Bringing Friends into the Loop of Recommender Systems: An Exploratory Study

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The recommender system (RS), as a computer-supported information filtering system, is ubiquitous and influences what we eat, watch, or even like. In online RS, interactions between users and the system form a feedback loop: users take actions based on the recommendations provided by RS, and RS updates its recommendations accordingly. As such interactions increase, the issue of recommendation homogeneity intensifies, which significantly impairs user experience. In the face of this long-standing issue, the newly-emerging social e-commerce offers a new solution – bringing friends' recommendations into the loop (friend-in-the-loop). In this paper, we conduct an exploratory study on the benefits of friend-in-the-loop through mixed methods on a leading social e-commerce platform in China, Beidian. We reveal that friend-in-the-loop provides users with more accurate and diverse recommendations than merely RS, and significantly alleviates algorithmic homogeneity. Moreover, our qualitative results demonstrate that the introduction of friends' external knowledge, consumers' trust, and empathy accounts for these benefits. Overall, we elaborate that friend-in-the-loop comprehensively benefits both users and RS, and it is a promising HCI-based solution to recommendation homogeneity, which offers insightful implications on designing future human-algorithm collaboration models.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Empirical studies in HCI**.

Additional Key Words and Phrases: friend in the loop; personalized recommender system; friends' recommendations; social e-commerce; human-in-the-loop

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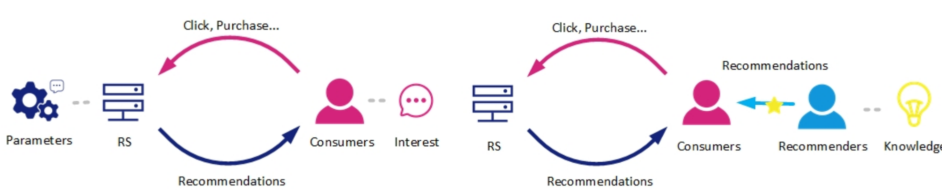
1 INTRODUCTION

In the era of information explosion, the recommender system (RS) is an advanced computer-supported information filtering system that supports people in making decisions [52, 66], which has been widely adopted by various online platforms, such as e-commerce [40], social media [22] and streaming media [68]. On these online platforms, interactions between RS and consumers form a feedback loop: as shown in Figure 1, RS provides recommendation service to consumers, and then consumers respond via actions such as clicks and purchases. Based on consumers' early responses, RS makes further recommendations. As such, RS gradually deepens the understanding of its consumers, and provides more personalized recommendations [72]. However, such feedback also leads to many unexpected consequences. One of the most severe consequences is that it might homogenize recommendations and consumers' behaviors [6]. Recommendation homogeneity, also recognized as "filter bubble" or "echo chambers", is widely detrimental to user experience [17, 69], and even intensifies many social issues, such as political polarization [3, 15], and unfairness for minorities [51, 58]. To address recommendation homogeneity, many algorithms, e.g., post-processing, determinantal point process, and learning to rank [69], trade a small portion of accuracy for diversity.



(a) Feedback loop on conventional e-commerce (b) Feedback loop on social e-commerce

Fig. 1. Comparison of the two feedback loops on e-commerce platforms. The main characteristic that distinguishes social e-commerce is bringing friends' recommendations into the feedback loop.

The recently emerging social e-commerce offers a novel human-computer-interaction (HCI) based approach to addressing recommendation homogeneity. In the past decade, social e-commerce platforms, e.g., Pinduoduo in China, Facebook Shop in America, and Meesho in India, spring up and have achieved great success. These social e-commerce platforms introduce friends as new recommendation providers to the conventional feedback loop: as shown in Figure 1(b), compared with conventional e-commerce, social e-commerce rewards users to recommend items to their friends. For simplicity, we refer to those who make recommendations as "friend recommenders". As such, consumers no longer depend merely on the items filtered by RS, but they can also get access to new items recommended by their friends, which makes it possible to break the homogeneous loop. In this paper, we aim to investigate the benefits of bringing friends' recommendations into the loop (friend-in-the-loop) on both users and RS. Specifically, our key research questions are: in what aspects friend recommenders can complement RS, whether friend-in-the-loop can address recommendation homogeneity of RS, and if friend-in-the-loop is effective, what is the reason behind it.

To answer these questions, we carry out an exploratory study through mixed methods, combining a large-scale data-driven quantitative study and qualitative studies including interviews and a forum analysis. Specifically, we conduct our quantitative study on a three-month full-scale dataset collected from Beidian, where both RS and friend recommenders can serve as recommendation providers. First, to understand in what aspects friends' recommendations can complement RS, we compare their recommendation quality from three aspects: the capabilities of matching consumers' preferences (suitability), feeding consumers' broad spectrum interests (diversity), and presenting novel and unique items (novelty). Then, we investigate the benefits of friend-in-the-loop on RS, with a special focus on whether and how it can address recommendation homogeneity. Furthermore, to explain our findings, we interview 14 Beidian users, along with analyzing the top 30 posts in the selling experience sharing section in Beidian Business Forum to enrich our materials with successful experience.

Our results show that RS and friend recommenders each have their own merits: RS can expose consumers to more novel and unique items, while friend recommenders can recommend a diversity of items and these items match consumers' preferences better. In this way, the friend-in-the-loop solution introduces such friends' recommendations to the feedback loop, effectively saving consumers' efforts on item exploration and satisfying consumers' diverse needs. Moreover, we demonstrate that friend-in-the-loop can significantly alleviate the homogeneity issue of RS, which enhances the algorithmic performance. Finally, we explain that the introduction of friends recommenders' external knowledge, consumers' trust, and empathy accounts for the benefits of friend-in-the-loop.

Our exploratory study reveals the benefits of friend-in-the-loop on both consumers and RS, offering insights on how to incorporate complex human factors into RS. More importantly, our findings indicate that with the support of advanced deep learning techniques and user interfaces, we can make better use of the power of RS and friend recommender cooperation, which provides a promising paradigm of human-algorithm-collaboration.

To conclude, the contributions of this work can be summarized as follows:

- Through a large-scale quantitative study, we uncover that the two recommendation providers – RS and friend recommenders each have their own merits in three aspects: suitability, diversity, and novelty, enabling the two providers to complement each other. This complementary form of friend-in-the-loop can satisfy consumers' diverse needs and save their efforts of item exploration.
- We elaborate that friend-in-the-loop can significantly alleviate the issue of recommendation homogeneity, which offers a human-computer interaction (HCI) based solution to this long-standing issue in the field of RS.
- We discover that friend-in-the loop can leverage external knowledge, trust, and empathy to benefit both consumers and RS. However, the current form of friend-in-the-loop lacks close cooperation between RS and friend recommenders. Our findings indicate there is unexplored power lying in between them, and thus we suggest that it is necessary to facilitate their cooperation with advanced machine learning techniques and user interface designs.

2 RELATED WORK

2.1 Two Recommendation Providers: Machine or Human

As a computer-supported information filter system, RS can automatically generate recommendations from an overwhelmingly large set of alternatives [31, 34] with the assistance of various information [10, 57] and advanced techniques [74, 78]. Despite the great success of RS, human is still a universal and irreplaceable provider of recommendations. Whether deciding what book to read, what movies to watch, or even whom to date, we rely on recommendations from other people [31]. Two important lines of studies that closely relate to our work are comparing RS with human recommendations, and incorporating human factors into RS.

Comparison between RS and human recommendations.

The comparison between RS and human recommendations has been consistently discussed. Krishan et al. [31] make a comparison between MovieLens' Collaborative Filtering (CF) algorithm and recommendations made by active MovieLens users. They discover CF outperforms humans on average, though some individuals outperform RS substantially. Kunkel et al. [34] also conduct an experiment in terms of a movie recommendation task. They find human recommendations can provide explanations of good quality and enhance users' trust. Yeomas et al. [73] compare RS and human recommendations in a task that offers human many advantages: predicting which jokes people will find funny. Through the experiments, they find RS outperforms humans in terms of accuracy. However, such high accuracy does not guarantee satisfaction. They argue RS must be interpretable, given people's aversion to "black box". However, these experimental settings significantly deviate from real-world scenarios in terms of whether RS or human recommendations. Specifically, from the perspective of RS, they only reproduce prototype RS, such as CF [31, 71, 73] and Matrix Factorization [34], which is much simpler than the applied RS on both the input information and techniques [68]. Moreover, in the real world, human make recommendations through face-to-face conversations or instant massaging platforms [9]. These deviations might potentially impair the authenticity and practicality of their findings. Complimenting these works, we conduct a large-scale exploratory study in a real-world setting and identify the differences between the two recommendation providers.

Incorporating human factors into RS.

Given that human outperform RS in various aspects [34, 73], another line of researchers attempt to incorporate human factors into RS. The well-known CF paradigm is deeply rooted in Social Choice Theory, which utilizes the similarity of preferences between users to make recommendations [23, 47, 77]. Furthermore, based on the social homophily assumption where users who have social relations are more likely to have similar interests, social relations are leveraged to improve the performances of RS [43, 52, 65, 66]. Here, social relations can be collected from external social media, e.g., Twitter, or from social components embedded in their own applications [20, 37, 65]. The latter method allows friends communicating conveniently within the application, which not only simplifies the process of collecting social relations but also enhances users' commitment and attachment [37]. Besides, many advanced techniques are adopted to make the best of social relations, thereby improve the effectiveness of recommendations, such as performing a co-factorization in the user-item matrix and the user-user social relation matrix [38, 64], using social relations for regularization [26, 39, 63], and leveraging emerging deep learning methods to model social recommendations [16, 18, 36]. Other than exploiting the similarity between socially-connected users, another branch of work strives to increase trustworthiness and interpretability by equipping RS with textual explanatory components, e.g., Amazon customer reviews [7, 34], though recent studies question the effectiveness of simple explanatory techniques and models [7, 49]. Therefore, it remains an open question how to incorporate more complex human factors, e.g., explanations, into RS, and make them productively collaborate [21]. Notably, in this paper, we delve into a successful case – Beidian, which involves the collaboration of RS and friends' recommendations. Through comparison studies on the two recommendation providers, we seek to answer the first research question:

***Research Question 1 (RQ1)**: In what aspects can friend recommenders complement RS?*

2.2 Understanding Recommendation Homogeneity from the Perspective of the Feedback Loop

Recommendation homogeneity has gained increasing attention for its significant impact on both user experience and social issues [3, 12, 15, 46]. It is widely acknowledged that diversity is one of the most important objectives of recommendation providers [79], which reflects the capability to cover users' diverse needs [27].

Traditional item diversification algorithms.

To feed users' diverse needs, Ziegler et al. [81] first introduce diversification to the field of RS and design a method for balancing and diversifying personalized recommendation lists. Sha et al. [56] propose a general framework to balance relevance, diversity, and the coverage of user interests explicitly by two hyper-parameters. Cheng et al. [11] propose a learning-based diversified collaborative filtering algorithm. Recently, the determinantal point process method enjoys great popularity for its superior performance, and many algorithms are proposed based on it [8, 68]. To sum up, partly because of the limitations of offline training and evaluations, these methods are stuck in making a trade-off between accuracy and diversity [35, 67]. However, in real-world online RS, the effects of user-algorithm interactions on recommendation homogeneity are indispensable, which are overlooked in some offline cases [2].

Understanding online RS in the feedback loop.

To model the online scenarios, some work views user-RS interactions as a form of feedback loop (see Figure 1(a)): RS provides recommendations to users, and users respond to the recommendations through different feedbacks, for example, likes or dislikes on social media; click, add cart, purchase or ignore on e-commerce. Then, RS learns from users' responses and provides the next recommendation [6, 41, 59, 62]. Chaney et al. [6] discover that this feedback loop results in homogenizing user behaviors, thereby decreases the utility gained by users, and presents a simulation to demonstrate how this effect occurs. Sun et al. [61] find that the feedback loop also introduces biases affecting the exposure of items, which leads to the unfairness of items. Through controlled experiments on three forms of iterated bias models (filter, active learning, and random), they further prove filter biases are prominent in personalized user interfaces, which might potentially polarize user preferences [62]. Recent work also utilizes causal inference techniques to decouple the interdependence between users and RS in the feedback loop [55, 59].

In line with these works, we seek to understand and address the issue of recommendation homogeneity from the perspective of the feedback loop. Furthermore, we extend prior work by assigning users a new role – recommenders. As such, RS is not the only recommendation provider, but users' friends, colleagues or family members join the feedback loop informing users to make purchase decisions, which we name as "friend-in-the-loop". We thus expect this form of friend-in-the-loop might offer a new solution to the issue of recommendation homogeneity, which leads us to the second research question:

Research Question 2 (RQ2)*: Can friend-in-the-loop address the issue of recommendation homogeneity?*

After investigating whether and how friend-in-the-loop benefits consumers and RS, we aim to explain the reasons behind it, by answering the following research question:

Research Question 3 (RQ3)*: If friend-in-the-loop is beneficial, what factors can account for it?*

3 BACKGROUND AND METHODS

3.1 Social E-commerce and Recommendation Service on Social E-commerce

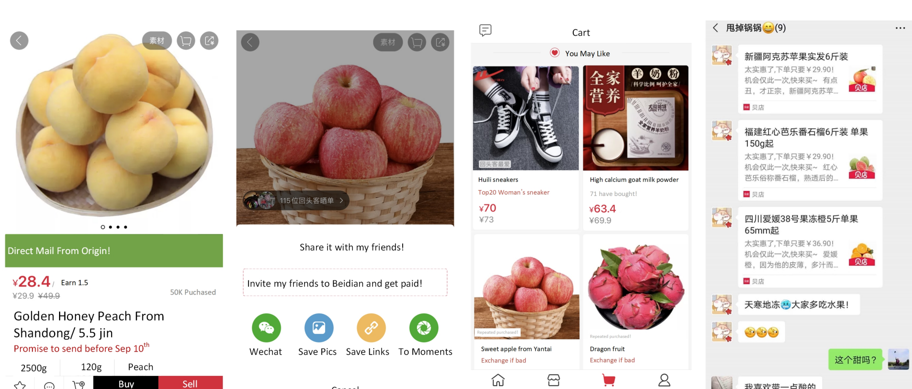
Recently, social e-commerce has been gaining attention from both academics and industries. Social e-commerce is a newly-emerging form of e-commerce that leverages users' social networks to promote the sales of items [48, 70] and manage customers [5, 75], where social relations include friends, colleagues, and family members. One important feature of social e-commerce is the utilization of the word-of-mouth strategy [5, 37, 70], which has been proved to be a key factor in the success of social e-commerce [70]. This feature offers us an opportunity to explore how RS and friends' recommendations are different, how they can complement each other, and how they can collaborate productively in the recommendation task.

3.2 Recommendation Service on Beidian

In this paper, we carry out our study on Beidian, one of the leading social e-commerce platforms in China. Beidian is built on top of Wechat and leverages users' existing social relations for marketing [4, 5, 48]. Different from conventional e-commerce, users on Beidian have two different roles on Beidian: recommenders and consumers. Recommenders select certain products and make recommendations to their friends via WeChat. Consumers can receive recommendations from both personalized RS on Beidian and friends who have become recommenders. To motivate users to transform from merely passive consumers to recommenders, Beidian provides recommenders with some monetary incentives if their recommendations successfully help consumers shop on Beidian. Besides, Beidian also offers social supports to recommenders by operating the Beidian Business Forum, where recommenders can communicate with each other and share their experience in the form of a post. Note that after becoming a recommender, the user can still get recommendation service and place an order as consumers do.

Indeed, it is worth mentioning that many other top social e-commerce platforms, such as Yunjiweidian[1], Miyuan[2], have a similar setting of "recommenders", indicating our study on Beidian can generalize to other social e-commerce platforms of this kind. This setting naturally allows us

[1]http://www.yunjiglobal.com/
[2]http://www.ppgps.cn/



(a) Page of Product Details (b) Page of Friends' Recommendations (c) Item Presentation of RS (d) Item Presentation of Friends' Recommendations (WeChat)

Fig. 2. Illustration of user interfaces on Beidian

to conduct a comparative study on scenarios of friend-in-the loop and merely RS, and further to answer our key research questions by investigating whether and how friend-in-the-loop can benefit the overall system. In this paper, we lay special focus on the two recommendation providers – RS and friend recommenders on Beidian. The following is a detailed introduction of them respectively.

Friend recommendations on Beidian

For recommenders' convenience, there are "Buy" and "Sell" buttons on the Page of Product Details (Figure 2(a)): Through clicking "Buy", recommenders themselves can purchase the item, and through clicking "Sell", recommenders can recommend the item to their friends. Right after clicking "Sell", recommenders will choose how to recommend the item to their friends, as shown in Figure 2(b), where WeChat is the most common channel. Then a web link used for recommendation will be automatically generated, which includes a picture and a brief introduction of the item. Figure 2(d) shows how friend recommenders use web links to recommend items on WeChat. Once an order is completed via a recommender's link, she/he will receive an adequate portion of the order as a fee for the recommendation. It is worth mentioning that recommenders cannot access logs of what their friends browse, search and purchase recently.

Designs of Personalized RS on Beidian

RS on Beidian is developed based on an advanced deep learning model – Wide&Deep [10], which takes a variety of information, including user demographics, item features, historical behaviors, and context information as input and estimates a score for each item with a neural network. The score represents to what extent the user will like the item. After scoring, the system will diversify item lists based on empirical rules. Specifically, a typical rule for a list of 10 items is to cover at least 3 categories. If the rule is not satisfied, items from repeated categories will be replaced by items of a lower score but from other categories. For practicality and interpretability, this item diversification method is widely adopted in the industry. Figure 2(c) shows a "You may like" recommendation list generated by RS on Beidian. Users can see these lists on the pages of Home, Cart, Product Details, Transaction, User Center, and Mini-Games, which cover all the main entries and modules on Beidian. It is worth mentioning that we exclude the ranked item lists that are generated by keyword searching, because we aim to evaluate the ability to handle users' needs and interests, but not the capability to respond to a specific search query.

3.3 Methods

We adopt mixed methods to provide a verifiable and explainable analysis of the effects of friend-in-the-loop. Specifically, we perform a data-driven analysis of recommendation and purchase behaviors on a three-month full-scale dataset on Beidian to provide quantitative evidence. Further, in order to explain our findings, we conduct qualitative studies including interviews with users in Beidian, along with a forum analysis of the selling experience sharing section in Beidian Business Forum.

3.3.1 Quantitative Study. The dataset for our quantitative study covers all the active users on Beidian for three months, i.e., from March 1st to May 31st in 2020. It contains fine-grained recommendation records, purchase records, user profiles, and item profiles. Specifically, the recommendation records capture the events of recommendations that consumers receive from both RS and friends, which include the consumer's id, item's id, recommender's id (only available in friends' recommendations), and the timestamp. The purchase records capture consumers' purchase behaviors, which consist of the customer's id, item's id, and timestamp. In addition, the user profiles contain the user's user type (whether he/she has become a recommender), register time, age, and gender. And the item profiles contain the item's 3 levels of hierarchical categories with 7, 256, and 1,640 in each level. The first level includes health, personal care, baby, fresh, foods, grocery, and clothing.

During the three months, 2,548,205 users interacted with 513,119 items. Among all users, 5.3% of them have received recommendations only from their friends, 55.6% only from RS, and 39.1% from both. Most recommendations are provided by RS (98.38%) while friend recommenders make up 1.62% of the overall times of item recommendations.

Ethical Considerations. In order to protect users' privacy, we take careful procedures to eliminate the risks. First, the Terms of Service for Beidian include consent for research studies. Second, data with users' privacy is sanitized and all potential personal identifiers are replaced with anonymous hashcodes. Third, all the research data is stored in an offline server where the access is only limited to authorized researchers bound by confidentiality agreements.

3.3.2 *Qualitative Study.* To complement the quantitative study with explainable evidence, we conduct a qualitative study including interviews and a forum analysis. First, we launch an interview study on Beidian's 8 friend recommenders and 6 consumers between August and September in 2020. The interviews are conducted in Mandarin either in-person or through remote audio calls and last for 30 minutes on average. One author fluent in both English and Mandarin manually transcribes and translates all interviews into English. Our interview protocols are semi-structured, and probe into questions about (1) consumers' usage of Beidian, their experience of RS and friends' recommendations, and their expectations for recommendation service, as well as (2) recommenders' experience on Beidian and how they make recommendations to their friends. Following grounded theory methods [13, 44], three authors develop our protocols through literature review and quantitative results, and constantly revise them by interviewing and analyzing the materials iteratively. We recruit interviewees via the stratified sampling method [44] with a special focus on four strata: gender, age group, role, and city level[3]. We continue collecting interview materials until theoretical saturation is reached where no new themes emerge from additional data [13]. Eventually, 14 interviews are conducted, and the basic information of participants is listed in Table 1. Our participants cover a diversity of subgroups, and ratios of each subgroup are similar to the corresponding distributions on Beidian. Note that the basic information is self-reported, where "-" represents no reports. Especially, the occupation column of recommenders contains two data fields: the former is the recommender's full-time job, and the latter is whether being a recommender on Beidian is a part-time job or a full-time one. Moreover, to protect the privacy of the interviewees, we have requested their oral consents for audio-tape and the use of relevant personal information is only for research purposes. We also use pseudo-anonymous names, e.g., R1 for Recommender#1; C9 for Consumer#9, to avoid any potential disclosure of privacy.

Second, we also include the posts in the selling experience sharing section of Beidian Business Forum to enrich our materials with successful experience from top recommenders. Therefore, we collect posts in order of popularity. Till no new themes emerge, we include the top 30 posts into our qualitative materials [13]. One author manually translates them into English. Here, we use P to represent the post, e.g., P1 for Post#1.

Three authors conduct the qualitative analysis on the redacted English transcripts. We code and analyze the interview transcripts using a hybrid approach. Deductive codes are informed by related work on user experience of RS, which points out that the gap between well-designed metrics and real-world user perceptions, as well as the current overlook of social factors, such as trust [27, 29, 30, 34, 50]. Inductive codes are added when being iteratively revised by authors. First, two authors read all materials and identify preliminary themes, which are developed into an initial codebook. Then, the other author codes 10% of the materials and all three authors discuss and

[3]According to the five dimensional indices of commercial resource concentration, urban hub, urbanite activity, lifestyle diversity, and future plasticity, the cities in China can be divided into five tiers. A higher tier represents a higher socio-economic status.

Table 1. The basic information of 14 interview participants and demographic distributions on Beidian

Id	Gender	Age Group	Role	City Level	Occupation
R1	F	20s	Recommender	First-tier	Clerk / Part-time
R2	F	20s	Recommender	First-tier	Student / Part-time
R3	F	30s	Recommender	Second-tier	- / Part-time
R4	F	30s	Recommender	Third-tier	- / Part-time
R5	F	40s	Recommender	Second-tier	- / Part-time
R6	F	40s	Recommender	Third-tier	Shopkeeper / Full-time
R7	F	40s	Recommender	Fourth-tier	Housewife / Part-time
R8	M	50s	Recommender	Fifth-tier	- / Part-time
C9	F	20s	Consumer	First-tier	Student
C10	F	20s	Consumer	Second-tier	Assistant
C11	F	30s	Consumer	First-tier	Designer
C12	F	30s	Consumer	Third-tier	Clerk
C13	F	40s	Consumer	Third-tier	Professor
C14	F	40s	Consumer	Third-tier	Teacher
Demographic distributions on Beidian:					
Gender: #male:#female = 0.08			Age group: 20s:30s:40s:50s = 0.20:0.47:0.26:0.07		
Role: #recommender:#consumers = 1.18			City level: 1st:2nd:3rd:4th:5th = 0.25:0.26:0.21:0.20:0.08		

refine the codebook until agreements are reached. After the initial coding process, the same three authors code the remaining transcriptions using the refined codebook. Through thematic analysis and categorization [60], the emerging themes are external knowledge, trust, and empathy.

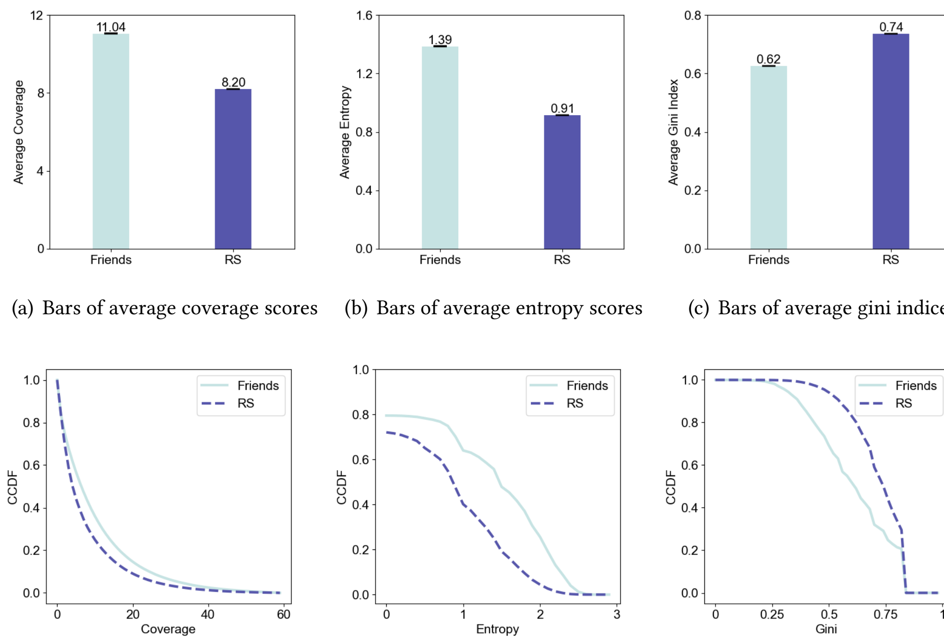
4 WHAT CAN FRIENDS' RECOMMENDATIONS BRING TO THE FEEDBACK LOOP?

In this section, we investigate the benefits of friend-in-the-loop on the two salient roles in the conventional loop – consumers and RS, through a large-scale quantitative study. First, to uncover in what aspects friend recommenders can complement RS (RQ1), we analyze their respective merits in recommendation with comparison studies. Second, we aim to analyze the benefits of friend-in-the-loop on RS with a special focus on the long-standing issue of recommendation homogeneity, through answering how friend-in-the-loop can address this issue (RQ2).

4.1 RQ1: In what aspects can friend recommenders complement RS?

To find out in what aspects friends' recommendations can complement RS, we consider three aspects that friends might potentially outperform RS, including the capability of matching consumers' preferences (suitability), feeding consumers' broad spectrum interests (diversity), and presenting novel and unique items (novelty). Based on the three aspects, we conduct comparison studies between RS and friends' recommendations. It's worth mentioning that considering demographics could be the most concerning confounding factors, we conduct this study on the same group of consumers who receive recommendations from both friends and RS (995,399 people in total). These overlapping consumers are naturally controlled in terms of demographics and other potential confounding factors.

4.1.1 Diversity. Diversity, representing the recommendation provider's capability of covering consumers' diverse needs, greatly influences user experience [27, 81]. On e-commerce, diversity manifests in different item categories in a recommendation list [27]. Thus, we adopt the coverage



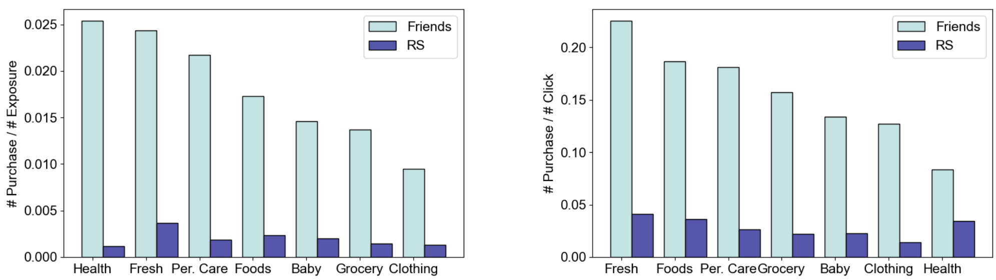
(a) Bars of average coverage scores (b) Bars of average entropy scores (c) Bars of average gini indices

(d) CCDF of coverage scores (e) CCDF of entropy scores (f) CCDF of gini indices

Fig. 3. Comparison between friend recommenders and RS on (a, d) coverage, (b, e) entropy, and (c, f) gini index, which are three indicators measuring the diversity of recommendations. A higher coverage and entropy represent a higher diversity, while a higher gini index represents a lower diversity. The error bars indicate the corresponding 95% confidence intervals and CCDF represents the complementary cumulative distribution function.

metric to evaluate how many different categories the provider can cover [32, 68], which is calculated as the number of fine-grained categories contained in the recommended list. Moreover, the balance of items across different categories is also important, for example, the list of 10 fruit and 10 clothing should be more diverse than that of 19 fruit and 1 clothing. Therefore, we adopt two metrics – entropy and gini index [32, 68], which measure the balance of the distribution of recommended items on coarsen-grained categories. Note that a higher entropy score represents a higher diversity, while a higher gini index represents a lower diversity.

Each consumer has two sequences of recommended items: one generated by RS, and the other by friend recommenders. We segment a sequence into 92 daily-basis lists and compute the coverage, the entropy as well as the gini index of each list. Then, we calculate the average of all lists' diversity metrics in the sequence of RS and the sequence of friends' recommendations respectively. From Figure 3, we observe that compared with RS, friends' recommendations exhibit significantly (a, d) higher coverage scores, (b, e) higher entropy scores, and (c, f) lower gini indices. These results indicate that compared with RS, friend recommenders provide more diverse items to their consumers in terms of both the number of different categories (higher coverage scores) and the balance across different categories (higher entropy scores and lower gini indices), exhibiting a greater capability of covering consumers' broad spectrum of interests. Our qualitative results corroborate the analysis, 85.7% of interviewees mention that friends can provide more diverse items than RS, and diverse recommendations make them feel *"motivated and engaged"* (B13) and *"satisfactory"* (B14). One



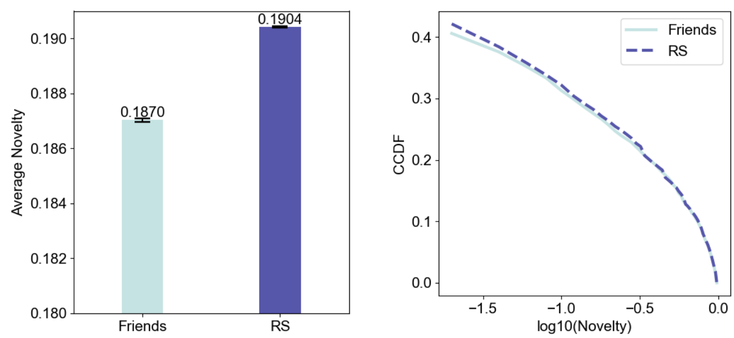
(a) Conversion rate from exposure to purchase (b) Conversion rate from click to purchase

Fig. 4. Comparison between friend recommenders and RS on purchase conversion rates among first-level categories: (a) conversion rate from exposure to purchase and (b) conversion rate from click to purchase.

interviewee explains: *"I don't think RS at present is well equipped with diversity features... I guess [the reason is] RS doesn't want to make big mistakes... However, my friend knows me better and she does not the concerns [on making big mistakes]"* (B9). These results inform the emergence of the theme external knowledge in the follow-up qualitative study.

4.1.2 Suitability. In the era of information explosion, finding suitable items with minimal efforts is an urgent need for consumers [53]. To measure to what extent the recommended items match consumers' needs, we adopt the metric purchase conversion rate [70], and consider two forms of purchase conversion rates: one is conversion rate from exposure to purchase and the other is from click to purchase. Conversion rate from exposure to purchase is calculated as the number of purchases divided by the number of exposures, reflecting the accuracy and efficiency of recommendations. A higher value indicates consumers are more likely to purchase items recommended by the provider. Conversion rate from click to purchase is calculated as the number of purchases divided by the number of clicks, reflecting the efficiency of each item exploration for the consumer. A higher value implies that consumers can spend few efforts finding the item that they want to purchase. Combining the two purchase conversion rates, we can more comprehensively evaluate the suitability of recommendations.

Overall, friends' recommendations have significantly higher purchase conversion rates from both exposure (regard a daily conversion rate as a sample, one-sided Student's t-test, $t = 42.87, p < 10^{-3}$) and click (regard a daily conversion rate as a sample, one-sided Student's t-test, $t = 54.24, p < 10^{-3}$) than RS. The higher purchase conversion rates imply that friends are more likely to recommend items that meet consumers' interests, and help consumers identify their desired items rapidly, saving their efforts of exploring items. We also calculate purchase conversion rates among first-level categories. For example, the conversion rate from exposure to purchase in the Health category is computed as the number of purchases on items in the Health category divided by the number of exposures. As shown in Figure 4, friends' purchase conversion rates are significantly higher among all the categories (regard a category's conversion rate as a sample, one-sided Student's t-test, purchase conversion rate from exposure: $t = 7.09, p < 10^{-3}$, purchase conversion rate from click: $t = 7.16, p < 10^{-3}$). The largest relative difference in conversion rate from exposure to purchase is in the Health category (20.31 times higher). One possible explanation is that trust plays an essential role in people's acceptance of health-related information [24] and friends can be more trustworthy than merely RS [21, 33, 34], therefore consumers are more likely to purchase health products recommended by their friends, which informs the emergence of the theme trust in the



(a) Bars of average novelty scores (b) CCDF of novelty scores

Fig. 5. Comparison between friend recommenders and RS on novelty. The error bars indicate the corresponding 95% confidence intervals.

follow-up qualitative study. To sum up, these results suggest that friend recommenders can predict consumers' interests and purchase intentions more accurately, thereby saving consumers' efforts of item exploration and improving user experience.

4.1.3 Novelty. The capability of presenting novel and unique items to consumers is also very important [27]. Different from diversity, novelty focuses on whether the recommended item is novel to the overall users, depicting the recommendation provider's capability of covering long-tailed or brand-new items. Typically, an item's novelty is defined as inversely proportional to its popularity [27]. Here, we adopt the relative ranking of item sales in the past year to represent its novelty score. For example, an item ranks first in the sales of last year, and the total number of items is 100, thereby its novelty score is 0.01. Figure 5(a) shows the average novelty scores of recommendations from RS and friend recommenders respectively. We observe items recommended by RS are significantly more novel than those by friend recommenders (one-sided Student's t-test, $t = 92.8, p < 10^{-3}$). Figure 5(b) depicts the complementary cumulative distribution function (CCDF) of recommended items' novelty scores. The recommended items of both providers are concentrated in the low-novelty range: 10% of the most popular, i.e., the least novel, items take up approximately 66% of the overall recommendation times.

These results indicate that friends are more likely to recommend more popular but less novel items than RS. We also observe that though RS gives some exposure to long-tailed items, these items are yet overlooked, which might lead to the unfairness of items and popularity bias [1].

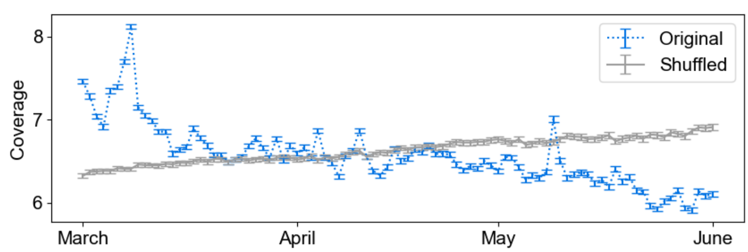
Through the full-scale data analysis, we discover that in the three aspects of recommendation, RS and friend recommenders each have their own merits: RS is better at pushing novel long-tailed items (4.1.3), while friend recommenders do better in recommending diverse items (4.1.1) and these items can match consumers' preferences better (4.1.2). As such, the introduction of friends' recommendations can complement merely RS in terms of diversity and suitability, thus effectively satisfying consumers' diverse needs and saving their efforts of item exploration.

4.2 RQ2: Can friend-in-the-loop address the issue of recommendation homogeneity?

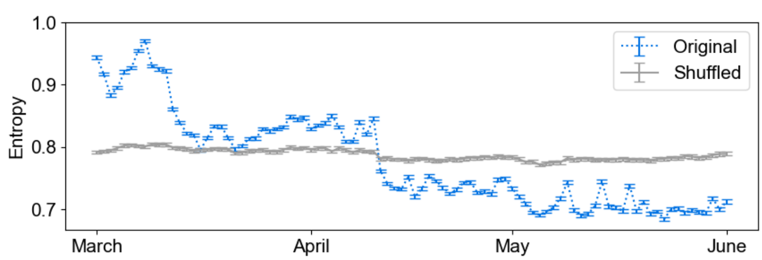
In the context of friend-in-the-loop, RS can additionally utilize information lying in consumers' feedbacks on friends' recommendations, we thus expect friend-in-the-loop should address recommendation homogeneity of RS to some extent. To answer our RQ2, we first examine whether recommendations are becoming homogeneous as interactions between consumers and RS in the feedback loop increases. Then we delve into how friend-in-the-loop can address the issue.

4.2.1 Recommendation Homogeneity in the Feedback Loop. To eliminate the effects of friends' recommendations on RS, we focus on the population that never receive any friends' recommendations during the observed three months. Typically, RS collects new data and updates its parameters on a daily basis, representing one round of interaction between RS and consumers. Therefore, we divide a consumer's recommended item sequence into 92 daily-basis sequential lists. As such, the change in the diversity of sequential lists can reflect whether recommendation homogeneity is increasing or decreasing over the interactions between RS and consumers.

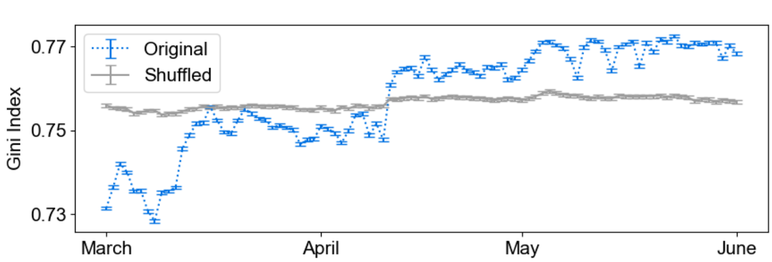
To validate whether the repeated interactions lead to recommendation homogeneity, we perform a shuffle test [45, 70]. The shuffle test is based on the idea that if the repeated interactions between consumers and RS do not affect the homogeneity of recommendations, the processes of homogeneity should be independent of the timing of making recommendations. That means we randomly shuffle the recommendation sequence, which ensures the shuffled sequence is independent of the timing



(a) Coverage



(b) Entropy



(c) Gini Index

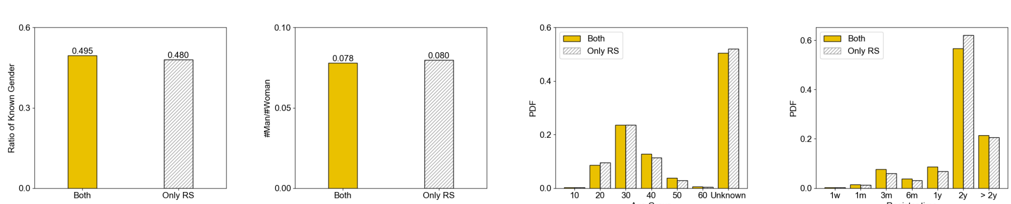
Fig. 6. Comparison between the original recommendation sequence and the shuffled one on the trend of diversity over time. The error bars indicate the corresponding 95% confidence intervals

of recommendations, and the disparity between the original sequence and the shuffled one reflects the causal relation between homogeneity and interactions. Thus, we shuffle each consumer's recommended item sequence and segment these shuffled sequences into 92 daily-basis sequential lists, resembling the previous segment on original sequences. Then we calculate the coverage scores, the entropy scores, and the gini indices of all lists in the original and the randomly shuffled sequences respectively, and average daily scores in terms of consumers who receive recommendations on that day. Finally, we obtain average coverage scores, entropy scores, and gini indices of every day.

Figure 6 shows the correlation of the timing of interactions and (a) the average coverage scores, (b) the average entropy scores, as well as (c) the average gini indices. As shown in Figure 6, compared with the shuffled sequence, the coverage scores and the entropy scores decline rapidly over time, while the gini indices increase over time. This demonstrates that the diversity of recommendations truly declines rapidly with the increase of interactions, and RS recommendations become more homogeneous with the increasing interactions between RS and consumers in the feedback loop.

Along with decline comes the fading of consumers' satisfaction. As mentioned by R6: *"Sometimes I feel annoyed with the unstoppable repetition."* (R6) Similar perspectives are also reflected by R2: *"The Brandy-Melville style is the most trending clothes in summer, and I enjoy watching Lisa in it... However, I cannot fit in it, but I cannot help clicking it... Instead of clothes that fit me, my flows are gradually taken by the BM style. It makes me a little nervous about my shape."* (S2) The essential reason is that in the feedback loop of barely RS and consumers, RS is repeatedly evaluated or trained with data from consumers who have been repeatedly exposed to the filtered information. With the repetition of interactions, mutual understanding is prone to fall into recommendation homogeneity.

4.2.2 Friend-in-the-loop Alleviates Recommendation Homogeneity. To investigate how friend-in-the-loop can address recommendation homogeneity, we perform a comparative study on two groups of consumers: the consumers who have only used RS during the observation period (Group Only RS) and the ones that have received recommendations from both friend recommenders and RS (Group Both). To minimize the potential effects of different demographic distributions on our comparison results, we first check the demographic distributions of the two groups. As shown in Figure 7, the two groups share a great similarity of demographic distributions, including genders, ages, and register time. Second, to further eliminate the potential concerns, we choose to compare the relative changes rather than the absolute values. For each consumer, we compute the Pearson correlation coefficients of the timing of interactions and the diversity of the corresponding RS recommendation list. The coefficient reflects how the diversity changes, for example, the positive coefficient of the timing and the coverage scores indicates RS recommendations received by the



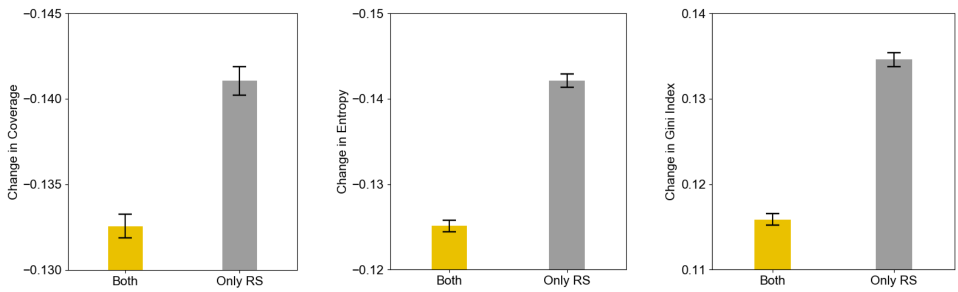
(a) Ratio of consumers with known genders

(b) Ratio of genders

(c) Distribution of consumer age

(d) Distribution of register time

Fig. 7. Validity check for demographic distributions of the group who only use RS (Group Only RS) and those who get recommendations from both friends and RS (Group Both).



(a) Change in coverage (b) Change in entropy (c) Change in gini index

Fig. 8. Comparison between Group Only RS and Group Both on the changes in diversity, i.e., the Pearson correlation coefficients. The changes in diversity are calculated individually and averaged in terms of consumers. The main bars indicate the average values and the error bars indicate the corresponding 95% confidence intervals. Note that the y-axes of (a) and (b) are reversed for illustration.

consumer become increasingly homogeneous. A higher absolute coefficient value represents a more rapid change.

Figure 8 shows the average changes in (a) coverage scores, (b) entropy scores, and (c) gini indices. Note that all the values are averaged in terms of consumers and the error bars indicate the corresponding 95% confidence interval. We observe that compared with Group Only RS, Group Both has significantly smaller absolute changes in the decline of coverage and entropy, as well as in the increase of gini indices, indicating that the phenomenon of recommendation homogeneity in Group Both is significantly weaker than that in Group Only RS. Besides, we also evaluate the recommendation performances of Group Only RS and Group Both using a widely adopted online RS evaluation metric: click-through rate (# of clicks/# of exposures) [2, 17, 78]. We observe that compared with Group Only RS, Group Both has a significantly higher click-through rate (regard a daily click-through rate as a sample, one-sided Student's t-test, $t = 1.74, p < 0.05$), indicating that friend-in-the-loop will not worsen the recommendation performances, but even bring additional gains (overall improve from 0.074 to 0.078). These results suggest friend-in-the-loop can significantly alleviate the recommendation homogeneity issue of RS without harming the performances.

5 RQ3: WHY CAN FRIEND-IN-THE-LOOP PROVIDE BETTER RECOMMENDATIONS?

In the above quantitative study, we demonstrate that friend-in-the-loop can not only make consumers enjoy more diversified and suitable recommendations, but also significantly alleviate recommendation homogeneity of RS. Further, we conduct a qualitative study to investigate what role friend recommenders play in the feedback loop and why friend-in-the-loop can make recommendations more diverse and suitable than merely RS from the perspective of users. We discover the introduction of friends' external knowledge, consumers' trust in friends, and the empathy of both account for the effectiveness of friend-in-the-loop.

5.1 External Knowledge

To make satisfactory recommendations, friend recommenders make full use of their knowledge about consumers, items, and contexts. However, most of the knowledge is external to RS, which means merely RS can hardly utilize, or even acquire it. Through incorporating friends' recommendations, friend-in-the-loop introduces friends' external knowledge into the overall system. Specifically, friends' external knowledge in recommendation can be reflected in two aspects: (1) friend recommenders have a comprehensive understanding of their consumers, (2) friend recommenders can capture subtle signals of a consumer's purchase intention.

5.1.1 Comprehensive Understanding. When asked about the merits of friends' recommendations, interviewees frequently mention friends, colleagues, and family members have a comprehensive understanding of them. Specifically, the comprehensive understanding includes their favorite color, design, flavor, and even their expectations. For example, C14 recalls the experience of receiving recommendations from her students: *" I hate staying out of style... My students always recommended face masks, the toner, the cartoon headphone case, and clunky sneakers which were very fashionable and popular among young people. I had never heard of them before. After purchasing and having a try, I found them excellent and fashionable. I feel I am keeping up with the trends."* (C14) Similar cases are also shared by R2, R6, C9, C10, C11, C12, C13, C14. On the other hand, recommenders also mention they try the best to understand their consumers comprehensively: *"The first thing after you become a seller is to analyze your potential customers, namely your friends on WeChat. You should pay attention to their age, status, occupation, consuming capability, and preferences."* (P1) Further, based on the comprehensive understanding, recommenders can make recommendations that better match their consumers' needs. As mentioned by R6: *"Most of my customers are 50-60 years old... They have consuming capabilities, but they are not familiar with online shopping. So I help them place an online order... For the selection of goods, I tailor the recommendations according to their age group and interests. For example, I seldom recommend makeups and fashionable jewelry but instead daily necessities."* (R6) Generally speaking, the comprehensive understanding is accumulated through recommenders' careful observations in real life, which only RS cannot obtain. Friend-in-the-loop leverages friends' external knowledge to fill the gap.

5.1.2 Subtle Signals. Furthermore, we observe that recommenders are good at capturing subtle signals of needs and interests. As mentioned by R2: *"I noticed his skin a little dry... So I recommended [brand name]'s moisturizing emulsion to him. He said he knew little about skincare, but it was perfect."* (R2) Similar examples are also reflected by R1: *"My colleague mentioned she missed her hometown [a kind of food] when we were chatting. On that evening, I found a discount on it, and I recommended it to her... She thanked me the next day."* (R1) Some subtle signals are hidden in daily communications, which are hardly noticed by only RS. However, friend-in-the-loop utilizes friends' capability of capturing and analyzing these subtle signals to complement RS in this domain.

5.2 Trust

Trust plays a significant role in consumers' purchase decision making [34]. A trustworthy recommendation can not only simplify the decision-making process but also greatly enhance consumers' satisfaction [21, 34]. Consumers' trust in friend recommenders originates from two ways: (1) recommenders can provide trustworthy recommendations based on their personal experience, and (2) consumers tend to believe that recommenders who have shared identity can provide matching recommendations.

5.2.1 Personal Experience. All the recommenders emphasize the importance of sharing their first-hand experience: *"Only if I have tried the item and tested the quality of it, I would like to recommend it... I cannot lie to my friends."* (R2) Recommenders' first-hand personal experience enhances consumers' trust and greatly helps consumers find their desired item: *"The recommenders made a video of her personal assessment on colors of lipsticks. She tried every color and explained which color matched my skin color... Without hesitation, I placed an order."* (C13) Friend-in-the-loop enables friends to share their first-hand personal experience, which can improve customers' trust in the recommended items and even the overall platform.

5.2.2 Shared Identity. Trust also comes from the shared identity of recommenders and consumers. As mentioned by C10: *"We are all students and we share similar life experiences, consuming concepts and capabilities... I think the things [my friends] recommend to me are suitable and worth a try."* (C10) R2 also reports similarly: *"We are classmates... I would like to choose the item that [my friends] recommend to me. Because I believe they know me better and I trust them... We have a tacit agreement that only to recommend good ones."* (R2) Similar perspectives are also reflected by 10 other interviewees. The shared identity makes consumers themselves better understood, and trust the recommendations. Moreover, the shared identity of a community can further enhance trust and thereby increase purchase behaviors. As mentioned by R5: *"We are all baby mothers... Sales of grapefruit are a great success. First, I bought it and found it delicious and worthy. Thus I recommended it to them. Some followed me and verified my words... Then more and more people [in the community] bought it."* (R5) The shared identity in friend-in-the-loop enables consumers to receive recommendations from very similar ones, which further enhance consumers' trust.

5.3 Empathy

As one of the human-exclusive characteristics, empathy is referred to as the capability to understand or feel what another person is experiencing from within their frame of reference [28, 42]. Friend recommenders can stand from the consumers' point of view, considering what they will like or dislike. As reflected by C10: *"I had almost bought [brand name]'s dress at 800 yuan... Lately [e-commerce platform] recommended a dress with the same picture at ONLY 200 yuan... Although I didn't know whether they were really the same, I yet got annoyed... My friends would never recommend such a thing."* (C10) It is extremely difficult for only RS to model complex human emotions, but friend recommenders can relatively easily avoid making such mistakes. Even if friend recommenders occasionally make mistakes, consumers exhibit more tolerance. As reflected by C9: *"It is OK. Maybe I fail to make myself understood."* (C9) Overall, consumers value their friends' efforts in selecting and recommending items. As mentioned by C14: *"I am pleased to receive recommendations from friends, because the items are well-selected, thoughtful and at good prices."* (C14) Compared with only RS, the introduction of the empathy of consumers and recommenders creates a harmonious atmosphere on the overall platform, which potentially enhances user experience.

In sum, friend-in-the-loop incorporates external knowledge, trust, and empathy into the feedback loop of RS, making full use of social capital contained in social networks. As such, consumers can receive better recommendation service, and the performance of RS can be improved (recommendation homogeneity in RS is significantly alleviated).

6 DISCUSSION

Based on the above quantitative results and qualitative evidence, we demonstrate that friend-in-the-loop benefits consumers and RS. Specifically, for consumers, friend-in-the-loop can satisfy their diverse needs and save their efforts on item exploration. For RS, friend-in-the-loop can significantly alleviate the issue of recommendation homogeneity. These findings have broad implications for the HCI and CSCW community, as well as for both academics and industries, which can be summarized as follows.

6.1 Collaboration between Human Recommendations and RS

Our work offers a large-scale data-driven analysis on a real-world e-commerce platform, filling a gap in the lack of empirical studies in prior work. Specifically, (1) we find out that friend recommenders have higher recommendation success rates, which deviates from the results in the work of Yeomans et al. [73]. One possible reason is that the current strategy of RS on real-world platforms is exposing excessive items to consumers for more sales, which leads to the increase in consumers' efforts on comparing items and the decrease in success rates. (2) Given the combination of recommended items could greatly influence consumers' purchase decisions [80], we are, to the best of our knowledge, the first to compare the recommendation quality of the two providers with a special focus on the overall quality of a recommendation list. We observe that friend recommenders are better at combining a variety of items in a list, which requires friends' external knowledge on the similarity of items and the complexity of consumers' needs. Friend-in-the-loop introduces this external knowledge to the overall system, which explains why the issue of recommendation homogeneity can be significantly alleviated. (3) We point out friend recommenders are likely to be a trend detector, rather than a long-tailed item explorer, which echos with observations in prior work [9]. One possible reason is that friend recommenders have limited access to long-tailed items. To address this issue, inviting friend recommenders to have a try on these items might be a promising solution. In this way, their first-hand experience will enhance consumers' trust in these long-tailed items and thereby improve their popularity. It is worth mentioning that both RS and friend recommenders overlook long-tailed items, which might lead to unfairness to less popular items, and popularity bias. Further work should investigate how to curb the phenomenon of the popularity divide.

Furthermore, how to make RS interpretable and informative to human decisions remains an open question [7, 19, 21]. Friend-in-the-loop directly leverages friend recommenders to interpret recommendations to consumers, which effectively enhances consumers' trust in both items and the overall platform. Moreover, modulated by social enrichment mechanism [54], consumers' affection towards the overall system will be enriched by their social relations with their friend recommenders.

6.2 Understanding and Addressing the Issue of Recommendation Homogeneity

To the best of our knowledge, we are the first to validate the dependency of recommendation homogeneity on interactions in the feedback loop. This result makes us reconsider this long-standing issue of recommendation homogeneity. Our findings indicate that recommendation homogeneity might be deeply rooted in the basic interaction model of online personalized RS. Designing a better interaction model could be a hopeful direction to address this issue. Furthermore, we offer a novel HCI-based solution – friend-in-the-loop, which can significantly alleviate recommendation homogeneity. Besides, we find out that friend recommenders have rich knowledge of diversifying recommendations. Thus, we expect that instructing RS to explicitly learn friends' diversification strategy could be a promising method.

6.3 Design Implications

Our findings offer novel design implications on how to make friend recommenders (human) and RS (algorithm) collaborate productively in recommendations. The productive collaboration between friend recommenders and RS can be mostly attributed to the special design of interactions: Beidian provides friend recommenders with monetary rewards (a small portion of a success deal) and social supports (Beidian Business Forum), which greatly motivate users to make recommendations actively and considerately.

From the perspective of the utilization of social relations, this form of friends' recommendations is similar to the common sharing features in most web applications, like Amazon. However, different

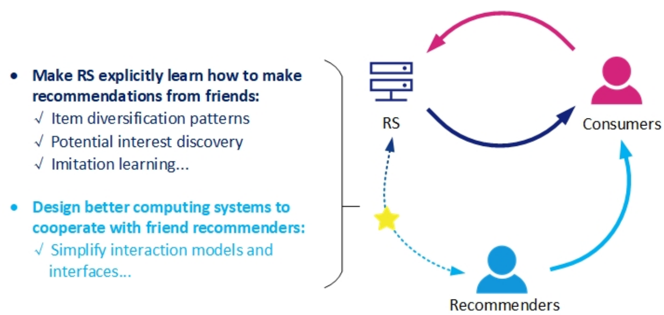


Fig. 9. Design implications for a better social e-commerce: the cooperation between friend recommenders and RS

from sharing behaviors, recommenders on Beidian are explicitly informed that they are making recommendations, instead of only sharing what they like. Besides, they are well motivated to proactively identify their friends' needs and make considerate recommendations by reciprocal beliefs and some external incentives. As such, this form of friends' recommendations is of great quantity and quality. On the other hand, the similarity between friend-in-the-loop and sharing features makes it feasible to upgrade the sharing features in web applications to this form of friends' recommendations through minor changes, for example, explicitly informing users that they are making recommendations but not barely sharing what they like, offering some rewards for successful recommendations, etc. In this way, the friend-in-the-loop method can be smoothly implemented in other conventional platforms.

Indeed, the current form of friend-in-the-loop explicitly benefits consumers by providing them diverse and matching friends' recommendations, but benefits RS implicitly by letting RS learn how friends recommend items merely from consumers' feedbacks on friends' recommendations. As shown in Figure 9, we thus expect that facilitating the cooperation between recommenders and RS can make "friends better in the loop".

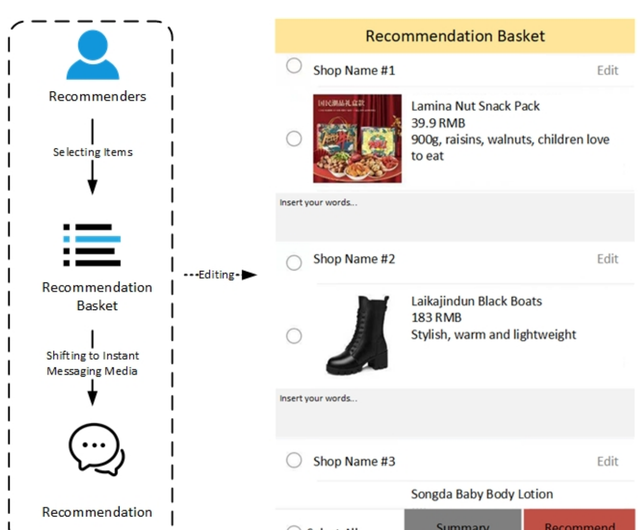


Fig. 10. Prototypical demonstration of a recommender-supporting system

Our findings show a promising direction of letting RS explicitly learn how to make recommendations from friend recommenders. Specifically, first RS can learn how to diversify item lists from friends' recommendation records. Our findings indicate that friend recommenders have rich external knowledge on combining items to generate a diverse item list. Through utilizing the patterns in how friends combine different items, RS can make use of the external knowledge to improve its capability of meeting consumers' diverse needs. Moreover, RS can capture a consumer's potential interests from what his/her friends have recommended to him/her. Our findings indicate friends can exploit consumers' underlying interests from subtle signals. From the recommendations from his/her friends, RS can learn these interests, enhancing its understanding of consumers. Probably the newly-emerging technique – imitation learning [25] which can automate the learning-from-friends process with a few successful friend recommendation data.

Another intriguing direction is designing better computing systems to cooperate with friend recommenders. One of the most urgent needs of recommenders is automating the recommendation procedures. As one seller mentioned: *"I need one-click recommending!"* (S2). Redundant procedures significantly impair the efficiency of recommendations and limit the scalability of friends' recommendations. Better interaction models and interfaces offer a feasible means to address the issue. Here, we present a prototypical demonstration of a recommender-supporting system in Figure 10. Recommenders first select all items that they want to recommend, and then arrange these items as well as edit explanatory words on the Page of the Recommendation Basket. As such, they can deliver all of the selected items to their friends at once. Though this prototype needs further refinement, it can effectively save friend recommenders' efforts and make friends' recommendations more reachable.

6.4 Limitations and Future Work

There are still some limitations in our work: first, our paper relies on data from one single social e-commerce platform in China. As such, our findings might be biased due to the platform design and cultural background. However, we focus on this form of friends' recommendations, which can be observed on many other social e-commerce platforms, such as Yunjiweidian, Miyuan, and Pinduoduo. Future work can consider conducting cross-platform analyses to further enhance the capability of generalization. Second, this work is an empirical study on a real-world platform with a special focus on online evaluation, which limits the model for comparison to the running Wide&Deep RS without other baselines. However, many online and offline experiments have proved the superior performances of the Wide&Deep model compared with many traditional recommendation baselines, such as collaborative filtering and matrix factorization [10, 14, 76]. These works indicate that the Wide&Deep model can be representative of a large stream of RS implemented in the real world and can serve as an adequate comparative baseline. Future work should further examine the effectiveness of friend-in-the-loop over other online RS across platforms. Third, socio-economic attributes, e.g., education background and income, might have effects on users' preference for RS and friends' recommendations. Though we tried to cover various user groups, considering the complexity of populations who use social e-commerce, we yet cannot ensure the comprehensive coverage of all cases. Future work should conduct large-scale analyses across platforms.

7 CONCLUSION

This work presents the first in-depth exploratory study on the benefits of bringing friends' recommendations into the feedback loop of RS in the context of social e-commerce. We conduct a mixed-method analysis combing a quantitative study on the three-month full-scale dataset of a leading social e-commerce platform in China, and qualitative studies including interviews and a forum analysis. We reveal that RS and friends' recommendations each have their merits in three aspects of recommendation quality: suitability, diversity, and novelty. We demonstrate that friend-in-the-loop can benefit the two salient roles – consumers and RS, comprehensively. We elaborate that friends' external knowledge, consumers' trust, and their empathy account for the benefits of friend-in-the-loop. These findings have insights on how to facilitate the collaboration of friend recommenders (human) and RS (algorithm).

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A INTERVIEW SCRIPTS

A.1 Recommenders

Introduction and Warm-up Questions

- (Greetings) Thank you for agreeing to help us with this project.
- The interview should take 30 to 45 minutes.
- Request for oral consents for audio-tape.
- Request for demographic information, and emphasize the use of relevant personal information is only for research purposes.
- We are concerned with your user experience on Beidian. Can you share some stories when you use Beidian?

Interview Questions

- Have you recommended items on Beidian? How? To whom? Which item? Feelings?
- How frequently do you make recommendations? Why?
- How do you select the recommended items? Do you consider the diversity of items?
- What are other key factors when you make recommendations?
- What kind of strategies have you adopted when making recommendations?/As a successful recommender, could you share some experience with newcomers?
- Have you browsed the page of “You may like”? How do you feel about it? What do you think about the diversity of items?
- Compared with “You may like”, what are the strengths or weaknesses as a human recommender?

Wrap-up

- Do you have any suggestions for Beidian? How can Beidian help you make recommendations more conveniently?
- Thank you for your participation. Please do not hesitate to call or e-mail if you have any questions or if you think of additional points.

A.2 Consumers

Introduction and Warm-up Questions

- (Greetings) Thank you for agreeing to help us with this project.
- The interview should take 30 to 45 minutes.
- Request for oral consents for audio-tape.
- Request for demographic information, and emphasize the use of relevant personal information is only for research purposes.
- We are concerned with your user experience on Beidian. Can you share some stories when you use Beidian?

Interview Questions

- Have you get recommendations from your friends on Beidian? From whom? Which item? Feelings?
- What do you think of the items recommended by your friends? If (or not) satisfactory/good/suitable, why?
- How about the diversity of the items recommended by your friends?
- Have you browsed the page of “You may like”? How do you feel about it? What do you think about the diversity of the items compared with those recommended by your friends?
- Compared with RS (algorithm/computer), what are the strengths and weaknesses of friends’ recommendations? Why?

Wrap-up

- Do you have any suggestions for Beidian? How can Beidian improve its recommendation service from the perspective of both RS or friends' recommendations?
- Thank you for your participation. Please do not hesitate to call or e-mail if you have any questions or if you think of additional points.

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