HINCare: An Intelligent Helper Recommender System for Elderly Care

Carrie Wang
The University of Hong Kong
carrie07@connect.hku.hk

Wentao Ning
The University of Hong Kong
nwt9981@connect.hku.hk

Xiaoman Wu
The University of Hong Kong
wxman@hku.hk

Reynold Cheng
The University of Hong Kong
ckcheng@cs.hku.hk

ABSTRACT

In Hong Kong, the number of elderly citizens will reach one-third of the population within the next decade. To mitigate this problem, *timebanking* has received attention in recent years. In timebanking, an NGO helper earns time credits through providing voluntary services (e.g., household duties) to elders. These time credits can be used to acquire other services.

Although timebanking has shown the promise of promoting mutual care in many countries, its potential has not been fully utilized, due to the lack of IT and data support. We thus develop HINCare, a software platform that supports timebanking for multiple NGOs. Besides providing convenience to NGO supervisors, helpers, and elders, HINCare makes use of a *heterogeneous information network* (HIN) for recommending suitable helpers to elders. This is the first time a graph-based recommender system is used for such purposes. Currently, HINCare is used by 12 NGOs to serve more than 5000 users in Hong Kong. In this demonstration, participants can play the role of helpers and elders in the HINCare environment.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Elderly Care, Recommender Systems, Heterogeneous Information Network

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1 INTRODUCTION

An aging population is causing a demographic change in Hong Kong, a problem shared by many advanced economies. The percentage of elderly citizens is rapidly increasing due to rising life expectancy and falling birth rates [1]. To address this issue, timebanking was proposed as a low-cost volunteering model in social care delivery [3, 5]. It monetizes time spent in volunteer activities by issuing time credits to encourage active mutual help among elders [3]. These earned time credits can be exchanged for another person's time, services, or tangible rewards provided by NGOs, or saved for future use. By bridging the gap between service providers and recipients, timebanking promotes resource-efficient and social capital-maximizing assistance among elderly citizens.

However, traditional timebanking relies on a culture of paternalism, where manual management and monitoring of volunteer activities by brokers is inevitable. This results in three key obstacles to sustainable timebanking operations: (i) the absence of personalized helper recommendations for elders, (ii) limited active

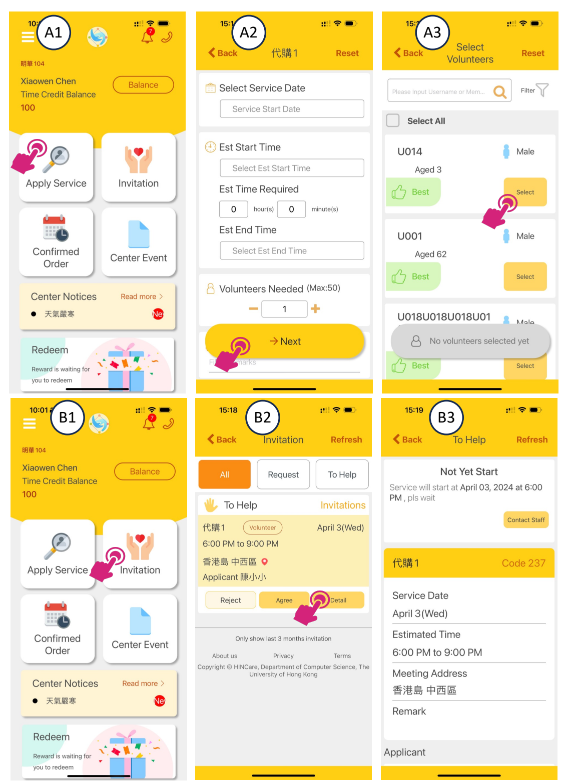

Figure 1: (A) Making and (B) accepting requests in mutual help among the elderly via HIN-based recommendation.

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participation among timebanking members, and (iii) challenges in scalability to operate across organizations [5].

In this demonstration, we introduce HINCare, an innovative timebanking application using recommendation engines to foster mutual help among the elderly while overcoming existing limitations. The system has three key designs to enhance its functionality.

- Firstly, we innovatively apply heterogeneous information networks (HINs) and recommendation algorithms to elderly care. HINs have shown effectiveness in recommendation [4, 6] so that we use them to represent user information and service histories. This network replaces the traditional manual matching process performed by brokers [2], enabling personalized and accurate helper recommendations.
- Secondly, HINCare provides a digital platform for registered users to request and provide different services, as shown in Figure 1, in the timebanking framework. This platform fosters effective mutual help and active engagement.
- Lastly, HINCare offers a customized back-end management system for multiple NGOs. It facilitates efficient management of community-based care service delivery, ensuring smooth operations and high-quality care.

In the demonstration, all participants will have the opportunity to role-play as either an elderly person or a volunteer. They will engage in mutual help by submitting service requests and accepting requests from others. Additionally, participants can exchange earned time credits for rewards and participate in group activities.

The paper is structured as follows. We introduce the background and the detailed HINCare recommendation engine in Section 2. Section 3 describes and presents two key functionalities of HINCare : (i) mutual help among the elderly via HIN-based recommendation and (ii) time credit exchange.

2 SYSTEM OVERVIEW

2.1 Helper Recommendation

In elderly care facilitated by timebanking, each elderly can act as a service provider or a service recipient. When an elderly requests help, an important task is to match the request with a suitable helper. Rather than displaying all users indiscriminately for selection, presenting a ranked list of users based on their matching score with the request is more time-saving and user-friendly. The prioritization ensures that the most matched candidates are highlighted, enhancing the user experience. The process of helper recommendations shares similarities with those in other domains, such as e-commerce, entertainment, and social media platforms. While those platforms recommend products, movies, or friends to enhance user experiences, increase engagement, and drive business outcomes, our platform recommends helpers for each service request to promote consistent and effective mutual help among the elderly.

What makes us novel is the application of recommendation systems [7, 8] tailored for elderly care in the timebanking framework. Matching helpers with the diverse and often nuanced needs of elderly individuals presents two unique challenges. First, elderly individuals often require specialized support according to their unique circumstances, such as medical conditions, mobility limitations, or cultural preferences. Aligning the skills and capabilities of the helpers with these specific requirements is essential to enhance

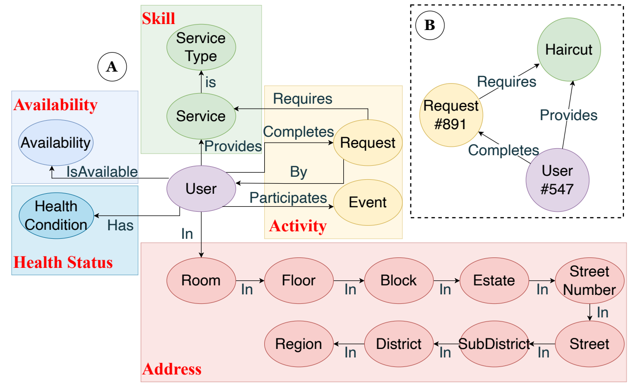

Figure 2: HIN Schema and Example

the quality of care and the satisfaction of service recipients. Secondly, matching helpers who are geographically close and available during the service time is crucial to ensure reliable and timely service delivery. Therefore, a robust recommendation engine is needed to accurately assess and match helpers to service requests.

2.2 HIN Construction

Heterogeneous Information Networks (HINs), are structured representations of knowledge, where entities are represented as nodes and edges are relations between entities. To model complex relationships among objects, HINs consist of multiple types of nodes and edges. Examples of HINs include bibliography and social networks.

We have identified that HINs are highly advantageous for recommending helpers in elderly care for two reasons. Firstly, mutual help among the elderly involves heterogeneous data, including elderly individuals, health conditions, services, and address information. By consolidating them into a unified HIN, we gain a comprehensive understanding of the mutual help operations. Secondly, elderly care is inherently multidimensional, involving complex relationships between different entities. HINs adeptly capture both direct and indirect associations among entities. Using the rich semantic information encoded in HINs, we can develop efficient recommendation systems for matching elderly individuals with appropriate helpers.

HINs also benefit elderly care in two aspects. Firstly, the scarcity of historical request records often poses challenges in making accurate recommendations. HINs effectively address this issue by capturing explicit preferences derived from historical request records and implicit preferences inferred from entity-entity interactions. This holistic approach ensures that elderly individuals receive personalized recommendations despite limited initial data. Secondly, given the vulnerability of many elderly individuals, ensuring the quality and professionalism of services is essential. Besides recommendation engines, a straightforward reasoning process is helpful for organizational staff to verify the suitability of recommendations. HINs facilitate this reasoning process by providing access to relevant nodes and paths in the structured graph-based representation.

HIN Construction. We construct our HIN based on past service records and information about the elderly, following the schema outlined in Figure 2(A). The HIN incorporates five factors, represented by different colored rectangles, to enable precise matching between elderly individuals and helpers, including skills, availability, health status, address, and activity. Each node corresponds to a specific attribute relevant to the matching process. For example, users' skill sets are important in determining their suitability to address a request. Additionally, address nodes, ranging from the most fine-grained 'Room' to the coarsest 'Region', enable effective assessment of proximity between users.

The HIN comprises 16 types of nodes and 16 types of edges. For instance, each user node maintains two relationships with a request node: a user completes a request (user-completes-request), and a request is made by a user (request-by-user). An illustrative example is shown in Figure 2(B). The triple *(user#547)-[provides]-(haircut)* indicates that user#547 has the service skill of haircut. *(user#547)-[completes]-(request#891)* and *(request#891)-[requires]->(haircut)* signify user#547 has fulfilled request#891, which requires a haircut.

2.3 HIN-Based Recommendation

The central component of HINCare is the recommendation engine. When an elderly person submits a request through the application, we use a scoring function (will be described later) to calculate a score between that user and all other users. Subsequently, we rank all other users based on their scores and recommend those with the highest scores to the service requester. After selecting a helper from the recommendation list, an invitation is sent out. Here, the scoring function is designed as follows:

$$score(u, v) = \boldsymbol{u} \cdot \boldsymbol{v} + \beta \cdot s_{u,v}, \tag{1}$$

where u and v are two users, while $\boldsymbol{u}$ and $\boldsymbol{v}$ denote the embeddings of u and v, respectively. The distance score, $s_{u,v}$, denotes the geographical distance between u and v, while β is a hyper-parameter that controls the weight of $s_{u,v}$.

First, to ensure that the helpers we recommend align with the preferences of elderly individuals, we follow the common recommendation algorithms and utilize historical service records and HIN to learn the user embeddings. Specifically, we generate embeddings for each user using TransE [2], a model that captures entity relationships within a HIN. In TransE, if a triplet (h, l, t) holds, the embedding of the entity t should be close to the summation of the embeddings of h and l. Following this principle, we learn embeddings for all entities and relationships in the HIN by minimizing the discrepancy between observed triplets. This is achieved through training the embeddings using the following loss function.

$$\mathcal{L} = \sum_{(h,\ell,t)} \sum_{(h',\ell,t')} \left[\gamma + d(\boldsymbol{h} + \boldsymbol{\ell}, \boldsymbol{t}) - d\left(\boldsymbol{h}' + \boldsymbol{\ell}, \boldsymbol{t}'\right)\right]_+, \tag{2}$$

where $[x]_+$ is the positive part of x, (h, ℓ, t) are existing triplets in the HIN and (h', ℓ, t') are sampled non-existing triplets in the HIN. $\boldsymbol{h}, \boldsymbol{\ell}, \boldsymbol{t}, \boldsymbol{h}', \boldsymbol{t}'$ are the embeddings of h, ℓ, t, h', t', respectively. $\gamma > 0$ is a margin hyper-parameter, $d(\cdot, \cdot)$ is the Euclidean distance function.

The scoring function also addresses the second challenge of helper recommendation. Since user distance is a key factor to decide if a user is willing to provide service, we introduce a distance score $s_{u,v}$. To achieve this, we categorize user distance into several levels (from far to near), with each level corresponding to a specific distance score. The closer the distance, the higher the score. This allows us to find nearby users for the service requester, thereby increasing the probability that the helper will accept the request. Also, we introduce a tunable hyper-parameter β to control its weight.

Table 1: HR@k scores on our HIN datasets with $k = 10$.

Data	BPR	Top-Pop	TransE	TransH
SKH-TKO	0.8143	0.8696	**0.9530**	0.9481
CFSC	0.8668	0.9606	0.9764	**0.9795**

Table 2: Size of dataset

Data	# User	# Requests	# nodes	# edges
SKH-TKO	278	855	14077	27162
CFSC	679	3089	6540	13466

We compare TransE with three recommendation algorithms—BPR, Top-Pop, and TransH—using data from two NGOs: SKH-TKO and CFSC. The summary statistics of two datasets are shown in Table 2. BPR [9] is a matrix factorization method trained by Bayesian Personalized Ranking (BPR). Top-Pop is a non-personalized approach that recommends the helper who have provided the most help in the past to all service requests. TransH [10], based on TransE, considers the complex mapping properties of relations. We evaluate their performance using the Hit Ratio (HR@k), a ranking metric commonly used in recommender systems. Table 1 shows that TransE and TransH use our HINs effectively and outperform other non-HIN-based methods. Because TransE is simpler to implement, we adopt it in the HINCare system.

3 DEMONSTRATION SCENARIOS

Since HINCare's launch in January 2020 in Hong Kong, it has won many awards [1], and been showcased in many exhibitions, as shown in Figure 3. Currently, it is used by 12 local NGOs with over 5000 users. To facilitate NGOs' management of elderly care service delivery, HINCare provides customized back-end management systems. Each organization operates in a separate user ecosystem. For instance, an elderly individual registered with an organization can only request help from users in the same organization. This separation of user ecosystems allows organizations to uphold administrative and privacy control and cultivate community bonding.

As a practical and operational system, HINCare offers a wide range of functionalities and designs tailored specifically for the elderly. For example, to accommodate vision impairments, the platform uses a large font size. Additionally, recognizing that some elderly individuals may not be proficient with smartphones, the platform features convenient "Call Institution" buttons on key pages.

This paper focuses on demonstrating two key functionalities of HINCare . Firstly, we present how the platform employs HIN-based recommendation techniques to facilitate mutual help among elderly individuals, as shown in Figure 1. Secondly, with Figure 4, we show how users can earn and spend time credits on the platform.

3.1 Mutual help among the elderly

Within the timebanking framework, registered users can exchange their services for time credits. Hence, users are encouraged to engage in mutual help actively. Any user can request a service or respond to service requests. The upper left screenshots in Figure 1

[1] Asia Smart App Awards 2020/2021 and Hong Kong ICT Awards 2021/2023

Figure 3: HINCare Exhibition in HKU

show three key steps for requesting a service. At first, a user can click the 'Apply Service' button on the homepage (A1) and proceed to fill in the necessary information (A2), such as the desired time, required services, and address. We simplify the information required to facilitate easier posting of requests for elderly users who may be less familiar with smartphones. In order to enhance smartphone accessibility, we collaborate with NGOs to provide offline application training sessions. Once the user submits the request details, our HIN-based recommendation engine generates a list of qualified helpers (A3) from all other users. The helpers are ranked according to their matching score with the service requester. Finally, the user can send a service request invitation to the chosen helper.

On the other hand, users can conveniently access and manage all request invitations they send or receive from the homepage (B1). Upon receiving an invitation, users can view its details (B3) and choose to either accept or decline it (B2).

3.2 Time credit exchange

To encourage reciprocity and community engagement through time credits, we prominently display the time credit balance at the top of the homepage, as shown in the green box of C1 in Figure 4. Time credits are spent when users request services from others and banked when they help others. To further incentivize active engagement, surplus time credits can be redeemed for prizes. By clicking the 'Redeem' button (C1), all available prizes published by the organization is displayed (C2). The time credit balance is clearly displayed at the top, while the specific time credit required for each prize is indicated next to it. This setup enables users to quickly assess their capability to redeem a prize. Clicking on a prize allows users to view its details and proceed with the exchange(C3).

Another way to stimulate active engagement using time credit is through group activities organized by NGOs. Users can access the available group activities by clicking 'Center Event' button from the homepage (D1). Group activities are categorized into credit-earning and credit-deducting ones (D2). Participating in a credit-earning activity increases the user's time credit upon completion (D3), and vise versa. Usually, NGOs determine the categorization of group activities based on its popularity or nature. In this way, they manage the allocation of time credits and the event participation to effectively foster stronger community connections.

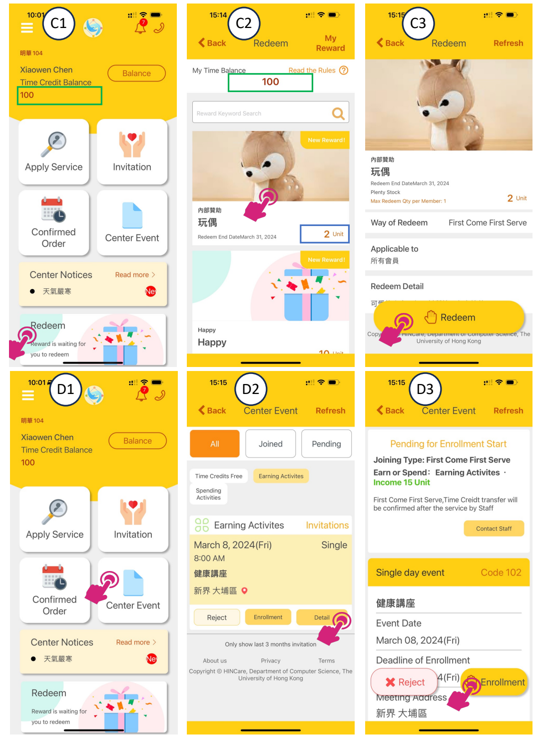

Figure 4: Illustrating user engagement in (C) prize redemption and (D) group activities during time credit exchange.

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REFERENCES

[1] Census and statistics department. https://www.censtatd.gov.hk/en/.
[2] A. Bordes, N. Usunier, A. García-Durán, J. Weston, and O. Yakhnenko. Translating embeddings for modeling multi-relational data. In *NeurIPS*, 2013.
[3] E. S. Cahn. *No more throw-away people: The co-production imperative.* Edgar Cahn, 2000.
[4] Q. Guo, F. Zhuang, C. Qin, H. Zhu, X. Xie, H. Xiong, and Q. He. A survey on knowledge graph-based recommender systems. *TKDE*, 34(8):3549–3568, 2020.
[5] R. Naughton-Doe, A. Cameron, and J. Carpenter. Timebanking and the co-production of preventive social care with adults; what can we learn from the challenges of implementing person-to-person timebanks in england? *Health & Social Care in the Community*, 29(5):1285–1295, 2021.
[6] W. Ning, R. Cheng, J. Shen, N. A. H. Haldar, B. Kao, X. Yan, N. Huo, W. K. Lam, T. Li, and B. Tang. Automatic meta-path discovery for effective graph-based recommendation. In *CIKM*, 2022.
[7] W. Ning, R. Cheng, X. Yan, B. Kao, N. Huo, N. A. H. Haldar, and B. Tang. Debiasing recommendation with popular popularity. In *WWW*, 2024.
[8] W. Ning, X. Yan, W. Liu, R. Cheng, R. Zhang, and B. Tang. Multi-domain recommendation with embedding disentangling and domain alignment. In *CIKM*, 2023.
[9] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *UAI*, 2009.
[10] Z. Wang, J. Zhang, J. Feng, and Z. Chen. Knowledge graph embedding by translating on hyperplanes. In *AAAI*, 2014.