A Context-Aware Service Recommendation System for the Social Internet of Things

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***Abstract*—The Social Internet of Things (SIoT) refers to the interconnection of Internet of Things (IoT) devices with the addition of a social layer, enabling them to mimic human-like behavior. This technology facet facilitates data and service sharing among devices, creating a scalable network of socially interconnected devices. However, this rapid increase in device numbers and generated data has led to the challenge of data explosion. To address this challenge, service recommendation systems play a crucial role in improving network navigability and service discovery within the SIoT context. However, existing research often overlooks important aspects that could make service selection more pertinent and relevant. Specifically, current service recommendation approaches focus on extracting social relationships between devices while neglecting the contextual presentation of service reviews. In this research, we introduce a service recommendation framework for SIoT context that integrates service-review aggregation and feature learning processes by utilizing the Factorization Machines to capture complex feature interactions unique to each SIoT device-service pair. Empirical results across three benchmark datasets demonstrate that the proposed CASR-SIoT framework consistently outperforms state-of-the-art baselines, achieving up to 14% improvement in Recall, 8% in Precision, and 15% reduction in RMSE, thereby validating its effectiveness in delivering accurate and context-aware service recommendations in SIoT environments.**

***Index Terms*—SIoT recommendation, Context-aware recommender system, Factorization Machine, Service Recommendation Systems.**

I. Introduction

THE rapid growth and proliferation of interconnected devices and technologies have given rise to the Internet of Things (IoT), transforming our everyday lives in unprecedented ways. The IoT refers to the network of cyber-physical objects embedded with sensors, software, and connectivity, enabling them to collect and exchange data autonomously [1]. However, as the IoT evolves, a new paradigm called the Social Internet of Things (SIoT) has emerged, extending the concept of connectivity beyond devices to include social interactions and human-centric services [2]. The SIoT represents a significant shift from a traditional device-centric model to a user-centric and socially interconnected environment. It utilizes the capabilities of IoT devices to not only enable communication but also establish social relationships between devices. By integrating social aspects into the IoT framework, the SIoT empowers devices to actively share information, collaborate, and engage in social interactions, leading to a revolutionary transformation in the discovery and composition of services [3], [4]. This paradigm shift facilitates the provision of personalized services, improves social interactions, and fosters innovative and meaningful connections among devices [5]. With the rapid expansion of the SIoT ecosystem, the diversity of services and applications available has become overwhelming. SIoT entities find themselves inundated with a vast number of choices when it comes to selecting the right services. Consequently, there is a pressing need for effective service recommendation systems that can assist in identifying and suggesting the most relevant services for specific groups of users or devices [6].

Several research works have focused on developing general service recommendation systems within the SIoT. However, these models often face significant challenges in adapting to the dynamic nature of the SIoT environment. For instance, one proposed solution for analyzing the social correlation of service requirements is the Social Correlation Group-based Recommender System (SRS) introduced in [7]. SRS generates target groups based on the social correlation of service requirements, using an architecture and procedures derived from Collaborative Filtering and Content-based Recommender Systems. However, this social correlation service recommendation system has limitations. It primarily relies on profile similarity, friend similarity, and interest individuality, overlooking the diverse content and different modalities of data across devices and users. Additionally, the system fails to account for evolving user preferences and the integration of new data into the model, relying solely on historical user-item interactions. This limitation can result in inaccurate recommendations that do not align with users' current preferences or situations. Another proposal is the time-aware smart object recommendation model discussed in [8]. This model considers users' preferences over time and the social similarity of objects to assist users in locating relevant smart objects in the SIoT. However, similar to previous works, this model lacks consideration for multi-modal data and contextual factors such as location and user characteristics. Incorporating these elements would enhance the accuracy and personalization of recommendations provided by the time-aware smart object recommendation model. The graph-based service recommendation framework presented in [9] jointly considers social relationships between heterogeneous objects in the SIoT and user preferences. This framework models users, objects, and their relationships using a knowledge graph

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and learns users' preferences from their object usage events with a latent variable model. However, relying solely on user preferences to form the graph knowledge may result in a lack of accuracy and reliability in providing relevant services. Neglecting other types of data, such as contextual information, trends, or correlations of user-object relationships, may decrease the system's ability to tailor recommendations for individual users accurately. In a different approach, [10] we proposed a service recommendation system that takes advantage of the relationships between device owners when recommending services. This system leverages effective community detection algorithms to identify specific communities and provide tailored service recommendations based on device owners' relationships within those communities. However, this work primarily focuses on device-device interactions and does not consider the service-service pair structure when dealing with large sparse data. In another previous research [11], we developed a service recommendation system that effectively utilizes multi-modal data, incorporates the diversity of generated data, and considers the relationships between different items/services within SIoT in order to get more accurate and personalized service recommendations to fit the dynamic and diverse SIoT environment. Therefore, existing models in the SIoT space have not effectively leveraged contextual data to provide tailored recommendations. Moreover, these models have primarily focused on device-device and device-service relationships in service recommendation systems, neglecting the potential use of context-aware recommendations that can encompass review-based and interaction-based recommendations with user preferences and content heterogeneity. To overcome these limitations, we aim to develop a contextually aware service recommendation system that explores the contextual representation of device-service pairs and captures latent feature interaction to enhance the service recommendation system within the SIoT environment. Thus, mining the contextual data as well as device-service interaction within the SIoT is crucial for delivering tailored service recommendations that meet the diverse needs of SIoT objects, including users and devices. The main contributions of our research are summarized as below:

- **Contextually Integrated Service Recommendation Framework**: Our framework jointly incorporates review-based contextual semantics and dynamic engagement patterns in SIoT. Unlike prior systems that primarily exploit static trust or time-aware contexts, our approach explicitly models multi-modal contextual signals (e.g., textual reviews and device–service interaction histories), thereby addressing the limitations of existing single-modal or static-context models.
- **Factorization Machines for Higher-Order Interactions**: To capture the complex latent dependencies between SIoT devices and services, we employ Factorization Machines to model higher-order feature interactions. This design goes beyond earlier models that rely mainly on shallow or pairwise associations, leading to a more comprehensive understanding of rating behaviors and improved recommendation accuracy.
- **Dynamic Weighting for Adaptive Context Utilization**: We propose a dynamic weighting mechanism that adaptively balances review-based and engagement-based features based on their predictive contributions. Unlike fixed-weight or heuristic-based schemes in earlier studies, our method prioritizes features with higher predictive accuracy, producing more adaptive and personalized service recommendations in the SIoT environment.

Throughout these contributions, and along with empirical validation, we aim to address the challenges of data explosion, improving network navigability, and enhancing service discovery within the SIoT context.

The remainder of this article is organized as follows: Section II provides a comprehensive review of recent literature on service recommendations in the SIoT. In Section III, we present the system modeling, including the framework overview, the review aggregation process, and the engagement feature learning process. The experimental evaluation of our proposed system is discussed in Section IV. Finally, Section V concludes the paper, highlighting our research contributions, and outlines future research directions in the context-aware service recommendation systems for the SIoT.

II. Related Works

In the SIoT, where devices autonomously establish social relationships and collaborate, effective service recommendation systems are crucial for enabling seamless service discovery and utilization. This section provides an overview of state-of-the-art SIoT service recommendation approaches, including trust-aware systems, time-aware models, graph-based frameworks, and decentralized human-centric methods. While these methods have made significant progress, they often face limitations in addressing the dynamic nature of SIoT environments, neglecting contextual data and multi-modal feature interactions critical for delivering personalized and accurate recommendations. The study in [12] deals with the challenges of service recommendation in the context of the SIoT. The authors introduce a trust-aware recommender system called RSCF. The study shows that the use of recommender systems with SIoT device trust relationships leads to better results. The trust-aware recommender system uses ideas from social networking sites and looks at how people interact socially. By adding trust information to recommender systems, the study proves to reduce problems like fake opinions and make better predictions about what users like in the SIoT world. The authors tested their proposed system in experiments and found that it works better than traditional recommendation methods. However, while the study successfully demonstrates improved performance in SIoT environments by incorporating trust in recommender systems, it has certain limitations. In particular, it primarily operates at the overall trust-aware recommender system level and lacks a specific focus on the intricacies of latent feature mining and specifically the contextual data.
Authors in [13] explores matrix factorization techniques for recommendation in social networks and introduce trust propagation into the model. Trust propagation, a crucial phenomenon in trust-based recommendation, is shown to substantially improve recommendation accuracy. The SocialMF

model addresses challenges such as cold start users and the limited availability of public social rating network datasets. It demonstrates improved performance compared to existing memory-based approaches, emphasizing the importance of considering trust dynamics. However, this research contributes significantly by incorporating trust propagation into matrix factorization for social network-based recommendations. It focuses primarily on general social networks, and its application to the SIoT context is not explicitly explored. Therefore, our work complements this by offering insights into these intricacies, providing a more specialized understanding of contextual data within SIoT environment. In [8], a time-aware smart object recommendation model combines user preferences over time and the social similarity of smart objects. Using a latent probabilistic approach, it embeds social relationships into a shared lower-dimensional space. Evaluation on real-world datasets demonstrates superior recommendation effectiveness compared to baseline approaches. However, relying on object usage events to learn user preferences may limit effectiveness with incomplete or unavailable usage data.

In [10], a service recommendation system is proposed that leverages social relationships between device owners to enhance accuracy and diversity in IoT services. However, it overlooks the limitations of relying solely on social relationships, failing to account for user preferences, contextual factors, and requirements related to latent feature extraction. The study [14] presents a human-centered decentralized architecture and a recommendation engine in SIoT a decentralized recommendation system that leverages DANOS to enhance the effectiveness of the recommendation while protecting the privacy of object owners in the context of SIoT. DANOS facilitates purposeful social connections among objects in a decentralized and private manner, exchanging only authorized and useful data for recommendations. This approach is related to social-aware and decentralized recommenders, but distinguishes itself by considering dynamic social networks and prioritizing privacy. However, it does not explicitly address complex feature learning and latent feature mining, which are critical to ensuring accurate and reliable recommendations in complex SIoT environments.

The study in [15] designs a decentralized SIoT recommender system by leveraging object pairing to provide tailored recommendations. Although aiming to avoid central control of distributed information among objects, the study overlooks the role of trust and its impact within the SIoT environment as well as latent feature mining, which could significantly affect the quality of recommendations.

The authors of [16] introduced a new SIoT service recommendation approach named SIoT-SR. This method combines the LSH Forest with a collaborative filtering algorithm to forecast the Quality of Service (QoS) data for users. The LSH forest utilizes binary search through sorting and can self-adjust parameters, achieving balanced performance in terms of memory usage, accuracy, efficiency, and privacy protection. The effectiveness of the scheme was validated using the WS-DREAM dataset, demonstrating high prediction accuracy and service recommendation accuracy. However, the research has potential limitations, particularly related to trust metrics and latent feature mining. The research did not adopt dynamic trust relationships and evolving user preferences. Trust metrics often rely on predefined types of relationships, user behavior, and interactions. Furthermore, latent feature extraction was not taken into account to capture complex user preferences and evolving patterns accurately which we aim to bridge this gap in this research. Authors in [17] Presented a Deep distributed learning-based POI recommendation method for mobile edge networks (MEN), addressing the challenge of sparse and uninformative user-location data by deeply abstracting hidden feature components from both local and global subspaces and conducting propagation operations to optimize expressions of the feature space, resulting in enhanced recommendation accuracy. However, this approach primarily focuses on abstracting hidden feature components from existing data without necessarily adapting to the evolving social dynamics within the context of the SIoT environment. In summary, although prior works have made valuable contributions in trust modeling, decentralization, and graph/time-aware recommendations, none simultaneously address latent feature interaction mining, dynamic trust aggregation, rich contextual awareness, and edge-compatible computation. The proposed CASR-SIoT framework fills this gap by integrating these elements into a unified, scalable, and real-time capable service recommendation system tailored for large-scale SIoT environments.

III. System Design and Modeling

In this section, we introduce our proposed framework, which aims to enhance service recommendation through a context-aware device-service representation learning model. The framework, as depicted in Figure 1, is designed to estimate rating scores for device-service pairs by leveraging two distinct sources of information: service reviews contributed by devices and the device-service interaction matrix. Consequently, the proposed framework comprises two separate feature learning components, namely review-based feature learning and engagement-based feature learning. In the subsequent sections, we provide a comprehensive explanation of the rating prediction framework, followed by a detailed description of the two learning components. Throughout this section, all preliminaries are explained and summarized in Table I.

A. Framework Overview

Traditional recommendation systems commonly employ the dot-product (DP) operation for rating prediction. However, this operation imposes a stringent constraint where the latent dimensions are treated as independent entities. Consequently, each dimension in a latent user vector can only interact with the corresponding dimension in the latent item vector. This independence constraint limits the capability to capture complex user–item rating behaviors that arise from higher-order feature interactions. Considering that our proposed framework is dedicated to SIoT devices that require tailored services, it aims to derive context-aware representations for each device–service pair, it is essential to model these higher-order latent feature interactions to gain a better understanding of

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rating behaviors. The Figure 2 illustrates the workflow of the proposed framework highlighting key components.

Framework Description. Our Factorization Machine (FM) models device–service interactions as a weighted sum of latent feature interactions, where $F_{d,s}$ captures device-specific and service-specific attributes (e.g., device type, service category). FM is chosen for its ability to handle sparse, high-dimensional SIoT data by factorizing feature interactions into low-rank embeddings, thereby outperforming traditional matrix factorization approaches in sparse implicit-feedback settings [18].

Formalization. In our approach, we adopt the Factorization Machine (FM) [19] to compute the rating score. Specifically, given a learned latent feature vector for a device–service pair, denoted as $F_{d,s}$, FM calculates the corresponding rating score using the following equation:

$$\hat{R}_{d,s}(F_{d,s}) = b_0 + \mathbf{a}^T_{F_{d,s}} + \frac{1}{2} F^T_{d,s} W_{F_{d,s}} \tag{1}$$

$$W_{j,k} = V^T_j, V_k, \quad j \neq k \tag{2}$$

where:
b_0: global bias,
a: coefficient vector for the latent feature vector $F_{d,s}$,
W: diagonal weighted matrix $(M_{i,j} = 0)$ representing second-order feature interactions.

The v-dimensional latent vectors v_j and v_k correspond to dimensions j and k of $F_{d,s}$. Equation 1 thus incorporates both first-order **a** and second-order M feature interactions for rating prediction.

In traditional recommendation systems, rating patterns encompass various inherent inclinations, referred to as biases. Previous research [20] has demonstrated that considering user and item biases can effectively account for rating discrepancies and consequently enhance prediction accuracy. In the SIoT environment, biases manifest when certain devices consistently assign higher scores to all services, or when some services tend to attract higher ratings across devices. Building upon these findings, we enhance the predictor by incorporating both device and service biases as follows:

$$\hat{R}_{d,s} = \hat{R}_{d,s}(F_{d,s}) + b_d + b_s \tag{3}$$

where b_d and b_s denote the biases associated with the device and service, respectively. $R_{d,s}$ represents the predicted rating.

To optimize the parameters, we utilize the square loss objective:

$$L_{d,s} = \sum_{(d,s)\in O} (\hat{R}_{d,s} - R_{d,s})^2 + \lambda_\Theta \|\Theta\| \tag{4}$$

where O represents the set of observed device–service pairs, $R_{d,s}$ is the true rating, and Θ includes all parameters. The regularization term prevents overfitting.

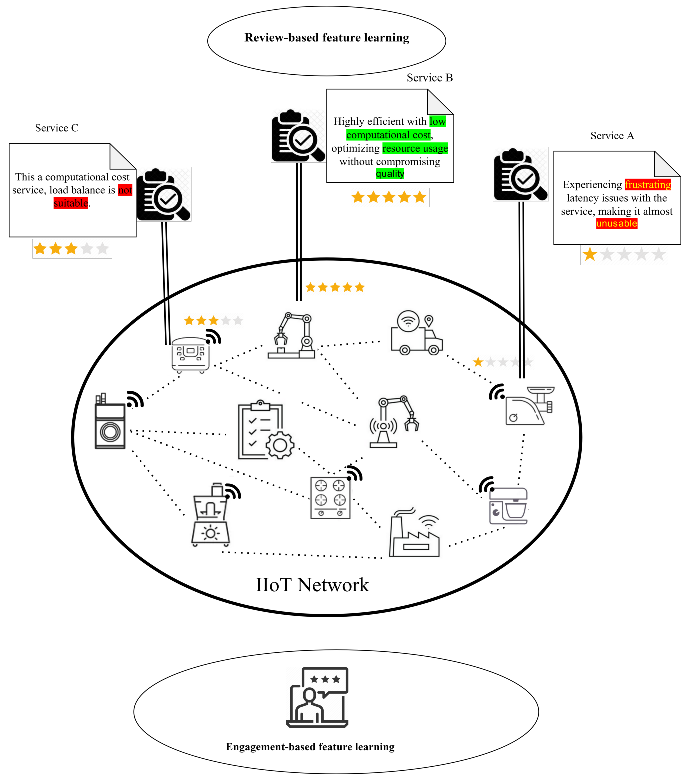

Fig. 1. Framework Overview

TABLE I
PRELIMINARIES

Symbol	Definition
$\hat{R}_{d,s}$	The rating predictor for a device-service pair
$F^T_{d,s}$	the latent feature vector for a device-service pair
$W_{j,k}$	A diagonal weighted matrix
D_r	Review collection
M_d	Collection matrix
$L_{d,s}$	Optimized predicted rate
λ_Θ	Regularization term function
σ	Sigmoid function (non-linear activation function)
CW^j_c	convolution weights associated with filter f_j
$ReLU(x)$	Rectified Linear Unit activation function
g^d_j and g^d_j	The pair of contextual feature vectors
R^k_j	The similarity scores matrix
$tanh$	hyperbolic tangent function
a^d and a^s	the selective weight vectors
$D^w_{h:h+s-1}$	slice of the matrix D obtained by selecting the elements within the sliding window starting at position
CW^j_a	the convolution weight vector
ρ	A non-linear activation function
$v_d$and v_s	device-service latent vectors
$F_{collection}$	The feature collection vector
β	Prediction score parameter
$\oplus$	Element-wise product operation
$e^{collection}_{d,s}$	The feature collection vector

B. Reviews-aggregation process

In this section, we present the review-based feature learning approach that we employed to enhance the recommendation process. In the context of SIoT environment, we recognize that when a device d reviews a specific service s, it reflects the preferences within the ecosystem. Thus, we aggregate all the reviews authored by the same device owners or devices to form a device review collection. Similarly, we merge all the reviews provided by a set of devices for a particular service to construct a service review collection. These two types of review collections are expected to encapsulate distinct semantic information. While a device review collection may

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encompass personal preferences of users, a service review collection primarily encompasses various aspects that hold significance for all relevant devices. Within our proposed frameworks, the primary objective of review-based feature learning is to deduce a latent feature vector for each device-service pair by jointly considering their respective review collections. Leveraging the convolution operation, which has proven successful in multiple natural language processing and information retrieval tasks such as collection representation learning.

we aim to extract diverse aspects covered within the review collections. Subsequently, a selective layer is employed to emphasize the relevant aspects by taking into account both the device's preferences and the characteristics of the service. Lastly, an abstraction layer is utilized to generate the final latent feature vector for the device-service pair. Figure 3 illustrates the network architecture for review-based feature learning.

1) Convolution Layer: In the convolution layer, we process a review collection $D_r = \{x_0....x_{i-1}, x_i, x_{i+1}......x_n\}^T$ Initially, a lookup layer maps each word x_i to its respective embedding $x_i \in \mathbf{R}^{1\times T}$. These embeddings are then concatenated in the order of their appearance within the constructed collection, forming a collection matrix $M_d = \{x_0....x_{i-1}, x_i, x_{i+1}......x_n\}$ Here, x_i represents the word embedding for the word at the i-th position in collection D_r. The matrix D maintains the word order, allowing the convolution layer to capture more precise semantic information compared to traditional bag-of-words approaches in traditional recommendation systems [21].

Specifically, we utilize a convolution filter f_j with a sliding window of size s to extract the contextual feature c_h^j from the local context. By utilizing the convolutional filters with a sliding window, the convolution layer can capture contextual information and extract higher-level features from the input. In the case of review-based feature learning, the convolution layer aims to extract semantic information from the review collection by analyzing the contextual relationships among the words. Specifically:

$$c_h^j = \sigma(CW_c^j D_{h:h+s-1}) \tag{5}$$

The function σ represents a non-linear activation function. The weight vector CW_j^c corresponds to the convolution weights associated with filter f_j. The notation $D_{p:+s-1}$ represents a slice of the matrix D obtained by selecting the elements within the sliding window starting at position p. By default, we adopt the Rectified Linear Unit (ReLU) as the activation function, defined as $ReLU(x) = max(0, x)$. To ensure consistent input dimensions, we append $s - 1$ zero vectors at the end of the collection matrix D. This padding ensures that n contextual features are produced, where n represents the length of the collection D_r To capture various contextual features with service reviews, multiple convolution filters are employed. Each filter utilizes a distinct convolution weight vector to extract contextual features for each word within its local context, spanning s consecutive words. Specifically, in this study, we employ two different sets of convolution weight vectors CW_c^*, to process the user review collection and the item review collection separately.

2) Selective Layer: Building on our previous discussion, we acknowledge that review collections—whether associated with devices or users—can capture personalized and diverse preferences for different services. Similarly, service review collections may emphasize aspects that different users consider important. Consequently, not all information in these review collections is necessarily relevant for predicting the rating score of a particular device-service pair. To effectively capture the useful information, we incorporate a selective layer that focuses on the review collections corresponding to the specific device-service pair. By applying a convolution operation to a review collection, we obtain a contextual feature vector c_p, which encodes the features of the word at the p-th position within that collection. In this framework, we define two matrices, D and S, to represent the device and service review collections, respectively. Here, c_j^d and c_k^s denote the contextual feature vectors for the j-th word in the device reviews and the k-th word in the service reviews.

$$\begin{cases} c_p = [c_p^1, c_p^2, c_p^3......., c_p^{f-1}, c_p^f] \\ \qquad\qquad \Downarrow \\ D = [c_1^d, c_2^d, c_3^d......., c_{n-1}^d, c_n^d] \\ S = [c_1^s, c_2^s, c_3^s......., c_{n-1}^s, c_n^s] \end{cases} \tag{6}$$

In order to determine the significance of each contextual feature vector for both D and S we introduce a selective matrix denoted as $A \in \mathbf{R}^{f\times f}$, Specifically, we project matrices D and S into a shared latent space and compute the pairwise relevance between each pair of contextual feature vectors, c_j^d and c_k^s, using the following approach:

$$R_j^k = \tanh(c_j^d A c_k^s) \tag{7}$$

According to equation 7, each row R_*^j in a column R_k^* represents the similarity scores between the vectors c_j^d and c_k^s in matrices U and S respectively. To calculate the similarity scores, a mean-pooling operation is performed on each row/column of the matrix R, which is mathematically expressed as:

$$\begin{aligned} g_j^d &= \mathbf{mean}(R_1^j, \ldots, R_m^j) \\ g_j^s &= \mathbf{mean}(R_k^1 \ldots R_k^n) \end{aligned} \tag{8}$$

$$\begin{aligned} l_j^d &= \frac{\exp(g_j^d)}{\sum_h^n \exp(g_h^d)} \\ l_j^s &= \frac{\exp(g_k^s)}{\sum_h^m \exp(g_h^s)} \end{aligned} \tag{9}$$

$$\begin{aligned} \mathbf{a}^d &= [a_p^d, a_p^d, a_p^d, \ldots, a_n^d] \\ \mathbf{a}^s &= [a_1^s, c_2^s, c_3^d, \ldots, a_n^d] \end{aligned} \tag{10}$$

By utilizing the mean similarity computed in equations 8, we can determine the significance of each contextual feature vector in D and S. This is expressed through the selective weights l_j^d and l_k^s, as shown in equation 9. Ultimately, the

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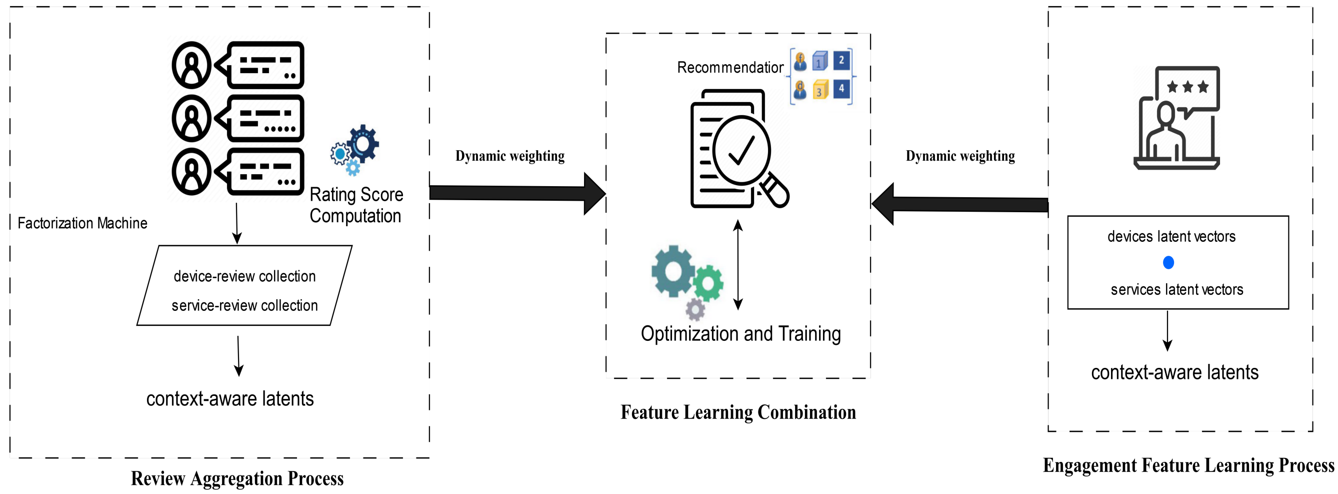

Fig. 2. The Workflow of the proposed framework

selective layer yields the selective weight vectors $\mathbf{a}^d$ and $\mathbf{a}^s$, as demonstrated in equation 10. These weight vectors represent the learned distribution indicating the level of importance assigned to the words in the device review collection and service review collection, respectively.

3) Feature Extraction Layer: In this subsection, we describe the process of extracting higher-level semantic features from device and service review collection using an abstraction layer. First, selective vectors represented as $\mathbf{a}^d$ and $\mathbf{a}^s$ are calculated based on the device and service collections. These attentive weights indicate the relevance of each contextual feature vector to the device-service pair. A higher weight signifies greater relevance (equation 11). While it is possible to represent the device and service by simply summing up the weighted contextual feature vectors, such a simplistic approach may introduce excessive noise due to the inclusion of irrelevant aspects from both review collections. To overcome this limitation, we adopt a more sophisticated approach by employing further neural transformations (a mean-pooling CNN network) based on the weighted contextual vectors D^w and S^w. One advantage of applying a mean-pooling CNN network over max-pooling on D^w and S^w is that it enables the extraction of latent features based on a larger context while taking into account the relevance weights as depicted in equation 12. Moreover, the mean-pooling strategy is selected over max-pooling due to its ability to capture the diversity of devices/user opinions across different aspects of service. For instance, when selecting a streaming service by a smart TV, consider not only the available content library but also the user interface, streaming quality, and subscription plans to enhance the user's entertainment experience.

Equation 13 describes the process. Where σ is sigmoid function applied along with the convolution weight vector $\mathbf{CW}_a^j$ and device item collection matrix $\mathbf{D}^w_{h:h+s-1}$. After the mean-pooling step, a shared MLP layer is stacked upon the mean-pooled vectors. As depicted in equation 13 The vectors H^d and H^s are transformed using the transformation matrix $\mathbf{CW}_1$ and bias vector $\mathbf{b}_1$ through the sigmoid function σ.The transformed vectors t_d and t_s represent the devices and services specific transformed features respectively.

The context-aware latent feature vector for the device-service pair is then formed by combining the review embedding, device-specific features t_d, and service-specific features t_d. This is illustrated in equation 14. The element-wise product enhances the interactions between the latent features. The resulting vector i.e. the feature collection vector, denoted as **Fcollection**, captures both the individual characteristics and their interactions, providing a comprehensive representation of the device-service pair. Overall, this abstraction layer takes the weighted contextual vectors, applies a mean-pooling CNN network to extract higher-level semantic features, and then employs a shared MLP layer for further feature extraction and its parameters are explained in Table II.

$$\begin{aligned} \mathbf{D}^w &= \mathbf{a}^d\mathbf{D} \\ \mathbf{S}^w &= \mathbf{a}^s\mathbf{S} \end{aligned} \tag{11}$$

$$\begin{cases} H_h^j = \sigma(\mathbf{CW}_a^j \mathbf{D}^w_{h:h+s-1}) \\ H_j = \mathbf{mean}(H_1^j, \ldots, H_n^j) \\ \mathbf{H}^d = [H_1, \ldots, H_f] \end{cases} \tag{12}$$

$$\begin{aligned} t_d &= \sigma(\mathbf{CW}_1 H^d + b_1) \\ t_s &= \sigma(\mathbf{CW}_1 H^s + b_1) \end{aligned} \tag{13}$$

$$F_{collection} = [\mathbf{e}_{d,s}^{collection} \oplus \mathbf{t}_d \oplus \mathbf{t}_s] \tag{14}$$

C. Engagement Feature learning Process

In order to capture the device's rating behaviors more comprehensively, we incorporate engagement-based feature learning. While textual reviews provide valuable information, the previously obtained review-based latent features alone may not fully represent the device's rating preferences. To overcome this, we introduce a separate set of latent vectors

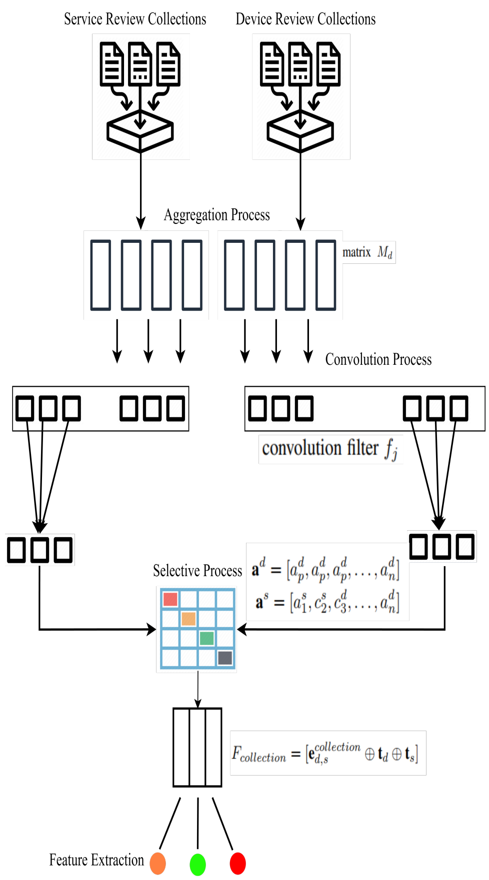

Fig. 3. Workflow of the review-based feature learning module, showing review aggregation, convolutional feature extraction, semantic selection, and generation of context-aware latent features for device-service pairs.

for devices and services. The devices and service identities are one-hot encoded and mapped onto their respective latent vectors $\mathbf{v}_d$ and $\mathbf{v}_s$ using matrices $\mathbf{D}$ and $\mathbf{Q}$ Since no contextual information like textual reviews is available, an element-wise product operation is used to extract engagement-based features. equations 15 and 16 depicted the process of engagement-based Feature extraction.

$$\begin{aligned} \mathbf{v}_d &= \mathbf{D}_{x_d} \\ \mathbf{v}_s &= \mathbf{S}_{x_d} \end{aligned} \tag{15}$$

$$\begin{aligned} \rho &= \mathbf{v}_d \circ \mathbf{v}_s \\ F_{engagement} &= [\rho \oplus \mathbf{v}_d \oplus \mathbf{v}_s] \end{aligned} \tag{16}$$

D. Feature Learning Combination

The combination process aims to integrate the context-aware latent features extracted from the two aforementioned processes, namely the review-based features $F_{collection}$ and the engagement-based features $F_{engagement}$. The objective is to leverage the strengths of both modalities to enhance prediction performance in SIoT environments. A simple approach is to linearly interpolate the estimated rating score $\hat{R}_{d,s}$ using a parameter β that controls the tradeoff between the two components. However, a fixed β value is insufficient, as user/device preferences may shift over time (e.g., seasonal service demand, evolving device usage patterns). To address this limitation, we introduce a dynamic weighting scheme where β is optimized via a meta-learner trained with gradient descent. Specifically, the meta-learner observes the prediction errors of the review-based and engagement-based components and adaptively adjusts β such that the component with stronger predictive power receives higher weight in the final prediction. This mechanism enables our framework to capture temporal shifts in device preferences and real-time SIoT dynamics. Formally, the final prediction is expressed as:

$$\begin{aligned} \hat{R}_{d,s} = {} & \beta_{d,s}\, \hat{R}_{d,s}(F_{\text{collection}}) \\ & + (1-\beta_{d,s})\, \hat{R}_{d,s}(F_{\text{engagement}}) + b_d + b_s \end{aligned} \tag{17}$$

where $\beta_{d,s}$ is adaptively learned by the meta-learner rather than heuristically fixed. Compared to static weighting schemes, our dynamic formulation allows personalized adaptation to device-service contexts. Furthermore, unlike learned attention mechanisms that require additional layers and parameters, our approach provides a lightweight yet theoretically grounded solution. This extends prior static weighting approaches by introducing gradient-based adaptation, enabling real-time responsiveness in SIoT environments.

IV. Experimental Evaluations

A. Dataset Description

While SIoT-specific datasets remain scarce, we employ the Amazon review dataset [22] (summarized in Table III) as a proxy for device–service interactions. The dataset provides user–item ratings and textual feedback, which align with SIoT scenarios where devices generate usage logs and qualitative feedback. For example, appliance reviews (e.g., smart fridges) and cellphone accessories (e.g., IoT-enabled cases) reflect real-world SIoT device interactions.

TABLE II
MLP Parameters

Parameter	Value
Latent dimensions (users & items)	30
Number of users	Check Table III
Number of items	Check Table III
Batch size	100-200
training epochs	80
Feature dimension size	10-300
Latent dimensions for word embeddings	300
Number of filters	50
Size of the window	3
Dimensionality of vectors	50
Learning rate	0.001
Regularization parameter for loss calculation	0.05
Dropout rate	0.5

TABLE III
Summary of the Amazon Review Dataset

Dataset	Users	Items	Ratings	Density
Appliances	1,565	1052	11,342	79.8%
Cellphones	6,019	3,281	66,239	44.8%
Electronics	7,529	3,657	39,256	32.7%

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B. Evaluation Methodology

In this section, we present a comprehensive evaluation methodology to assess the performance and effectiveness of the proposed recommendation approach. We outline the metrics used as baselines for comparing and evaluating the proposed framework. The evaluation focuses on various metrics that measure the quality of recommendations and their ability to address the unique challenges posed by the SIoT environment. The baseline metrics considered include recall, precision, Normalized Discounted Cumulative Gain (NDCG), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics provide valuable insights into the accuracy, relevance, and ranking of the recommended items. By considering these metrics, we provide a comprehensive performance evaluation and comparison of our proposed approaches with existing recommendation methods such as Matrix Factorization (MF), Graph-Based Service Recommendation (GBSR), Smart Object Recommendation Framework (BLA), Object Recommendation with Text-Topic Information (ORTJ), and Multi-Modal Recommendation System (MMRS).

1) Baseline: The baseline approaches discussed in this section provide reference models for evaluating the proposed recommendation methods. They encompass Matrix Factorization (MF), Graph-Based Service Recommendation (GBSR), Smart Object Recommendation Framework (BLA), Object Recommendation with Text-Topic Information (ORTJ), and Multi-Modal Recommendation System (MMRS).

- MF: It is a collaborative filtering method used to enhance recommendation accuracy by reducing data sparsity in the user-item matrix [23]. It creates user and item matrices, where each row/column represents a vector for the corresponding user/item. The predictive score of user i for item j is calculated by multiplying the corresponding vectors in the two matrices. The matrices are adjusted during training to minimize the least squared error between the actual and predicted values.
- GBSR: It is a framework proposed to address the service recommendation problem in SIoT [9]. It models the SIoT service recommendation as a knowledge graph completion problem. The framework leverages the user's preferences and object usage events, including rich spatial-temporal information, to uncover the user's preferences. Specifically, it models the hidden factors of the user's object usage and constructs a knowledge graph based on the service usage value, which is reflected by the service usage frequency.
- BLA: It is a framework designed to recommend smart objects based on user requirements in the SIoT [24]. This model utilizes Bi-LSTM and BERT to generate vectors for matching and recommendations. It employs self and global attention mechanisms to dynamically adjust the weights of vectors for improved performance. Additionally, the model incorporates Thing-thing relationship data to better utilize user requirements in generating reasonable representations of smart object attributes and characteristics. The authors evaluate the model using an extended original MovieLens dataset in SIoT scenarios.
- ORTJ: It is a proposed approach for recommending smart objects in the IoT [25]. It considers both the attributes and text-topic information of the objects. To enhance recommendation accuracy, a "thing-thing" relationship is introduced as an attribute for smart objects. The ORTJ model, based on maximum a posteriori estimation, is developed, and experiments are conducted to compare its performance with other models.
- MMRS: It is one of our previous works in the service recommendation for SIoT. MMRs is a multi-modal service recommendation system that considers the diversity of data generated in the SIoT environment [11]. The proposed system analyses the multimodal features such as item-item relationships to provide tailored service recommendations in SIoT environment. It provided an adaptive service recommendation system that can learn from item-item structure and improve the accuracy of future recommendations.

2) Metrics: In order to conduct a comprehensive evaluation of the proposed framework, we employed a set of widely used and effective evaluation metrics to measure its effectiveness. These metrics provide valuable insights into the performance of the framework and facilitate a thorough assessment of its recommendation quality. The evaluation metrics we considered include precision, recall, mean absolute error (MAE), and root mean squared error (RMSE).

- Precision is a metric that measures the accuracy of the recommended items. It quantifies the proportion of relevant items among the recommended ones. Recall, on the other hand, evaluates the coverage of the recommendation system by measuring the proportion of relevant items that have been successfully recommended.
- MAE measures the average magnitude of the errors between the predicted ratings and the actual ratings. It provides a straightforward evaluation of the absolute accuracy of the recommendations.
- RMSE, similar to MAE, assesses the accuracy of the recommendations by measuring the square root of the average squared differences between the predicted ratings and the actual ratings. It penalizes larger errors more heavily than MAE.

The following are the equations to calculate these metrics:

$$\begin{aligned}\textbf{Recall@k} &= \frac{\text{Correctly Recommended Services}}{\text{Total Relevant}} \\ &= \frac{1}{n}\sum_{i=1}^{n}\frac{TP_i}{TP_i+FN_i}\end{aligned}$$

$$\begin{aligned}\textbf{Precision@k} &= \frac{\text{Correctly Recommended Services}}{\text{Total Recommended}} \\ &= \frac{1}{n}\sum_{i=1}^{n}\frac{TP_i}{TP_i+FP_i}\end{aligned}$$

$$\textbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\mathbf{Pr}_i - \mathbf{R}_i|$$

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$$\textbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathbf{Pr}_i - \mathbf{R}_i)^2}$$

3) Evaluation Details: In this section, we present the evaluation details of our context-aware service recommendation system for the SIoT. We aim to address three specific research questions that pertain to the performance and effectiveness of our system. These questions are as follows:

- **RQ1**: How does combining review-based feature learning and engagement-based feature learning enhance the performance of the service recommendation system in the SIoT?
- **RQ2**: What is the impact of different hyperparameter settings on the accuracy and effectiveness of the service recommendation system in SIoT?
- **RQ3**: How effectively does the selective layer in the review-based feature learning component identify relevant semantic information from devices-service pairs ?

*4) Performance Comparison (**RQ1**):* To address our first research question, we conducted experiments using the aforementioned three categories of datasets. In order to establish a comparison, we evaluated the performance of the proposed framework against various baseline methods. In the following subsection, we present a comprehensive performance comparison in terms of recall and precision for the Appliances, Cellphones, and Electronics categories.

As shown in Figure 4, and Table IV respectively, the performance comparison clearly indicates that the proposed framework consistently outperforms the baseline methods across all three datasets (Appliances, Cellphones, and Electronics) in terms of both recall and precision. Moving forward, we delve into a detailed analysis of the recall and precision metrics for the Appliances, Cellphones, and Electronics datasets, focusing specifically on the performance comparison between the proposed framework and the baseline methods for the service recommendation system in the social domain. Our proposed framework, CASR-SIoT, demonstrates superior performance across all aspects of the service recommendation system in the SIoT domain. By combining review-based feature learning and engagement-based feature learning, which enables context-aware analysis, CASR-SIoT consistently achieves higher recall and precision values. This indicates its effectiveness in retrieving relevant and accurate services for devices. Furthermore, the results highlight that the MMRS method, incorporating multi-modal features, performs competitively in terms of recall and precision. However, the MF (Matrix Factorization) approach, relying solely on matrix analysis, falls short in comparison to the proposed framework. In summary, our findings consistently demonstrate that the proposed framework outperforms the baseline methods in terms of both recall and precision across all three categories. This compelling evidence indicates that the integration of review-based feature learning and engagement-based feature learning significantly enhances the performance of the service recommendation system in the social domain. By effectively retrieving more relevant services and providing more accurate recommendations, the proposed framework surpasses the capabilities of the baseline methods.

*5) Different models and hyperparameters comparison (**RQ2**):* In this section, we aim to address the second research question by conducting a comparison of various models with different feature dimension size parameters. The objective is to validate the performance of the proposed frameworks under different settings. We investigate the impact of altering the feature dimension size and explore the use of Linear Regression as an alternative to the factorization machine model. By separating the models, we can thoroughly evaluate their respective performances and make meaningful comparisons.

a) Feature dimension size: In order to evaluate the performance of the proposed framework, we calculated the RMSE and examined its performance across different dataset categories. Figure 5 clearly demonstrates the consistent outperformance of the proposed framework for all three categories (electronics, cellphones, appliances). Notably, even with a threshold value of $f = 10$, the proposed framework exhibited strong performance across all categories. It is worth noting, however, that higher values of the feature dimension parameter (f) showed slight improvement performance at the expense of increased computational costs, given the utilization of the Factorization Machine method. To balance performance and computational efficiency, we decided to fix the feature dimension at $f = 20$ for the subsequent analysis and evaluation of the proposed framework's performance. The details of the shared MLP parameters are depicted in Table II.

b) Factorization Machine and different Models Investigation: The impact of using the Factorization Machine (FM) method compared to the commonly used Linear Regression, as well as the investigation of the effectiveness of models separately, were studied to evaluate the performance of the recommendation system in SIoT environment in the context of review-based and engagement-based learning. The study aimed to determine which method yields better results in terms of accuracy and the obtained results are summarized in Table V. The table provides a comparison of different methods used for prediction in three categories: Electronics, Cellphones, and Appliances. Each method is evaluated based on the Mean Absolute Error (MAE) metric, which measures the average absolute difference between the predicted values and the actual values. Among the models, the rating-based alone demonstrates the highest MAE values in the all-dataset categories, indicating its lower accurately predicting ratings for these types of products when it is solely relies on ratings. The review-based method performs better than rating based approaches but shows slightly higher MAE values for the dataset appliances. Which proves that review provided for this category of dataset are not well relevant. On the other hand, the LR-based method and FM-based (Factorization Machine-based) method have lower MAE values across all three categories. However, it is important to note that the FM-based method shows better performance than the LR-based method in terms of MAE values. To quantify the difference in performance between FM and LR, the percentage difference of MAE values between the FM-based method and the other methods shows that the FM-based method has a 12.50%, 19.46%, and 13.97% lower MAE values for Electronics, Cellphones, and Appliances respectively. Therefore, which the accuracy

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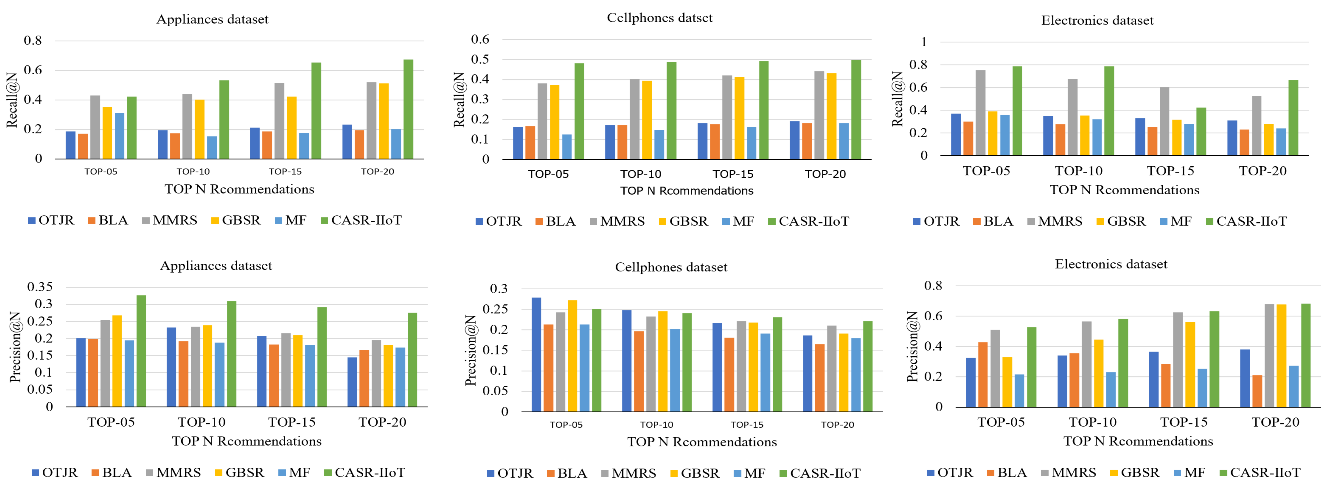

Fig. 4. Results of the precision and recall with different baseline on 3 different datasets

TABLE IV

PERFORMANCE COMPARISON OF THE PROPOSED RECOMMENDATION SYSTEM COMPARED TO BASELINE IN TERMS OF RECALL@15, PRECISION@15, AND RMSE@5. THE IMPROVEMENT LINE REPRESENTS THE PERCENTAGE OF RELATIVE ENHANCEMENTS COMPARED TO THE BEST BASELINE

Model	Appliances			Cell Phones			Electronics		
	R@15	**P@15**	**RMSE@5**	**R@15**	**P@15**	**RMSE@5**	**R@15**	**P@15**	**RMSE@5**
MF	0.175	0.181	0.981	0.163	0.191	1.502	0.253	0.282	1.432
GBSR	0.423	0.098	1.982	0.412	0.218	2.121	0.563	0.318	1.932
BLA	0.185	0.182	0.891	0.176	0.181	1.253	0.284	0.254	1.142
ORTJ	0.212	0.208	0.980	0.182	0.217	1.258	0.962	0.331	1.001
MMRS	0.513	0.215	0.781	0.421	0.221	0.889	0.621	0.303	0.745
CASR-SIOT	0.652	0.292	0.632	0.492	0.231	0.874	0.631	0.411	0.695
Improvement	**14%**	**8%**	**15%**	**7%**	**1%**	**2%**	**1%**	**11%**	**5%**

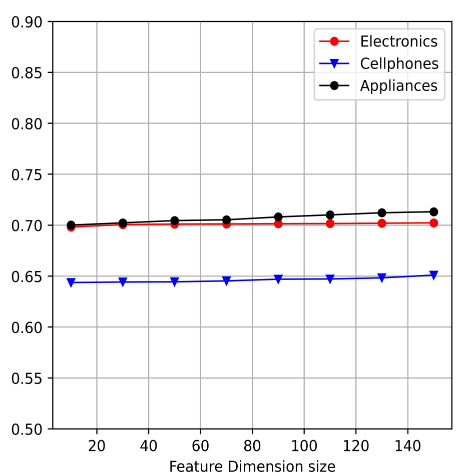

Fig. 5. RMSE values variations according to the Feature dimension size with different datasets

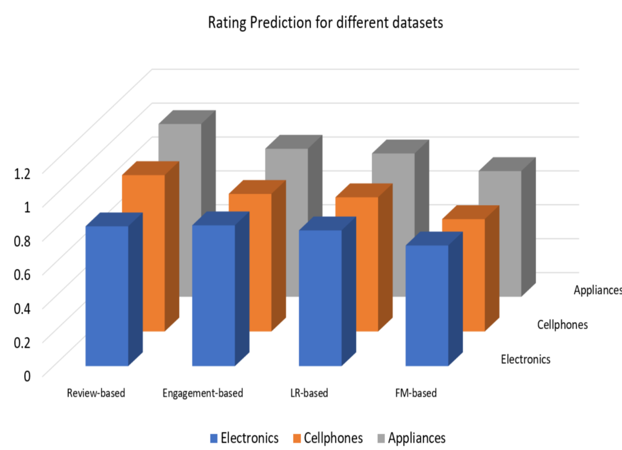

Fig. 6. Rating predictions for different datasets

results across all dataset categories, showcases the superiority of FM over Linear Regression. The FM method consistently achieves higher accuracy values, highlighting its capability to generalize well to unseen data and handle feature engagement that are not explicitly specified. Moreover, FM demonstrates its effectiveness in handling sparse and high-dimensional data, which is particularly important in the context of these datasets. The results clearly demonstrate that employing the FM method outperforms the traditional Linear Regression approach across all three categories of datasets. FM, known for its flexibility and ability to capture complex feature interactions, proved to be highly effective in this study. By decomposing feature interactions into latent factors through factorization, FM can capture both pairwise and higher-order interactions, leading to improved accuracy. In contrast, Linear Regression assumes a linear relationship between the features and the target variable, disregarding complex interactions or non-linear patterns. Although Linear Regression is computationally efficient and suitable for cases where the relationship between features and the target variable can be approximated by a linear function, it falls short in capturing the intricate feature interactions present in the datasets considered in this study.

TABLE V
COMPARISON OF METHODS FOR RATING PREDICTION

Method	**Electronics**	**Cellphones**	**Appliances**
Review-based	0.825	0.923	1.020
Engagement-based	0.831	0.812	0.874
LR-based	0.801	0.792	0.846
FM-based	**0.712**	**0.663**	**0.7423**
Percentage Diff.	12.50%	19.46%	13.97%

*6) The selective layer impact on the review-based feature learning process (**RQ3**):* In this section, we focus on the impact of the selective layer within the review-based feature learning component, specifically for device-service pairs, to identify relevant semantic information effectively. In the proposed recommendation system, the review-based learning component extracts latent features from user reviews and service documents to capture semantic interactions between devices and services. This process contributes to the creation of device-service representations. To test the effectiveness of the selective layer, we conducted a removal experiment in which we eliminate the selective layer and conduct the review-based approach without it. The results of the experiment are shown in Table V and Figure 6 respectively. As It is clearly shown that the removal of these element-wise product-based latent features from the review and rating learning components results in performance degradation, signifying their relevance in identifying relevant semantic information as depicted in Figure 6.

C. Ethical and Privacy Implications

The proposed CASR-SIoT framework processes large volumes of device-generated textual reviews and long-term interaction logs to deliver context-aware service recommendations. Although these data sources enable highly accurate and personalized suggestions, they simultaneously raise significant ethical and privacy concerns that require explicit consideration before real-world deployment. First, textual reviews frequently contain personal information about device owners (e.g., daily routines, health conditions inferred from smart-home appliance feedback, location patterns). Even when anonymized at the device level, aggregated review collections can still permit re-identification attacks through linkage with external datasets or inference of sensitive attributes via latent feature representations learned by the FM and convolutional layers. The selective attention mechanism, while improving recommendation accuracy, effectively highlights the most predictive review segments—often the most privacy-sensitive ones—thereby increasing the potential for privacy leakage. Second, the engagement-based feature learning component relies on fine-grained device-service interaction histories (frequency, duration, timestamps, implicit feedback). In a SIoT environment where devices establish ownership, parental, co-location, or co-work relationships, such interaction patterns can reveal sensitive behavioral profiles (sleep cycles from smart lights, dietary habits from connected refrigerators, mobility patterns from wearables). The dynamic weighting scheme further compounds this issue by continuously adapting to evolving preferences, resulting in an evolving behavioral fingerprint. Third, the lack of fully decentralized computation in the current architecture implies that review texts and interaction matrices require to be transmitted to or stored on central servers for model training and inference, exposing them to breaches, unauthorized access, or lawful interception. Even federated or edge-based extensions would need rigorous differential privacy guarantees, because the gradient updates or latent embeddings exchanged during collaborative training can still leak sensitive information. From an ethical standpoint, the proposed recommendation performance risks creating a “accuracy-vs-privacy” trade-off that could incentivize excessive data collection. Users and device owners may not fully understand that their routine voice notes, maintenance reports, or implicit usage patterns are being transformed into persistent latent profiles used for commercial or third-party service recommendations. Moreover, vulnerable populations (elderly users, children whose devices are parent-managed devices) may lack meaningful capacity to provide informed consent. To mitigate these risks, future deployments of CASR-SIoT must incorporate:

- On-device review preprocessing and embedding, enforced by strict k-anonymity or local differential privacy, to mitigate device- or behavior-level fingerprinting.
- Cryptographic techniques (homomorphic encryption or secure multi-party computation) for the FM inference phase,
- Explicit consent mechanisms and granular data minimization controls at the SIoT object level.
- Transparency reports detailing what latent features are learned and how long interaction histories are retained.

Without these safeguards, the performance gains of context-aware recommendation in SIoT systems risk undermining user trust and violating emerging data-protection frameworks (e.g., GDPR, CCPA, and forthcoming IoT-specific regulations). Consequently, privacy-preserving mechanisms must be treated not as optional features but as fundamental architectural requirements from the start.

V. CONCLUSION

The emergence of the SIoT has revolutionized the way interconnected smart devices share data and services, leading to the development of personalized service recommendations. Despite these advancements, existing research in this field has often overlooked crucial aspects that could significantly enhance the accuracy and relevance of recommendations within the SIoT context. Specifically, while some techniques have considered social relationships between devices, they have failed to adequately incorporate the contextual presentation of service reviews. This work addresses these limitations by introducing a context-aware service recommendation system tailored for the SIoT environment. Our investigation revolves around three primary research objectives: firstly, assessing the impact of combining review-based feature learning and engagement-based feature learning on the performance of the service recommendation system; secondly, examining the influence of different hyperparameter settings on the accuracy and effectiveness of the recommendation system; and lastly, evaluating the effectiveness of the selective layer in review-based feature learning in identifying relevant semantic information from device-service pairs. To achieve these objectives, we conducted experiments using three categories of datasets and performed a comprehensive performance comparison of the proposed framework, CASR-SIoT, against various baseline methods. The results consistently demonstrated that CASR-SIoT outperformed the baseline methods across all datasets, exhibiting superior recall and precision values in the Appliances, Cellphones, and Electronics categories. The integration of review-based and engagement-based feature learning enabled truly context-aware analysis, yielding more precise and relevant service recommendations. Our research findings hold significant implications for the domain of SIoT service recommendation systems. Existing models have struggled to adapt to the highly dynamic nature of the SIoT environment, often relying on limited data sources and neglecting diverse content modalities. The success of CASR-SIoT underscores the value of context-awareness in future SIoT recommendation frameworks, paving the way for more personalized and situationally appropriate service suggestions. Despite the notable performance improvements achieved by the proposed framework, we acknowledge certain limitations and identify potential future directions. The current approach relies on the availability of textual reviews, which may be sparse or absent in many real SIoT deployments. Future work will explore synthetic review generation using GANs to alleviate cold-start problems. Additionally, although the model already adapts to evolving preferences through dynamic weighting of review and engagement signals, explicitly incorporating spatiotemporal context—such as device location, time of day, or environmental conditions—could further refine recommendation accuracy in highly dynamic scenarios (e.g., vehicular networks or smart cities). Extending the framework to run partially on edge nodes is also a natural next step to reduce latency and enhance privacy preservation in large-scale SIoT ecosystems. Beyond the empirical validation, the proposed CASR-SIoT framework is specifically designed for real-world Social Internet of Things deployments. In smart-home ecosystems, appliances and entertainment devices continuously generate usage logs and textual feedback (e.g., voice notes or maintenance reports); our model can recommend energy-management services, predictive-maintenance providers, or personalized content-streaming applications by jointly exploiting review semantics and long-term engagement patterns. In industrial IoT environments, thousands of sensors and actuators connected through ownership, co-location, or co-work relationships can benefit from tailored recommendations of firmware updates, anomaly-detection services, or optimal reconfiguration strategies by interpreting diagnostic logs as review-like input. In smart healthcare and wearable networks, the framework can suggest wellness applications or emergency-response services by combining physiological interaction histories with patient/caregiver feedback. Finally, in smart-city and vehicular SIoT settings, the lightweight dynamic weighting mechanism enables rapid adaptation to evolving device preferences and usage patterns, making the framework especially suitable for future extensions that explicitly incorporate real-time signals such as location, time-of-day, and traffic density. When augmented with these spatiotemporal cues, CASR-SIoT can seamlessly support real-time recommendation of navigation, parking, pollution-mitigation, and other mobility-related services. These practical deployment scenarios clearly demonstrate how the proposed context-aware, multi-modal approach significantly enhances service discovery, resource utilization, and overall satisfaction in operational SIoT systems. The results presented in the previous section show that this work substantially advances SIoT service recommendation systems. By jointly leveraging review semantics and long-term engagement signals through dynamic feature weighting and higher-order interaction modeling, CASR-SIoT consistently delivers more accurate and personalized recommendations than existing baselines. As the SIoT ecosystem continues to grow, this study underscores the critical role of rich contextual modeling in improving the user experience and unlocking the full potential of socially interconnected devices.

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