Control and Compliance Processes	2.481	0.090
4	Customization and personalization	2.184	0.079
5	System Accessibility and Response Time	1.992	0.072
6	Design of Engaging and Brand-Aligned UI	1.938	0.071
7	Strong Authentication, Penetration Testing, and Continuous Security Assessment	1.539	0.056
8	Reliability, Transparency, and Service Efficiency	1.521	0.055
9	Development of a Multi-channel (Omni-Channel) Platform	1.386	0.050
10	Design of a Simple and Assistive User Interface for People with Disabilities	1.365	0.050
11	Ability to Track and Access Records	1.227	0.045
12	Cost Management and Optimization (Operational, Security, Marketing, etc.)	1.152	0.042
13	Offering Reduced pricing and Designing Cost-Effective Solutions	1.152	0.042
14	Optimization of IT Infrastructure	1.077	0.039
15	Intelligent Advisory System Alongside Interactive Channels	0.981	0.036
16	UX Design Based on customer Behavioral Analysis	0.819	0.030
17	Data and IT Infrastructure security	0.801	0.029
18	Personalization and Interaction Capabilities with FinTechs	0.513	0.019

The findings indicate that transaction accuracy, with a weight of 0.246, price and cost with a weight of 0.128, financial consultation with a weight of 0.109, and customer responsiveness with a weight of 0.100, hold the highest weights among the nine customer needs. Transaction accuracy, by a significant margin, is the most important customer need. The primary technical requirement that has the greatest impact on transaction accuracy is the design of artificial intelligence algorithms. In the schematic diagram below, shown in Figure 5, the four key customer needs and the corresponding technical requirements that address each are presented:

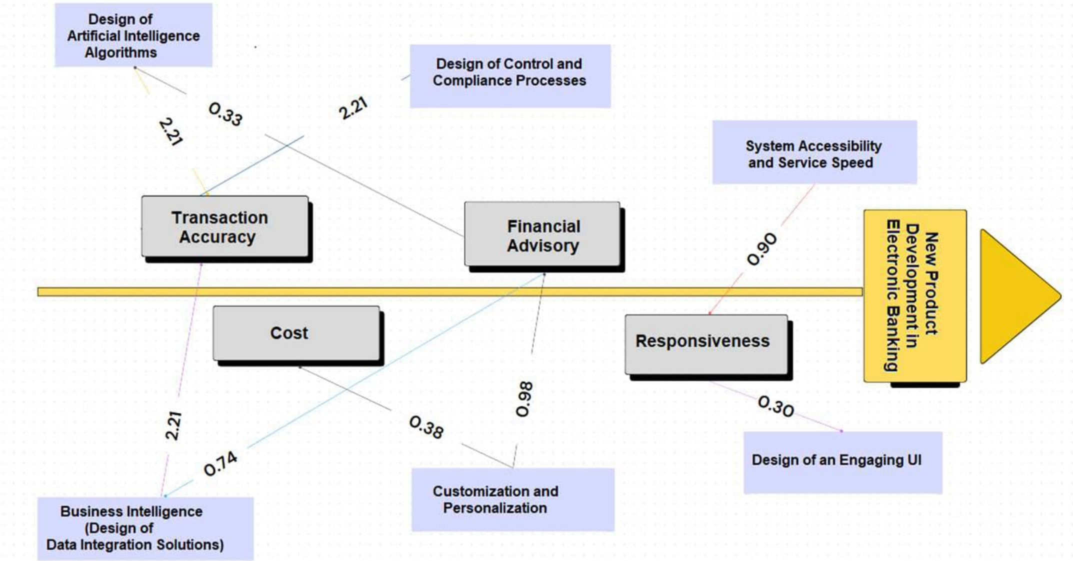


Figure 5: The relationship between the four key customer needs and their corresponding technical requirements.

The weights shown in the schematic above were obtained by multiplying the weight of the technical requirement by the weight of the customer need. The technical requirements of "designing artificial intelligence algorithms," "implementing business intelligence and integration solutions," and "designing control and compliance processes" were identified as the highest priorities with a coefficient of 2.21, because they cover high-weight customer needs (especially transaction accuracy with a weight of 0.246). Following these, the technical requirement of "customization and personalization" is important due to its impact on cost and financial consulting needs. Finally, the technical requirements of "service accessibility and speed" and "designing an attractive UI" are next in importance because of their influence on the responsiveness indicator.

5 Conclusion and Future Recommendations

Rapid technological advancements over recent decades have fundamentally transformed the role of banking. The findings of this study highlight the significant impact of fast technological changes, including the use of artificial intelligence, on the banking industry in recent decades. Electronic banking has emerged as a digital paradigm enabling quick access to financial services and creating a competitive landscape for banks. However, in the digital era, the banking sector faces multiple challenges, including rising customer expectations, increasing competition, and continuous demand for innovation. Banks possess substantial transactional and behavioral data from sources such as customer loyalty programs and customer interactions. This research shows that if analyzed correctly, this vast volume of data can provide valuable insights for improving services and products. This contrasts with many banks' continued reliance on traditional product development methods, which often do not align with actual customer needs. Traditional methods typically gather customer feedback via surveys, whereas this study utilized text mining. It is important to note that text mining focuses on customers' sentiments and opinions, while survey analysis mainly deals with structured quantitative results. Furthermore, this study clusters customers and identifies those with higher value to the bank, thereby focusing and prioritizing product development based on these customers' needs. Text mining on the opinions of this selected customer cluster provides a deeper understanding of needs compared to traditional surveys. This study proposes that integrating Business Intelligence (BI) and the Quality Function Deployment (QFD) technique can offer a framework for customer-needs-based product development. Business Intelligence delivers valuable analytical insights from data, while QFD is a powerful product development technique that translates customer needs into technical features. The combination of these two tools can potentially lead to the creation of new products that are both up-to-date and satisfying from the customer's perspective. This research adopted a combined analytical-descriptive and exploratory approach using compatible quantitative and qualitative methods for data analysis. As mentioned in the research findings, in prioritizing technical requirements, it was determined that the bank should initially focus on "designing artificial intelligence algorithms," "implementing business intelligence solutions (integrated data frameworks)," and "designing control and compliance processes." The analysis of weights obtained from applying QFD shows that accuracy in banking operations, especially in the digital era, is considered by customers as more valuable than other features. Following that, cost, financial consulting, and responsiveness are ranked in priority order. Accuracy is categorized as a fundamental and essential customer need—customers consider it obvious, and neglecting this need strongly affects customer dissatisfaction. Responsiveness, categorized under functional needs, indicates that poor performance in this area causes dissatisfaction, while increased attention to this need results in greater satisfaction. Cost and financial consulting represent attractive needs for customers; although their absence may not cause dissatisfaction, they have a significant impact on attracting customer satisfaction. In conclusion, the integrated BI-QFD model presented in this study provides a practical and data-driven approach that helps translate customer priorities into technical capabilities and offers a framework for effective and customer-centered electronic banking product development in Iran. By providing this framework, the study aims to assist banks in becoming more efficient and customer-focused. While this research proposes the model and identifies its components, several areas for future research are suggested as follows:

- A more detailed examination of the impact of implementation phases on specific indicators by developing the QFD technique into multiple stages is proposed as a potential area for future research.
- Analyzing the relationships among technical requirements (the roof of the quality house), which show the degree of interaction among technical requirements, could be considered as a parameter for the new product development model in future studies.
- Another future suggestion is to develop multilayer operational processes for each quality house requirement using Business Process Management (BPM). Customer needs change over time, which in turn demands different operational processes. It is recommended that continuous research be conducted to identify and predict changes in customer needs so that, by leveraging BPM techniques, multilayer operational processes for each technical and executive requirement can be managed within process management frameworks.

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