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Customer-Oriented Knowledge Management Modeling Using the MLP Method

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Abstract

Customer-oriented knowledge management is a comprehensive approach aimed at developing a broad and integrated organizational vision, with its primary focus on achieving innovation and organizational effectiveness. This study examined customer-oriented knowledge management in technology-based companies located in Tehran using an artificial neural network approach. The research method was quantitative, survey-based, and applied in nature. Data were collected through a questionnaire administered to 386 managers and experts. To predict and evaluate patterns, a Multilayer Perceptron (MLP) neural network was utilized. The results indicated that input components such as customer-oriented knowledge management processes and behavioral data had strong correlations with output variables including customer satisfaction, innovation, and customer loyalty. The model demonstrated high predictive accuracy based on evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2). The R^2 value of 0.83 reflected the model's desirable performance. In the learning curve analysis, both training and testing errors decreased rapidly and stabilized, indicating optimal learning of the model and prevention of overfitting. The findings suggest that neural networks can serve as an effective tool for implementing customer-oriented knowledge management in technology-based companies, contributing to improved strategic decision-making processes and enhanced customer satisfaction.

Keywords: Knowledge Management, Customer-Oriented, Neural Network

1. Introduction

Customer knowledge management (CKM) has moved from a peripheral support function to a strategic core capability for firms navigating digital competition, data proliferation, and rapidly evolving customer expectations. Organizations increasingly recognize that sustained advantage depends not only on accumulating data, but on transforming dispersed customer information into actionable knowledge that improves relationship quality, personalization, innovation, and performance. CKM integrates processes for acquiring, sharing, and applying customer knowledge across marketing, operations, and innovation systems; when combined with analytics and artificial intelligence (AI), it can reconfigure how firms sense demand, design offerings, and orchestrate service encounters at scale (Castagna et al., 2020; Migdadi, 2021; Raymond et al., 2020). At the same time, managerial research has emphasized the complementary roles of IT infrastructure, leadership, and organizational culture in enabling CKM to translate into measurable outcomes such as customer satisfaction, loyalty, and innovation quality



(Chaithanapat et al., 2022; Chatterjee et al., 2020; Sair et al., 2024). Against this backdrop, modeling CKM with machine learning—especially neural networks like multilayer perceptrons (MLPs)—offers a promising pathway to capture nonlinear relationships among input processes and customer-centric outcomes (Wang et al., 2024; Zhao et al., 2022).

The strategic logic behind CKM rests on the premise that deep insights into explicit and tacit customer needs can reconfigure value creation. Foundational studies show that CKM capabilities intertwine with absorptive capacity and knowledge-oriented leadership to improve innovation and competitive performance, particularly in resource-constrained small and medium-sized enterprises (SMEs) (Chaithanapat et al., 2022; Raymond et al., 2020). In digitally transforming contexts, SMEs confront technology and skills gaps yet can leapfrog by structuring CKM around clear processes (collection, integration, dissemination) and enabling technologies (CRM, analytics, AI), which together amplify strategic agility and project outcomes (Castagna et al., 2020; Haider & Kayani, 2020). Moreover, empirical research indicates that CKM affects downstream markers such as customer retention and satisfaction, making it a central lever for sustainable growth (Kabue, 2021; Quijano & Schneider, 2023).

Complementary organizational antecedents reinforce CKM's impact. Knowledge-oriented leadership aligns incentive systems and routines for knowledge sharing, while customer orientation and technological capabilities underpin effective CRM deployment; CKM often mediates the path from these antecedents to superior relationship outcomes (Chaithanapat et al., 2022; Jayasekera et al., 2023). In agile and project-based settings, firms must also manage the challenges of capturing timely customer knowledge across iterations and teams; identifying and prioritizing those challenges is critical for execution discipline in complex initiatives (Jafari et al., 2024). In parallel, suppliers increasingly co-create knowledge with customers to enable data-driven service innovations, expanding CKM beyond the firm boundary and into ecosystems (Saarnilinna et al., 2024). These perspectives converge on a managerial imperative: CKM must be architected as an end-to-end, cross-functional system that is technologically enabled, behaviorally supported, and analytically driven.

Digitalization intensifies the data deluge from omnichannel touchpoints—web, mobile, social, IoT—and demands analytic architectures that can synthesize multimodal signals into coherent customer knowledge. In marketing for startups, AI-enabled CKM helps overcome resource constraints by automating insight generation and decision support across acquisition, engagement, and retention funnels (Idrus et al., 2023). Social media environments introduce real-time, high-variety data streams where frameworks such as SMARTUR help translate user-generated content into smart CKM solutions for destination and service design (Muniz et al., 2022). In telecommunications and service sectors, structured CKM practices institutionalize continuous learning about churn drivers, perceived value, and service quality—including the use of text, clickstream, and interaction histories—to refine personalization and reduce defection (Ng et al., 2024; Panni & Hoque, 2022). Across these contexts, the central challenge lies in mapping heterogeneous inputs (feedback, behaviors, demographics, lifecycle markers) to multi-dimensional outcomes (satisfaction, loyalty, innovation, competitive advantage), a problem well-suited to machine learning models capable of capturing nonlinearities and interactions (Zhao et al., 2022).

Neural networks and deep learning bring specific advantages to CKM modeling. Lightweight MLP variants can efficiently learn relationships in multivariate settings and provide accurate forecasts when data exhibit complex latent structures (Wang et al., 2024). In customer analytics, hybrid architectures—e.g., fusing Gaussian Mixture Models (GMM) with MLPs—improve categorization when features are noisy or multi-modal, a frequent condition in behavioral and engagement data (Naseer & Jalal, 2024). Deep learning ensembles have also proven effective for customer churn prediction, where high-dimensional predictors and nonlinear thresholds characterize switching behavior; such models can outperform conventional learners and provide actionable early-warning signals for retention campaigns (Vu, 2024). In related AI-knowledge management applications, big data neural networks have been used to design and evaluate enterprise knowledge strategies, highlighting the reciprocity between knowledge processes and algorithmic capability (Zhao et al., 2022). Together, these advances justify adopting MLP-based approaches to integrate CKM inputs and predict strategic outputs at scale.

The CKM–innovation link has received sustained theoretical and empirical support. Studies show that CKM fosters innovative work behaviors, which in turn mediate the effect of CKM on sustainable product innovation—underscoring people-



centric mechanisms through which knowledge becomes novelty (Bratianu et al., 2021). At the organizational level, CKM augments innovation capabilities by tightening the feedback loop between market sensing and solution design, especially when jointly orchestrated with CRM processes (Migdadi, 2021). In e-CRM settings, fuzzy cognitive map approaches illuminate the interdependencies between marketing performance and knowledge constructs, offering a complementary lens to interpret neural model outputs and to reason about causality in complex systems (Shabankareh & Sarhadi, 2023). Relationship marketing research in B2B contexts similarly indicates that social media engagement and relational investments can strengthen CRM effectiveness, word-of-mouth, and loyalty—where CKM often acts as the analytic substrate making these interactions learnable and optimizable (Dao et al., 2025).

Beyond marketing, AI-augmented CKM capabilities are permeating adjacent organizational domains. In education, sustainable adoption of AI chatbots depends on knowledge management factors that influence user experience, trust, and continuous use—parallels that resonate with CKM governance in firms deploying conversational interfaces for customer service and sales (Al-Sharafi et al., 2023). In engineering contexts, extensive applications of neural networks and machine learning illustrate the methodological maturity and transferability of MLP-based modeling across complex, data-rich problems; this cross-domain evidence strengthens the case for rigorous MLP adoption in management research (Kaveh, 2024). More broadly, AI can catalyze “collaborative driving effects” on knowledge innovation management, aligning human and machine contributions to accelerate exploration and exploitation cycles (Liu, 2021). These streams suggest that the methodological toolkit for CKM modeling should draw from proven AI practices while remaining sensitive to domain-specific constraints, such as data governance, interpretability, and organizational absorptive capacity (Raymond et al., 2020).

Managerially, CKM’s influence extends to agility and project performance. Evidence shows that CKM capability enhances strategic agility—enabling faster reconfiguration of resources and market responses—which partially mediates the link to superior project outcomes (Haider & Kayani, 2020). Agile project management environments, however, face distinct CKM challenges: fragmentation of knowledge across sprints, volatility in customer input, and the need to prioritize limited analytic bandwidth; structured identification and prioritization of CKM challenges becomes essential to keep projects customer-focused and knowledge-rich (Jafari et al., 2024). In parallel, the mediating role of knowledge management between customer orientation and CRM effectiveness underscores why CKM cannot be an afterthought in CRM deployments: without robust knowledge processes, technology and orientation do not reliably translate into performance (Jayasekera et al., 2023; Sair et al., 2024). For service businesses like fitness clubs, relationship quality often mediates CKM’s effects on retention, hinting at practical levers (e.g., feedback loops, personalized programs) that managers can operationalize (Ng et al., 2024).

The social and platform-embedded nature of contemporary customer interactions places CKM at the interface of community management, co-creation, and analytics. CKM practices in social media contexts—when grounded in systematic frameworks—guide the conversion of diffuse, user-generated signals into structured knowledge for product–service refinement (Muniz et al., 2022). Focus on key customers, coupled with CKM, predicts satisfaction in institutional settings such as higher education services, reinforcing that CKM principles extend to non-traditional “customers” (students, citizens, patients) where expectations for personalization and responsiveness are rising (Quijano & Schneider, 2023). Startups, in particular, benefit from CKM-oriented AI playbooks that scale insight generation despite lean teams, enabling evidence-based experimentation across targeting, content, and offer design (Idrus et al., 2023). As firms integrate conversational AI into customer journeys, CKM factors determine sustainable use and learning efficacy over time, reaffirming the need for governance routines around data quality, consent, and knowledge reuse (Al-Sharafi et al., 2023).

Methodologically, neural modeling choices matter for CKM applications. Lightweight MLPs can deliver state-of-the-art efficiency for multivariate forecasting while remaining tractable to train and deploy in production, which is attractive for managerial settings requiring responsiveness and cost discipline (Wang et al., 2024). Hybridization—for example, combining generative clustering (GMM) with discriminative learners (MLP)—can improve classification and segmentation, relevant for persona discovery or next-best-action systems (Naseer & Jalal, 2024). Deep architectures integrating temporal encoders have proven effective for churn prediction, where early detection enables targeted retention strategies that are themselves knowledge-

intensive; these advances align with CKM's objective to transform signals into timely interventions (Vu, 2024). Complementing these techniques, big data neural approaches provide a meta-level capability: they can help firms iteratively refine their knowledge management strategies by simulating policy effects and monitoring value realization (Zhao et al., 2022). Collectively, such models are particularly apt for CKM because they accommodate multicollinearity, capture interaction effects among processes (e.g., lifecycle management $\times$ feedback intensity), and scale with feature sets representative of omnichannel environments.

The literature also underscores risks and design principles. CKM initiatives fail when data remain siloed, when leadership underinvests in knowledge-sharing norms, or when CRM technology is deployed without embedding knowledge processes that make customer interactions cumulative and learnable (Castagna et al., 2020; Chaithanapat et al., 2022). Studies emphasize the importance of aligning CKM with clear governance and capability-building to ensure that analytics translate into process change and innovation—especially in SMEs where resource slack is limited (Migdadi, 2021; Raymond et al., 2020). In algorithmic implementations, firms must manage issues of overfitting, drift, and interpretability; yet practical evidence from adjacent domains shows that robust validation and monitoring can support reliable, domain-specific applications—from civil engineering to audit analytics—highlighting the portability of ML rigor to management problems (Kaveh, 2024; Rahimzadeh et al., 2025). This portability is salient as organizations contemplate CKM deployments that must adapt to shifting customer behaviors and regulatory landscapes.

Recent managerial research extends CKM into broader relational architectures. In B2B markets, social media marketing and relationship marketing strengthen CRM effectiveness and loyalty, with CKM acting as an integrative backbone connecting signals, content, and relational investments (Dao et al., 2025). In consumer services such as fitness clubs, relationship quality mediates CKM's retention effects, indicating that well-governed CKM not only refines offers but also shapes the felt experience of the relationship (Ng et al., 2024). Meanwhile, supplier–customer knowledge co-development enables data-enabled service innovations, illustrating a meso-level shift from firm-centric to network-centric CKM where knowledge flows across organizational boundaries (Saarnilinna et al., 2024). These insights call for CKM models that incorporate multi-actor inputs and outputs, and that are sufficiently flexible—both statistically and operationally—to evolve with ecosystem dynamics.

Finally, as AI permeates CKM, organizations must treat model development as a socio-technical system. Evidence suggests that CKM's effects on sustainable product innovation are serially mediated through innovative work behaviors, implying that managers should cultivate human competencies in parallel with deploying analytic tools (Bratianu et al., 2021). CRM technology adoption and a customer-centric culture are more likely to yield business performance when CKM routines mediate and translate technology affordances into learning and action (Jayasekera et al., 2023; Sair et al., 2024). Practical frameworks for e-CRM and cognitive mapping can guide the interpretation of neural outputs and inform decision rules, while sectoral studies in telecom, education, and startups demonstrate that CKM principles are contextually adaptable (Al-Sharafi et al., 2023; Idrus et al., 2023; Panni & Hoque, 2022; Shabankareh & Sarhadi, 2023). Put together, the literature converges on a clear opportunity: employ efficient neural architectures (e.g., MLPs) to model how CKM inputs—such as lifecycle management, feedback intensity, behavioral and demographic data, and data-driven personalization—predict outcomes such as satisfaction, loyalty, innovation, competitive advantage, and sales growth in technology-based firms (Castagna et al., 2020; Migdadi, 2021; Ng et al., 2024; Wang et al., 2024; Zhao et al., 2022).

Accordingly, the aim of this study is to develop and validate a multilayer perceptron (MLP) model that links customer-oriented knowledge management inputs to key customer and firm outcomes—specifically customer satisfaction, innovation in products and services, customer loyalty, sustainable competitive advantage, and sales growth—in technology-based companies.

2. Methods and Materials

This research employs a quantitative, survey-based, and applied method. In this study, to measure the examined variables, a questionnaire was used as the primary data collection tool. The sample consisted of 384 managers and experts from technology-based companies located in Tehran. The questionnaire items, which included both input and output components of the neural network model, were developed based on the research literature and through expert consultations with professionals



in the technology sector (Table 2). The sampling method used in this study was cluster sampling, and the sample size was determined using Morgan's table. The questionnaire was researcher-developed and constructed based on the research literature and Table 1. The content validity of the questionnaire was confirmed through expert judgment, and its reliability was assessed using Cronbach's alpha coefficient, which was calculated at 0.87. In this study, the Multilayer Perceptron (MLP) neural network method was employed to predict and evaluate the target model's accuracy. The software used for data analysis was Python.

3. Findings and Results

To evaluate the accuracy of the extracted model, the neural network method was utilized. In this stage, each of the output and input components was formulated as a questionnaire item. The statistical population consisted of 386 managers, specialists, and experts from the technology sector, who were asked to assess the status of each identified indicator within their organizations. The subsequent stages of this study focus on explaining the results of this phase. Initially, to execute the model, an abbreviated code was created for each related indicator.

Table 1. Abbreviations for Input and Output Components

Component Name	Component Type	Abbreviation Code
Customer-Oriented Knowledge Management Process	Input	KMP
Continuous Customer Feedback	Input	KMF
Customer Behavioral Data	Input	KMB
Customer Needs Assessment	Input	KMQ
Demographic Data	Input	KMD
Customer Experience Analysis	Input	KME
Customer Lifecycle Management	Input	KMC
Customer-Oriented Organizational Learning	Input	KML
Market and Competitor Knowledge with a Customer Orientation	Input	KMM
Customer-Related Organizational Knowledge Management	Input	KMO
Customer Digital Knowledge Management	Input	KMS
Product/Service Analysis with a Customer Orientation	Input	KMPS
Customer Data-Based Personalization and Innovation	Input	KMPI
Customer Knowledge Technologies	Input	KMT
Customer-Based Data-Driven Strategy	Input	KMST
Customer Relationship Data Management	Input	KMCRM
Improvement of Customer Satisfaction	Output	KMOUTS
Innovation in Products and Services	Output	KMOUTI
Increase in Customer Loyalty	Output	KMOUTL
Creation of Sustainable Competitive Advantage	Output	KMOUTC
Sales Growth	Output	KMOUTSA

Implementation Steps Based on the CRISP-DM Framework

The CRISP-DM cycle includes six primary stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. This process is designed to be non-linear and iterative, allowing the analyst to make improvements as needed at any stage. The main advantages of CRISP-DM include providing a clear structure for data-mining projects, reducing project failure risk, enabling backward iteration for correction, enhancing decision-making quality in data analysis, and offering high adaptability across different industries. This standard framework helps organizations to manage their data analysis processes systematically, efficiently, and purposefully.

Step 1: Business Understanding

In this stage, based on the available data (386 samples), the goal is to investigate whether the output variables (KMOUTS, KMOUTI, KMOUTL, KMOUTC, KMOUTSA) can be predicted from the input components (KMT, KMST, KMP, ...). The use of the neural network aims to operationalize this model. The input components were identified through literature review and refined through interviews with experts in the field. Therefore, these components are both theoretically grounded and operationally aligned with the target business context.

Step 2: Data Understanding

At this stage, the final dataset—derived from the average of participants' responses to the relevant questionnaire items (subcomponents)—was saved in CSV format. During the data understanding phase, it was verified that all columns contained

386 non-missing values (i.e., no missing data existed in the dataset). This indicated that there was no need for imputation or row deletion. Furthermore, all variables were of the *float64* data type, which is appropriate for numerical data; hence, no data type conversion was required.

Nevertheless, to ensure data integrity, the distribution of data was examined, as presented below:

Table 2. Descriptive Statistical Characteristics of the Data

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
KMP	386	3.51376	1.5013	3.596	3.95	4.065	4.192	4.55
KMF	386	3.54804	1.5161	3.636	3.99	4.105	4.232	4.59
KMB	386	3.48119	1.4872	3.558	3.912	4.027	4.154	4.512
KMQ	386	3.4673	1.4812	3.5418	3.8958	4.0108	4.1378	4.4958
KMD	386	3.5069	1.4983	3.588	3.942	4.057	4.184	4.542
KME	386	3.4805	1.4869	3.5572	3.9112	4.0262	4.1532	4.5112
KMC	386	3.46867	1.4818	3.5434	3.8974	4.0124	4.1394	4.4974
KML	386	3.44861	1.4731	3.52	3.874	3.989	4.116	4.474
KMM	386	3.4529	1.4749	3.525	3.879	3.994	4.121	4.479
KMO	386	3.47296	1.4836	3.5484	3.9024	4.0174	4.1444	4.5024
KMS	386	3.44604	1.472	3.517	3.871	3.986	4.113	4.471
KMPS	386	3.50107	1.4958	3.517	3.9352	4.0502	4.1772	4.5352
KMPI	386	2.37376	1.0121	2.266	2.62	2.735	2.8023	3.22
KMT	386	3.46636	1.4807	3.5407	3.8947	4.0097	4.1367	4.4947
KMST	386	3.48144	1.4873	3.5583	3.9123	4.0273	4.1543	4.5123
KMCRM	386	3.52507	1.5062	3.6092	3.9632	4.0782	4.2052	4.5632
KMOUTS	386	3.46908	1.4793	3.6	3.92	4.02	4.13	4.43
KMOUTI	386	3.48254	1.4858	3.62	3.89	4.02	4.14	4.52
KMOUTL	386	3.46684	1.4802	3.53	3.88	4.015	4.14	4.51
KMOUTC	386	3.46387	1.4795	3.49	3.88	4.01	4.15	4.52

The descriptive statistics table provides essential information about the distribution and characteristics of the dataset. The mean values for most features fall within the range of 3.46 to 3.52, suggesting that the data are concentrated in the upper segment of the 1–5 scale. This indicates that most respondents tended to choose higher scores (around 4). The standard deviation, approximately 1.5 for most variables, demonstrates a relatively consistent spread of data across the variables, implying moderate variability.

Minimum values for most features are around 3.5, and maximum values are close to 4.5, indicating that the data are distributed within a relatively narrow range and that no variable exhibits extreme values. Furthermore, the 25th percentile, median (50th percentile), and 75th percentile clearly show that most data points are concentrated in the higher part of the scale. Overall, these quartile values indicate that the majority of the responses fall above the median range.

These distributional characteristics suggest that the data generally lean toward higher scores, with few very low or very high outliers. In conclusion, this table demonstrates that the data are predominantly clustered within a specific segment of the measurement scale, reflecting respondents' overall tendency to select higher options in the questionnaire. This insight assists analysts in making informed decisions about feature selection and data preprocessing in subsequent modeling stages.

Examination of Data Distribution

In the data understanding phase, the distribution of the data holds significant importance. Therefore, in this step, the data distribution was examined.



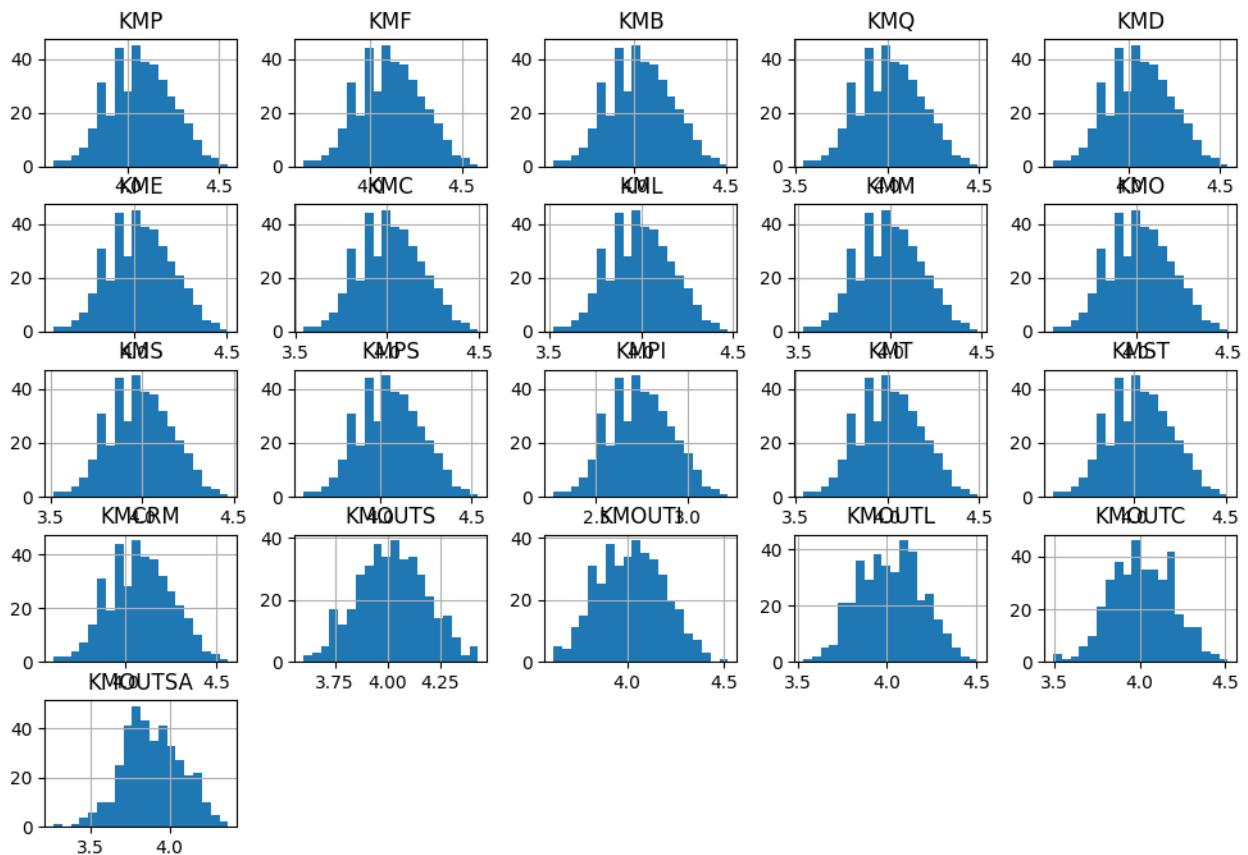


Figure 1. Data Distribution Status

This figure presents a series of histograms illustrating the distribution of various data features within the dataset. Each feature is concentrated within a specific range of the 1–5 scale, particularly in the upper regions of the scale, indicating that most respondents tended to select higher scores. These distributions are primarily concentrated within the 3.5–4.5 range, suggesting that the data are clustered toward the upper end of the response scale. For example, features such as KMP, KMF, KMB, and KMQ are clearly concentrated within this range, reflecting similar scoring patterns among respondents.

The figure also shows that certain features, such as KMP, KMF, KMB, KMT, and KMO, exhibit relatively homogeneous distributions, meaning that most of their values are concentrated within a specific segment of the scale. In contrast, features such as KMOUTSA and KMO display more diverse distributions, indicating greater data dispersion.

Given that most data points are concentrated in the upper portion of the scale, it is evident that the features may have differing scales. These variations can influence the performance of machine learning models—particularly distance-based algorithms such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM)—which are sensitive to scale differences and perform optimally when data are normalized.

The conclusion is that, to ensure all features contribute equally to the model training and prediction process, data normalization is essential. Normalization ensures that all variables are scaled to a comparable range, allowing the model to utilize the entire dataset efficiently. This step prevents problems arising from scale differences and improves the accuracy of machine learning models. Therefore, in the next stage, data were normalized using the **StandardScaler** function from the *scikit-learn* library, which scales the data by applying zero mean and unit variance. This normalization process helps the machine learning models learn faster and achieve better results.

Step 3: Modeling

In this phase, the machine learning model is trained to predict output features based on input features. Various algorithms can be used for this purpose; in this study, the **MLPRegressor** method was applied.

Data Splitting into Training and Test Sets

Data splitting into training and test sets is a crucial step in the machine learning modeling process, aiming to evaluate the model's performance on unseen data. The dataset is divided into two main subsets: the training set, used to train the model and

learn patterns, and the test set, used to assess the model's performance after training and evaluate its ability to predict new data. Commonly, the dataset is divided in an 80–20 or 70–30 ratio—meaning that 80% of the data are used for training and 20% for testing. This division helps prevent overfitting and ensures that the model's generalization ability is properly evaluated.

Modeling Using the MLP Method

After dividing the data into training and test sets, the MLP method was applied. The following configuration was used in Python:

```
MLPRegressor(hidden_layer_sizes=(64, 32), max_iter=1000, random_state=42)
```

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At this stage, the analyst trained a Multilayer Perceptron Regressor (MLPRegressor) model for numerical prediction tasks. This neural network model is designed for regression problems and effectively learns complex, nonlinear relationships between input and output features. The model consists of two hidden layers: the first with 64 neurons and the second with 32 neurons. This architecture enables the model to capture complex patterns in the data and perform accurate predictions.

The parameter `max_iter=1000` indicates that the model was trained for a maximum of 1,000 iterations (epochs), allowing sufficient optimization of weights while preventing overfitting. Given the complexity of neural networks, a higher number of iterations can enhance model precision.

The `random_state=42` parameter ensures the reproducibility of the training process, enabling the analyst to replicate the model's results for validation and further evaluation.

This MLP model is specifically designed for regression problems, assisting the analyst in predicting output values from input data. The structure of the hidden layers and the number of neurons were chosen to effectively capture the complex, nonlinear relationships present in the dataset. This choice allows the model to outperform simpler models such as linear regression.

At this stage of modeling, the analyst is prepared to evaluate the model using the test dataset and to apply various performance evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 (Coefficient of Determination). These evaluations help ensure model accuracy and guide any necessary optimizations, such as hyperparameter tuning or structural modifications. Overall, this step represents progress in the modeling process, as the analyst can now use the model for more accurate predictions and refine it if needed.

Step 5: Model Evaluation

Evaluation Using Test Data

- MAE: 0.0535932230927483
- MSE: 0.005243205973816898
- R^2 : 0.8317792092966364

The model evaluation using test data yielded three key performance metrics: MAE (Mean Absolute Error), MSE (Mean Squared Error), and R^2 (Coefficient of Determination). Each metric provides distinct insights into model performance, helping the analyst assess prediction accuracy.

MAE = 0.0536

MAE represents the average absolute difference between the model's predictions and the actual values. Here, $MAE = 0.0536$ indicates that, on average, the model's predictions deviate from actual values by only 0.0536 units. The low value of MAE reflects the model's high accuracy and minimal prediction error.

MSE = 0.0052

MSE measures the average squared differences between predicted and actual values, penalizing larger errors more heavily. The obtained MSE value of 0.0052 demonstrates that the model's overall prediction error is low and that large errors are rare, confirming its strong predictive accuracy.

$R^2 = 0.8318$

R^2 indicates the proportion of variance in the actual data explained by the model. In this case, $R^2 = 0.8318$ means that the model explains approximately 83.18% of the variance in the dataset, suggesting that it effectively captures the underlying data patterns and performs with high accuracy on test data.

These results collectively demonstrate excellent model performance. The low MAE and MSE values indicate minimal errors, while the high R^2 value confirms strong predictive power. Overall, the model fits the test data well and produces reliable,



precise predictions. Such performance suggests that the model has effectively learned from the data and is suitable for future predictive applications.

Learning Curve Evaluation

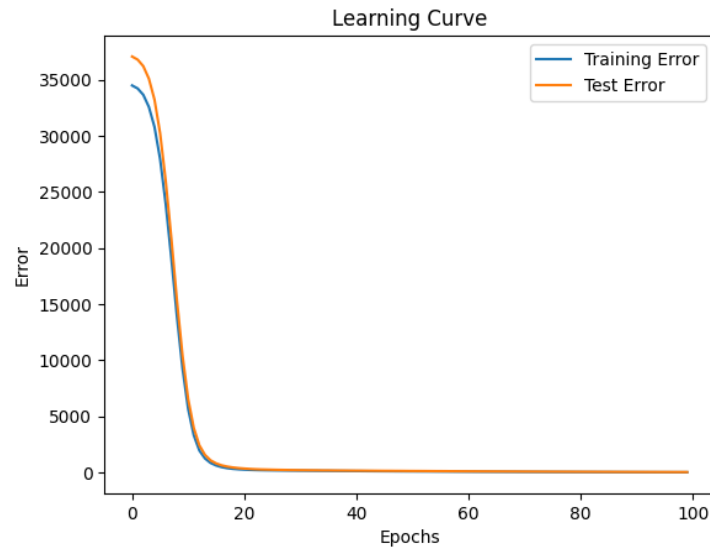


Figure 2. Learning Curve

The figure illustrates the model's learning curve, comparing training and test errors over time (number of epochs). Initially, both training and test errors are high but rapidly decrease. After a certain number of epochs, both errors drop significantly and stabilize. This pattern indicates appropriate model learning.

Since the training and test errors follow a similar trajectory and converge to stable values, it can be concluded that the model has learned effectively while avoiding overfitting. This confirms that the model is optimally aligned with the data and demonstrates robust performance.

Step 6: Deployment

In the deployment phase, following comprehensive model evaluation and confirmation of prediction quality, the developed MLPRegressor-based model was implemented in a real or simulated environment. Based on the obtained evaluation metrics—low MAE (0.0536), minimal MSE (0.0052), and acceptable R^2 (0.8318)—the model demonstrated strong accuracy and predictive capability. It can therefore be employed as a decision-support tool for predicting outcomes derived from customer-oriented knowledge management input components.

Deployment involves the detailed documentation of modeling procedures, preparation of the final executable code, and design of user-friendly interfaces for non-technical users. The deployment process was structured to enable end users to input new data easily and receive predicted outcomes.

For this purpose, a data processing system was developed to automatically normalize new input data, aligning them with the structure of the training dataset before feeding them into the model. The normalized data are then processed by the model, and the predicted results are displayed in an interpretable format for users. Maintaining input data quality and ensuring consistent normalization procedures are critical factors for successful model deployment.

Finally, to ensure continuous model performance after deployment, a monitoring and review program was established. In this program, the model's prediction results are periodically evaluated, and if performance degradation or shifts in input data patterns are detected, retraining or updating procedures are initiated. Additionally, to enhance efficiency, opportunities for model optimization through hyperparameter tuning and the adoption of more advanced learning techniques are considered. Thus, deployment is viewed not as an endpoint but as the beginning of a continuous improvement cycle.

4. Discussion and Conclusion

The present study aimed to model customer-oriented knowledge management (CKM) using a Multilayer Perceptron (MLP) neural network to predict customer-related outcomes in technology-based firms in Tehran. The results demonstrated that the

input components—including customer-oriented knowledge management processes, behavioral and demographic data, continuous customer feedback, customer needs assessment, customer lifecycle management, and data-driven personalization—exhibited strong and statistically significant relationships with the output variables such as customer satisfaction, innovation in products and services, customer loyalty, sustainable competitive advantage, and sales growth. The model's predictive accuracy was confirmed through performance indicators, including a Mean Absolute Error (MAE) of 0.0536, a Mean Squared Error (MSE) of 0.0052, and a coefficient of determination (R^2) of 0.8318. These metrics indicate that the neural network effectively captured the nonlinear relationships between CKM inputs and performance outcomes and provided high predictive validity.

This finding aligns with prior research emphasizing the crucial role of CKM in strengthening organizational performance, innovation capability, and customer retention (Migdadi, 2021; Raymond et al., 2020). As demonstrated in this study, effective integration of customer feedback, behavioral insights, and digital interaction data contributes significantly to firm-level innovation and customer satisfaction. Previous works have noted that CKM systems enhance innovation quality and overall competitiveness by improving the firm's absorptive capacity and facilitating knowledge-oriented leadership (Chaithanapat et al., 2022). The present model empirically supports these findings, showing that when CKM processes are systematically organized and supported by AI-driven analytics, organizations can anticipate customer needs, develop innovative services, and maintain long-term loyalty.

The high R^2 value obtained in this study (0.8318) indicates a strong explanatory power of the MLP-based model, confirming that neural networks can successfully predict outcomes based on complex customer knowledge variables. This result is consistent with previous studies demonstrating the suitability of neural network architectures for multivariate forecasting and customer relationship modeling (Naseer & Jalal, 2024; Vu, 2024; Wang et al., 2024). Neural architectures like MLP are capable of capturing nonlinear dependencies between customer behavioral data and strategic outcomes, outperforming conventional linear models (Zhao et al., 2022). For instance, (Wang et al., 2024) designed a lightweight MLP model that achieved efficient performance in multivariate forecasting, demonstrating its ability to extract latent patterns from complex datasets—a feature mirrored in the present study's results. Similarly, (Vu, 2024) and (Naseer & Jalal, 2024) showed that deep learning models combining MLP with probabilistic frameworks could accurately predict churn and customer classification, reinforcing the predictive strength of such approaches in CKM applications.

The observed positive influence of customer-oriented knowledge processes on satisfaction, loyalty, and innovation also reflects a well-established theoretical foundation in CKM literature. As shown by (Bratianu et al., 2021), CKM promotes innovative work behavior, which in turn mediates sustainable product innovation. The findings of this study support this mediation effect: companies that leverage customer knowledge effectively foster organizational learning environments that encourage creativity and responsiveness. Moreover, firms that systematically manage feedback and behavioral data are more likely to exhibit higher adaptability and customer-centric agility, consistent with findings by (Haider & Kayani, 2020), who highlighted CKM's mediating role in enhancing strategic agility and project performance.

A noteworthy result of the present analysis is the strong relationship between data-driven personalization (KMPI) and output measures such as customer satisfaction and loyalty. This correlation underscores the growing relevance of personalized knowledge systems, where customer data are utilized to tailor experiences dynamically. Studies such as (Ng et al., 2024) and (Panni & Hoque, 2022) have shown that relationship quality and targeted service customization serve as mediators between CKM and customer retention in service industries. The present findings align with these results, suggesting that when organizations employ CKM-enabled personalization through behavioral and demographic insights, they can improve customer engagement and long-term loyalty.

Furthermore, the results confirmed that innovation in products and services is a direct outcome of customer knowledge integration. This result aligns with prior studies linking CKM with innovation capability, such as those by (Migdadi, 2021) and (Castagna et al., 2020), who demonstrated that CKM enhances innovation performance, especially in digital transformation contexts. In addition, the strong association between CKM processes and competitive advantage is in line with (Raymond et al., 2020), who emphasized that knowledge-based resources are the main drivers of absorptive capacity and competitiveness in small and medium enterprises. By extending this logic, the current study provides empirical evidence that



AI-based modeling of CKM strengthens strategic decision-making and enhances competitive differentiation through customer insight optimization.

The analysis of the learning curve revealed that the model achieved convergence without overfitting, indicating optimal training dynamics. This performance pattern echoes previous work by (Rahimzadeh et al., 2025), who demonstrated that machine learning algorithms, when properly tuned, can maintain predictive efficiency and generalizability even with complex data structures. Similarly, the effective use of the MLPRegressor in this study corroborates findings by (Kaveh, 2024), who reported robust outcomes in engineering domains using similar architectures. These parallels highlight the cross-disciplinary reliability of neural networks for predictive modeling and their adaptability to management data, where interpretability and precision are equally essential.

Another dimension emerging from the study is the role of continuous feedback (KMF) and organizational learning (KML) as key drivers of sustainable performance. These components demonstrated substantial influence on innovation and satisfaction, aligning with the view that dynamic learning systems enhance customer knowledge circulation and prevent information obsolescence (Chaithanapat et al., 2022; Chatterjee et al., 2020). The findings confirm that firms employing structured CKM frameworks—integrating data collection, sharing, and application—can transform tacit and explicit knowledge into actionable insights, which is a prerequisite for sustainable innovation (Bratianu et al., 2021). Moreover, consistent with (Idrus et al., 2023), startups and technology-based companies that integrate digital transformation and artificial intelligence within their CKM strategy can overcome resource constraints and accelerate their market learning cycles.

The empirical results also reaffirm the strategic role of CRM technologies and organizational culture in shaping CKM effectiveness. The positive correlations observed between customer relationship data management (KMCRM) and business outcomes resonate with the findings of (Sair et al., 2024) and (Jayasekera et al., 2023), who argued that CRM technology adoption and a customer-centric culture enhance business performance through CKM mediation. The integration of CRM and CKM allows firms to close the loop between customer interactions and strategic decision-making, ultimately leading to improved relationship quality and innovation (Shabankareh & Sarhadi, 2023).

Similarly, the study's evidence that knowledge-sharing and feedback mechanisms directly influence satisfaction and loyalty finds strong support in (Kabue, 2021), who observed that customer retention improves significantly when CKM mechanisms are designed to capture and respond to customer knowledge continuously. This finding is reinforced by (Quijano & Schneider, 2023), who established CKM as a key predictor of satisfaction among service recipients. By validating these effects using neural modeling, the present study extends previous linear analyses and highlights the utility of AI techniques for understanding and predicting customer-centric outcomes.

The results also support the proposition that CKM mediates between digital technology adoption and firm performance, as emphasized by (Al-Sharafi et al., 2023) and (Dao et al., 2025). These studies identified that AI-based systems and social media marketing strengthen customer relationship management through enhanced knowledge flows and relationship learning. The current findings demonstrate that similar mechanisms operate in technology-based firms in Tehran, where CKM serves as an integrative process linking digital capability and performance outcomes.

Finally, the strong performance of the MLP model in predicting CKM outcomes highlights the growing potential of AI-knowledge management convergence. Consistent with (Zhao et al., 2022), who applied big data neural networks to develop enterprise knowledge management strategies, and (Liu, 2021), who examined AI's collaborative effects on innovation management, the results of this study demonstrate that neural architectures can meaningfully capture and forecast the multidimensional impacts of customer knowledge systems. The observed performance metrics confirm that MLP models can support managerial decision-making by providing reliable predictions for satisfaction, innovation, and loyalty, thereby facilitating strategic agility and long-term competitiveness.

Despite the robustness of the results, several limitations should be acknowledged. First, the study's sample was limited to technology-based firms in Tehran, which may constrain the generalizability of findings to other industries or geographical contexts. Second, the study relied on self-reported data collected through questionnaires, which may introduce common method bias or social desirability effects. Third, although the MLP model achieved high predictive accuracy, the study did not compare alternative machine learning algorithms such as Random Forest, Gradient Boosting, or Support Vector Machines that might

offer additional insights into model performance or interpretability. Fourth, while the study focused on quantitative variables, qualitative factors such as leadership behavior, cultural readiness, and interdepartmental collaboration were not captured, potentially overlooking contextual elements that influence CKM effectiveness. Finally, the cross-sectional design precludes causal inference, meaning that the relationships observed should be interpreted as associative rather than strictly causal.

Future studies should extend the scope of this research in several directions. Comparative analyses across multiple industries, including manufacturing, healthcare, and financial services, would test the external validity of the CKM–MLP model and explore sector-specific knowledge structures. Longitudinal research designs could examine how CKM variables evolve over time and how neural models adapt to changing customer dynamics. Additionally, incorporating unstructured data—such as textual feedback, social media interactions, or voice transcripts—into CKM modeling would enhance the comprehensiveness of input features and improve model interpretability. Researchers may also explore hybrid modeling frameworks combining MLPs with explainable AI (XAI) techniques to balance predictive accuracy and transparency. Finally, qualitative approaches such as case studies or interviews could be used to contextualize quantitative findings and provide deeper insights into organizational processes that support customer knowledge creation, sharing, and utilization.

Managers and practitioners should view CKM as a dynamic and strategic capability that can be amplified through AI-driven modeling. Firms are encouraged to integrate data analytics platforms with CRM systems to capture behavioral and experiential insights systematically. Investing in employee training on data literacy and cross-functional collaboration will ensure that customer knowledge is effectively transformed into innovation and competitive advantage. Organizations should also adopt feedback mechanisms and continuous learning loops to sustain the accuracy and relevance of CKM data. Implementing MLP-based predictive tools within business intelligence systems can enable decision-makers to forecast satisfaction, loyalty, and sales trends, enhancing responsiveness to customer needs. Finally, maintaining robust data governance and privacy standards is essential to ensure ethical and sustainable deployment of CKM analytics in the evolving digital landscape.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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