



Personalized Medical E-Commerce Platform

S.Vaitheeswari, M.Sc., M.Phil., B.Ed.^[1], V. Shrisudhi^[2]

Department of Computer Science, Sakthi College of Arts and Science for Women, Oddanchatram, Tamilnadu, India^[1]

M.Sc (Computer Science), Department of Computer Science, Sakthi College of Arts and Science for Women,
Oddanchatram, Tamilnadu, India^[2]

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ABSTRACT: The aim of the study is to explore the theoretical and conceptual foundations of the implementation of e-commerce in health care. The methodology of the study consists of theoretical views and conceptual and methodological approaches derived from foreign scientific research conducted in the relevant direction. The practical significance of the research lies in the fact that the findings can be applied to the implementation of e-commerce in the healthcare sector. The results of the study are related to the assessment of the role of e-commerce in improving the quality of medical services and their more effective organization, as well as the adoption of more effective measures to intensify the development of the health sector. The originality and scientific novelty of the study lies in the identification of theoretical and methodological approaches to the role of e-commerce in the effective organization of medical services in a global digital transformation.

KEYWORDS: Medical E-Commerce, Personalized Healthcare, AI Recommendation System, Health Informatics, Online Pharmacy, Prescription Verification, Digital Health Records, Drug Interaction Detection, Healthcare Analytics, E-Health Systems, Patient-Centric Care, Smart Healthcare Platform

I. INTRODUCTION

Today's health care sector has become one of the largest and most dynamic industries in terms of job creation, innovation, and spending. Impressive advances have been made in improving the quality of public health, life expectancy, and universal convergence. However, there are always questions about the scarcity of resources and how to use them, how to improve the equity, efficiency, and effectiveness of health care services. E-commerce is a great solution for health care because it uses limited resources in the most efficient way that can support the health of the nation.

II. LITERATURE SURVAY

Within the realm of social recommendation systems, the digital economy has facilitated the integration of social connections and user-item interactions. This convergence is evident in the growing body of research that leverages social network data to enhance recommendation accuracy, reflecting the digital economy's emphasis on harnessing diverse data sources for improved user engagement and satisfaction (Mouzhi, Giovanni, and Fabio [Citation2023](#); Ren, Song, and Song [Citation2017](#)). The majority of early studies primarily focused on Matrix Factorization (MF) techniques, as MF possesses an excellent Gaussian prior probability basis, it can deftly make use of previous data. However, the MF approach is ineffective in modeling complex, non-linear interplay between interpersonal user relationships and their interactions with products (Shokeen and Rana [Citation2019](#)).

The expansion of social networks has led to the development of several recommendation systems that use social network structure to ease the cold start problem. These social network-based recommendation methods are inspired by social influence theories. Typically, these techniques evolve from standard matrix factorization models, blending social network details into the matrix of user-item ratings. Such as, Ma et al. ([Citation2008](#)) presented SoRec, a model that integrates social and rating data by utilizing a unified user latent feature matrix across both domains, and applies Probabilistic Matrix Factorization (PMF) (Salakhutdinov and Mnih [Citation2008](#)) to synthesize these elements into a cohesive framework. Jamali and Ester ([Citation2010](#)) proposed SocialMF, a recommendation technique that assimilates trust transfer into its matrix framework, constructing each user's vector from the vectors of their immediate social network friends. To mitigate the statistical bias shift issue, Tao et al. ([Citation2022](#)) have put forward GDSRec, a decentralized social recommendation system built on graph-based collaborative filtering, which captures the statistical



bias shift through decentralized neighborhood aggregation and defines the strength of social connections based on preference similarity.

Furthermore, the interactions among users and between items are equally significant and should not be disregarded. Fan et al. ([Citation2019](#)) introduced a social recommendation method powered by graph neural networks (GraphRec). By using a graph structure, this strategy encompasses user-item and user-user interaction data. Wu et al. ([Citation2019](#)) introduced DiffNet, a neural network designed to address social recommendations by diffusing influence. This model enhances the recommendation system's ability to capture user preferences by emulating the process of influence diffusion within social networks. Subsequently, they advanced this research by proposing an enhanced model, DiffNet++ (Wu et al. [Citation2020](#)). Building upon

DiffNet, DiffNet++ incorporates both user interests and social influence, creating a more intricate neural network that diffuses influence and interests, thereby improving the performance and precision of social recommendations. These two studies illustrate the evolution of neural network models in the domain of social recommendation and demonstrate how mimicking the complex interactions within social networks can refine recommendation outcomes. Wu et al. ([Citation2019](#)) introduced a model known as Dual Graph Attention Networks (DualGAT), which constructs a dual graph structure comprising users and items. By leveraging graph attention mechanisms to capture intricate social interactions and user preferences, the model elevates the effectiveness of recommendation engines and enhances the precision of individualized recommendations. Song et al. ([Citation2019](#)) employed dynamic graph attention networks to capture real-time dynamic user behaviors and their social connections within recommendation sessions (DGREC), enhancing the recommendation system's ability to grasp immediate user needs and social contexts. Lin, Chen, and Wang ([Citation2022](#)) introduced a graph neural network model that integrates dynamic and static representations for social recommendation systems.

This research constructs a framework capable of capturing complex interactions and user preferences within social networks by merging users' static attributes and dynamic behaviors. Wang et al. ([Citation2023](#)) introduced a novel social recommendation model, DUI-SoRec, which extends graph neural networks to address social inconsistency and over-smoothing issues within the context of user-item and social graphs. Zhou et al. ([Citation2023](#)) investigated the potential of multi-graph neural networks for social recommendations, looking into the synergy between diverse social graphs and user-item interactions to boost algorithmic effectiveness. In summary, the core idea behind these efforts is to represent interactions between users and items as a basic graph structure with direct links, then apply multiple layers of graph neural networks to identify node interdependencies.

Recent studies have explored various enhancements to social recommendation systems, leveraging graph-based methods to address key challenges such as data sparsity and social influence modeling. For instance, Yang et al. ([Citation2024](#)) proposed a Graph Bottlenecked Social Recommendation model that focuses on identifying critical social connections that significantly impact recommendation accuracy.

This approach highlights the importance of graph structure in capturing influential social interactions, which aligns with our use of graph attention mechanisms to uncover hidden social correlations. Li and Yang ([Citation2024](#)) introduced GSIRec, which incorporates graph side information to enrich user and item representations. Their work emphasizes the role of auxiliary graph data in improving recommendation performance, a concept that resonates with our integration of social graphs to enhance user embeddings. By leveraging both user-item and user-user interactions, our model aims to provide a more comprehensive view of user preferences and social influences. Gulati and Eirinaki ([Citation2018](#)) focused on influence propagation in social graphs, proposing a method to model how social influence spreads through a network. This study underscores the dynamic nature of social interactions, which our model captures through dynamic graph attention mechanisms. By modeling real-time social influences, our approach can better adapt to changing user preferences and social contexts. Hu et al. ([Citation2024](#)) proposed a Hierarchical Denoising method for robust social recommendation, addressing the issue of noise in social data. Their work highlights the need for robustness in social recommendation systems, which our model achieves through graph contrastive learning. By comparing different samples and mitigating exposure bias, our model enhances recommendation accuracy and reliability.



III. THEORETICAL BACKGROUND

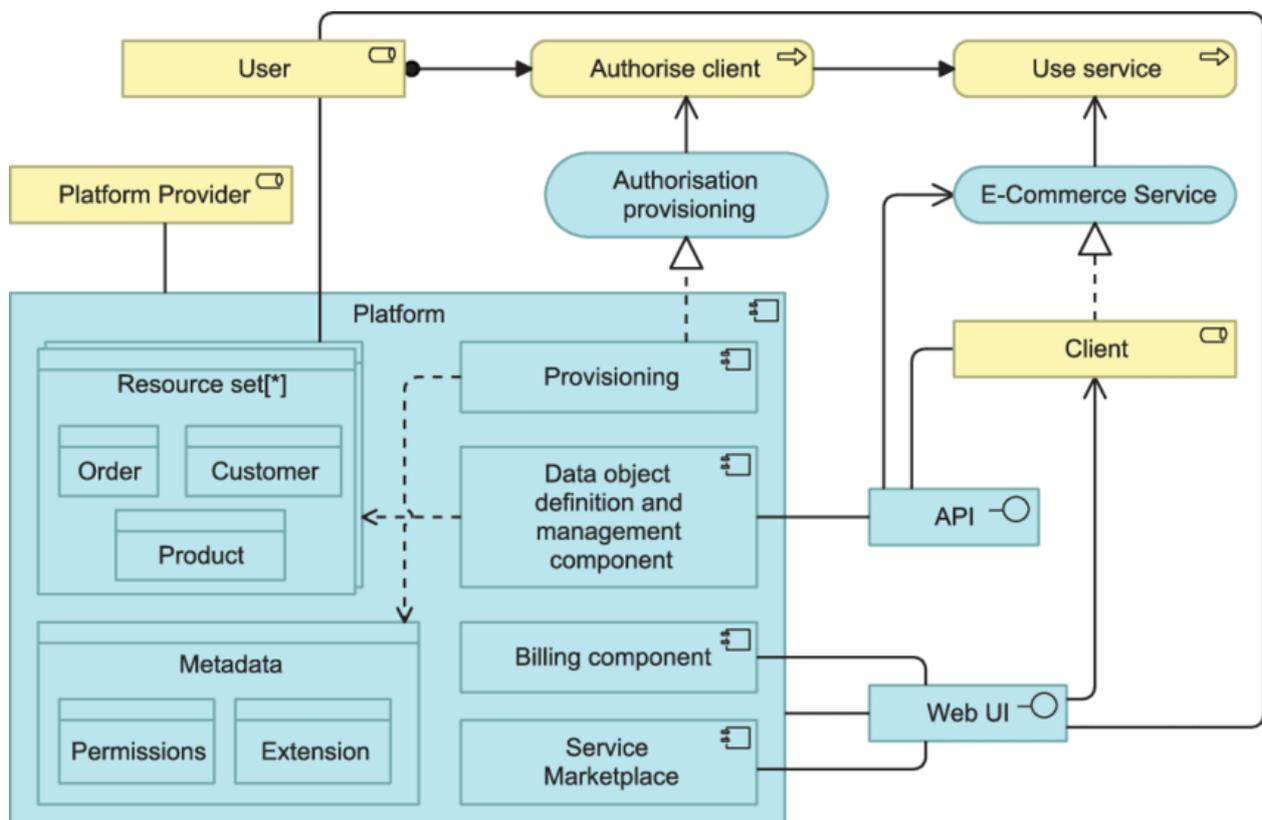
3.1 PROBLEM IDENTIFICATION

• In the existing scenario, most medical e-commerce platforms function as general shopping websites without personal health customization. Users manually search for products without guidance or medical validation. Prescription-based medicines require complicated upload processes, and often there is no real-time verification. Many platforms fail to warn users about allergies, drug interactions, or unsafe products. Furthermore, customers receive generic recommendations, not tailored to their medical profile. This lack of personalization, safety checks, and medical consultation leads to confusion, usage errors, and potential health risks.

3.2 PROBLEM SOLVING

• The proposed **Personalized Medical E-Commerce Platform** provides medically-safe product shopping using personalized recommendations based on user health profiles. Users fill in details such as allergies, diseases, age, and ongoing treatments. The AI recommendation engine suggests products suitable for their unique health needs while filtering out unsafe items. Prescription medicines require doctor/pharmacist approval through the system. Real-time alerts warn users about potential side effects or drug interactions. The system ensures secure transactions, digital health records, order tracking, and subscription-based medicine refills. This personalized approach enhances trust, safety, and convenience for medical product buyers.

3.3 SYSTEM ARCHITECTURE



IV. SYSTEM IMPLEMENTATION

4.1. MODULE:

1. User Authentication Module
2. Health Profile Management Module
3. Product Catalog & Search Module
4. Personalized Recommendation Engine
5. Prescription Upload & Verification Module



6. Shopping Cart & Order Module
7. Payment Module
8. Admin/Pharmacist Module

4.2 MODULE DESCRIPTION:

1. User Authentication Module

Handles registration, login, wallet creation, and secure access with multi-factor authentication.

2. KYC & Identity Verification Module

Ensures legal compliance by verifying user identity through documents and global KYC APIs.

3. Smart Contract Payment Module

Executes automated payments when conditions are met:

- Transfers funds
- Validates sender balance
- Locks/release payments

4. Currency Conversion & Oracle Module

Fetches real-time exchange rates using decentralized oracles (e.g., Chainlink) to ensure accurate conversions.

5. Transaction Initiation Module

User enters recipient details, amount, and currency; the system creates a smart contract instance to handle the payment.

6. Blockchain Ledger Module

Stores transaction details immutably on the blockchain for transparency and auditing.

7. Notification & Status Tracking Module

Provides real-time updates, confirmations, and failure alerts to users.

8. Admin & Compliance Module

Manages user KYC, monitors transactions, and ensures compliance with international regulations.

V. CONCLUSION

5.1 CONCLUSION

The **Personalized Medical E-Commerce Platform** revolutionizes online medical shopping by offering customized product suggestions based on individual health needs. The platform ensures safe purchasing through medical profiling, prescription validation, and AI-based recommendations. It simplifies user experience, improves safety, and enhances medical accessibility. This system is ideal for pharmacies, hospitals, and healthcare e-commerce businesses aiming to offer personalized healthcare solutions.

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