Social Circle-Enhanced Fashion Recommendations System

Aayesha Aayesha[1,*], Muhammad Afzaal[2] and Julia Neidhardt[1]

[1]Christian Doppler Lab for Recommender Systems, TU Wien, Austria
[2]Department of Computer and Systems Sciences (DSV), Stockholm University, Sweden

Abstract

When shopping for fashionable clothing items, consumers frequently experience indecision and struggle to make choices, resulting in a stalling of the purchasing process. In such scenarios, most often they need support of their friends from their social circle to choose suitable clothes for different events. To provide decision-making support, considerable research has focused on generating social-aware recommendations that incorporate input from the user's social circle. However, there has been minimal research dedicated to develop and evaluate such systems that could assess the importance of social circles in producing social-aware fashion recommendations and identifying factors that might enhance these recommendations. This paper addresses these limitations by developing a Social Circle-Enhanced Fashion Recommendation (SCEFR) System that encompasses friends feedback to generate recommendations. The SCEFR system was evaluated by conducting a user study, comparing system-generated recommendations with user choices as rank correlation coefficients. The findings indicate that inputs from the social circle alone have limited potential in generating effective social-aware recommendations. However, when the user's shopping preferences were shared with their social circle, the quality of these recommendations significantly improved, as evidenced by a qualitative analysis of user feedback. Furthermore, in comparative analysis with the state-of-the-art (SOTA) approaches of recommendation generation, the SCEFR system informed by user's shopping preferences demonstrated superiority.

Keywords

Social-context in recommendations, Fashion recommendations, Shopping decision support, Social-circle feedback

1. Introduction

Fashion is one of the most mature and rapidly growing segments of e-commerce, driven by the increasing adoption of digital platforms for shopping [1]. As online fashion shopping becomes more prevalent, fashion recommender systems have emerged as essential tools for enhancing user experience and boosting sales for retailers [2]. However, despite significant advancements in developing personalized recommendation approaches, there is a noticeable gap in understanding the social context that influences fashion choices. The role of social context is particularly important in scenarios where consumers face decision fatigue or uncertainty in choosing the right fashion items [3, 4]. In such cases, individuals often seek advice from their social circles such as friends, family, and peers to make more confident purchasing decisions [5, 6].

In the existing literature, several studies [7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18] have explored social-aware recommendation (SAR) systems that offer personalized and relevant recommendations not just based on the preferences of individual users but also take into account the preferences and influences of their social networks, including friends, people they follows, and their followers. This leads to a more tailored and engaging shopping experience. However, these works were not able to seamlessly integrate social circle feedback into the recommendation generation process in real-time [19, 20]. Furthermore, there is limited research on how user's shopping preferences informed by social-circle feedback can shape recommendations for different shopping intents, such as selecting attire for business meetings, casual outings, or home use etc. This paper aims to address these gaps by introducing a novel approach to fashion recommendations that leverages real-time feedback from users' social circles. Our research

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*Corresponding author.
aayesha.aayesha@tuwien.ac.at (A. Aayesha); muhammad.afzaal@dsv.su.se (M. Afzaal); julia.neidhardt@tuwien.ac.at (J. Neidhardt)
0000-0001-6730-4605 (A. Aayesha); 0000-0003-2054-0971 (M. Afzaal); 0000-0001-7184-1841 (J. Neidhardt)

focuses on the following question:

- **Research Question:** What is the contribution of shopping preferences-informed social circle feedback to generating fashion recommendations for various shopping intents?

To answer this question, we propose the development of a Social Circle-Enhanced Fashion Recommendation (SCEFR) system. This system combines a web-based interface for clothing selection with a chatbot that provides recommendations based on social-circle feedback. By incorporating users' shopping preferences, such as clothing type, color, and style, along with analyzing feedback from their social circles, the SCEFR system aims to offer more personalized and contextually relevant fashion recommendations tailored to specific shopping intents (e.g., outdoor events, business meetings, or home use). The proposed SCEFR system is evaluated by conducting a user study that assess the effectiveness of generated recommendations based on social-circle feedback and compare these outcomes with existing state-of-the-art approaches. Moreover, we analyse qualitative feedback of users to understand the impact of informed social-circle feedback on their decision-making process. This research makes three main contributions:

1. Development of a SCEFR system that seamlessly integrates social-circle feedback to generate social-aware fashion recommendations.
2. Evaluation of the SCEFR system through comprehensive user study, focusing on impact of social-circle feedback informed by the user's shopping preferences.
3. Comparative analysis of the SCEFR-generated recommendations with state-of-the-art approaches.

This study aims to enhance online fashion shopping experiences and provide valuable insights for developing more effective e-commerce applications. It contributes to the growing body of knowledge on social-aware recommendation systems and offers practical solutions for leveraging peer feedback to support consumers in making informed fashion choices. The remaining paper is structured as follows: section 2 gives an overview of relevant literature, section 3 explains the methodology, section 4 describes the results, and section 5 discusses the findings, limitations and future directions.

2. Literature Review

In the existing literature several studies worked on social-aware recommendations by incorporating social context for recommendation generation. For instance, P. Bonhard and M. A. Sasse [8] and Yaw Asabere et al. [11] considered the target user's preferences, profile, ties, and personality traits similarity with its social circle to generate recommendations. In addition Feng Xia et al. [12] analysed the strength of interpersonal relation and personality matching for generating weighted hybrid recommendations. Similarly, Xiwang Yang et al. [13] worked on utilising the trust strength between user and its social circle people to generate circle-based recommendations. On the other hand, Manqing Dong et al. [14] analysed trust relation as a supporting factor for trustworthy recommendations. In the same way, Chong Chen et al. [16] proposed a transfer learning framework on user's preferences to generate personalized recommendations that was found useful when limited user-item interaction data was available. However, these works did not incorporate interpersonal influences within a social circle. These limitations addressed by some other studies that explored the influence of individuals in a social circle and incorporated interpersonal influence between users and their social circle along with their interpersonal and personal preferences [9, 10, 17, 18]. For example, Le Wu et al. [18] aggregated the influences and interests of higher-order people (not directly connected) in social circle to determine target user preferences for recommendation generation where lower and higher-order people were assigned weights by a multi-level attention network. However, these works ignored to analyse the social circle influences regarding the content (e.g. attributes) of user's preferred items. In order to address this limitation several studies analysed the social circle relations from multi-aspect attribute-wise perspective of preferred items [17, 15, 10]. For example, Hao Wang et al. [17] calculated the hyperbolic distance of user-item pairs to generate recommendations. Likewise Xueming Qian et al. [9] incorporated shopping item attributes along with social factors referred to the interpersonal preferences and influence but ignored the evaluation of user preferences impact for diverse shopping intents.

Overall, the existing literature ignored to propose an effective way of seamlessly integrate social circle feedback that could not only evaluate the significance of the social circle for generating social-aware recommendations but also evaluate the influence of user's shopping preferences to enhance these recommendations for various shopping intents. The current study, however, addresses these limitations by offering a comprehensive methodology.

3. Methodology

This section proposes and evaluates a Social Circle-Enhanced Fashion Recommendation (SCEFR) system Link[anonymous due to peer review policy] designed to assist in the decision-making process through the incorporation of feedback from a user's social circle. Initially, a comprehensive dataset was compiled, encompassing detailed information related to various clothing items. Then, based on the data that was gathered, a SCEFR system was developed that utilises the feedback obtained from the user's social circle in order to generate recommendations. Lastly, an evaluation was performed on the newly designed system to determine the significance of the social circle in the generation of recommendations.

3.1. Data Collection

This study utilises the H&M dataset [21], a publicly available online collection of fashionable clothing items. The dataset under consideration encompasses a collection of over 50,000 distinct clothing items, exhibiting a wide range of diversity. Every item is accompanied by a comprehensive set of attributes, such as color, type, appearance, image, and a detailed description.

3.2. Social Circle-Enhanced Fashion Recommendations System

The proposed system consisted of two main components: (1) a web-interface that gathers user and products (items) data, including the user's preferences and detailed information on items that they wish to purchase. (2) a chatbot that shares collected preferences and wish lists of items around the social circles of the user for the purpose of generating recommendations. A chatbot is implemented as an applicatin of messaging platforms Telegram and Facebook Messenger. It is integrated to the web-shop and comes up with three main functionalities; first it allows user to share clothing selection with its social circle, second it allows friends in its social-circle to rank the clothing items, and third aggregates the ranked outputs of friends to generate final list of recommendations. Furthermore, assistance regarding user's shopping intent is also forwarded to the social circle in generating specified fashion recommendations.

3.2.1. Preferences and Products Selection

A shopping web-interface was created using the H&M dataset, which displayed a collection of filters together with corresponding clothing items, as shown in Figure 1. Within this interface, first user is allowed to decide on shopping intent (the purpose or reason of buying e.g. Home, Outdoor, Gym, Party, and etc) then a grid view of clothing items appears, every garment item is shown with its corresponding category, name, and image. In addition, two buttons are included for each item: "add to wishlist" and "remove from wishlist". These buttons allowed the users to easily choose any number of products from the shopping interface. Due to the varied selection of clothing items and potential individual preferences, users were specifically requested to indicate their shopping preferences [1]. These preferences included several garment aspects such as type, colour, style, fitting, and etc. The gathered preferences also

[1]https://dev-fashionshopon.pantheonsite.io/fashion-shopping-preferences

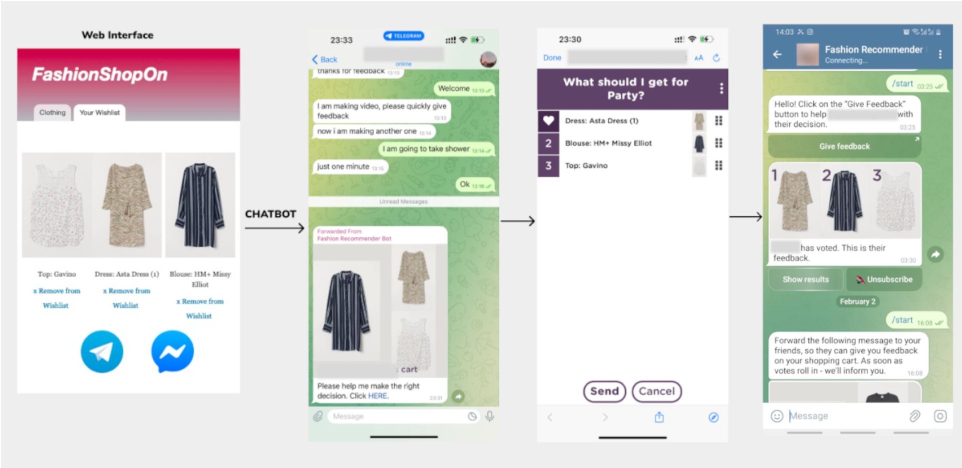


Figure 1: Social Circle-Enhanced Fashion Recommendation System

included the user's clothing preferences for several buying intents, including Home, Outdoor, Gym, Party, and etc.

3.2.2. Social Circle

After users provided their preferences and selected products, the information was subsequently propagated among their social circle in order to ask for their feedback. To accomplish this task, the developed chatbot was employed. Firstly, it extracted the social network of the users, specifically focusing on the connections established through popular social platforms such as Telegram and Facebook Messenger. After that, the user's product selection (clothing choices made by the shopping interface for a particular shopping intent) and preferences were disseminated to all individuals within their social circle. Then, social circle was allowed to rank items based on both the provided product selection and preferences for given particular shopping intent. Finally, the social circle individuals feedbacks were provided as a list of ranked items separately.

3.2.3. Recommendation Generation

Subsequently, the individual feedback, in the form of rankings, provided by individuals within a given social circle were aggregated in order to generate recommendations. For aggregation we employed the "Borda Count" strategy [22] that is well-established and widely applied aggregation strategy because of its robustness and simplicity. This approach allowed us to aggregate the individual feedback received, resulting in a selected set of clothing items that were highly ranked by a majority of individuals within their respective social circles. The aggregated output was displayed to the user in the chatbot as presented in Figure 1.

3.3. Evaluation

This section is dedicated to the evaluation of the proposed SCEFR system link[anonymous due to peer review policy] by conducting a user study. The primary objectives of this evaluation are to assess the influence of user's shopping preferences on the process of generating social-circle aware recommendations and then examine the effectiveness of generated recommendations by qualitative analysis of users feedback and comparative analysis with SOTA.

3.3.1. Participants

A total of 75 individuals voluntarily participated in the conducted user study, having provided their informed consent. The participants were friends of each other and their ages ranged from 20 to 35, and they had a variety of interests and hobbies. The majority of participants were male and fell between the age range of 20-25 years old. However, there was also a considerable number of participants aged 26-30. In hobbies, ”Sports” was the predominant hobby among the participants, interests such as Nature, Entertainment, Study/Work, and Arts were comparatively less popular. Moreover, the majority of participants had a moderate degree of expertise in their use of advanced chatbots (e.g. ChatGPT [23]) and similar technologies. The purpose of considering chatbot expertise was to assess the user's familiarity of using chatbots.

3.3.2. Procedure

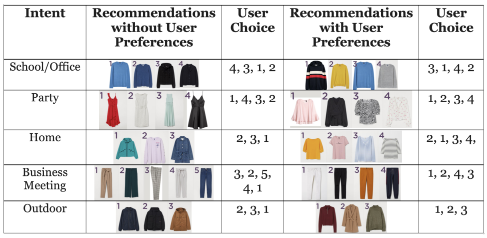
Initially, the participants were divided into 15 social circles or groups, with each circle consisting of 5 individuals. Within these social circles, communication was restricted only to the platforms of Telegram and Facebook Messenger. Subsequently, all participants were provided access to the SCEFR system (that includes a web-based interface for showcasing clothing items from H&M's collection as well as a chatbot), to assist them in making purchasing choices by incorporating feedback from their social circle members.

The effectiveness of the system was evaluated by quantitative, qualitative, and comparative analyses. For quantitative analysis, two experimental scenarios were designed to assess the influence of target users' (the one seeking recommendations) shopping preferences on system generated recommendations. In the first scenario, the members in the social circle were unaware of the preferences of the target user. However, in the second experimental scenario, the social circle members were given access to the target user's shopping preferences. Both experimental scenarios were employed on each social group and respective SCEFR system generated recommendations were comparatively analysed with user's final choices. On the other hand, for qualitative analysis, a questionnaire [2] was prepared to inspect users responses about SCEFR system effectiveness. However, for the comparative analysis, SOTA approaches including multimodal LLM-based recommendations [24], knowledge-based recommendations [25], and content-based recommendations [26] were compared with SCEFR system.

3.3.3. Data Collection

In quantitative analysis, within each experimental scenario, a target user performed five rounds of shopping selection, during which they selected clothing items and then shared their selected items with their social circle. Overall, each user in a social circle made five times clothing selection to get social-circle assistance and twenty times assisted its friends for generating recommendations. Furthermore, for each shopping round the user's final choices about clothing selection were recorder to compare with system generated recommendations. The result of each round of shopping selection was documented as two lists of rankings. As shown in Figure 2, for given experimental scenarios, the order of SCEFR system based recommendations about clothing selection are provided under the columns ”Recommendations without User Preferences” and ”Recommendations with User Preferences” while ”User Choice” columns refer to the user's personal rating preferences for the ranked items. These personal rating preferences highlight to the user's final decision after getting recommendations. The rank records of 750 iterations of shopping selections, 50 iterations per group (as each group consists of 5 members) were used for further analysis. On the other hand, for qualitative analysis users responses were collected for the questions referring to social-circle feedback assistance, decision making support, and SCEFR system recommendations usefulness. Regarding first question about social-circle feedback, the users were asked that during all shopping rounds to what extent friends feedback was found helpful. The purpose of this question was to assess the significance of social-circle for assisting in shopping. On the other hand, second question was asking about the effectiveness of system generated recommendations for decision support in shopping. It was aimed at to analyse the effectiveness of system generated recommendations. However, third question was about the user perception for system generated recommendations wtih the rationale of investigating that to what extent the generated recommendations were found align to

[2]https://dev-fashionshopon.pantheonsite.io/qualitative-analysis-questionnaire



Intent	Recommendations without User Preferences	User Choice	Recommendations with User Preferences	User Choice
School/Office	1 2 3 4	4, 3, 1, 2	1 2 3 4	3, 1, 4, 2
Party	1 2 3 4	1, 4, 3, 2	1 2 3 4	1, 2, 3, 4
Home	1 2 3	2, 3, 1	1 2 3 4	2, 1, 3, 4,
Business Meeting	1 2 3 4 5	3, 2, 5, 4, 1	1 2 3 4	1, 2, 4, 3
Outdoor	1 2 3	2, 3, 1	1 2 3	1, 2, 3

Figure 2: Data Collection

Given a person with the following clothing preferences.
Liked clothes: {liked clothes}
Cloth shopping preferences: {cloth shopping preferences}
Could you rank all linked clothes considering cloth shopping preferences for the event of { rec goal}.

Additional instructions:
1. Write the answer in the format of a JSON file with the attribute recommendations that is an array with the attributes: title and rank number.
2. The title attribute must be the title of the recommended cloth and the rank number must be a number indicating which clothing item should be prior in recommendation than other.
3. Do not include any additional text besides the JSON.

cloth shopping preferences:
In clothing selection, I prefer Style, Color, Cloth fabric, Cloth fitting, and Cloth Matching.
For Home, I prefer Casual style
For Business meeting, I prefer elegant style
For Gym/Sport, I prefer Sporty style
For Party, I prefer Stylish style
For Outdoor, I prefer Basic style
For School/Office, I prefer Classic style
For Meetup with Friends & Family, I prefer Festive style
For Club or Bar, I prefer Festive style
rec goal: Business meeting
liked clothes: <a list of attached images of items>
It is possible with Plus and Enterprise versions by coding so will perform through its interface.

Figure 3: Prompt for LLM-based Recommender

the user's final choices. In case of comparative analysis, SOTA approaches-based recommendations were collected that refer to the ranking of user's selected items. To determine these rankings, a prompt was created for large language model (LLM)-based recommendations as shown in Figure 3, rules were derived for knowledge-based recommendations, and clothing images were analyzed for content-based recommendations.

3.3.4. Data Analysis

In order to investigate the importance of the social circle, a correlation analysis was conducted between the rankings of recommendations generated by the system and the final choices shared by users. Three Rank Correlation Coefficient (RCC) measures were employed that are commonly used in various fields of research namely Kendall's Tau [27], Spearman's correlation [28], and Weighted Kendall's Tau [29]. The selection of these measures relies upon their inherent capability to determine the correlation coefficient between any two provided sets of items [30]. Moreover, the influence of user's shopping preferences on the social-aware recommendations generation was investigated to perform correlation analysis in both experimental scenarios separately. Subsequently, a set of t-tests were performed on the outcomes of the correlation analysis in order to determine the statistical significance of shopping preferences. The present study aimed to evaluate the null hypothesis that user's shopping preferences have no impact on the improvement of social-aware recommendations. To assess this hypothesis, a significance level of 0.05 was set for the tests conducted. For qualitative analysis, the user's opinions as their textual responses about given questions were analysed by sentiment analysis [31] , being a computational study of user opinion. In this analysis, the collected responses were categorised into three classes i.e. positive, negative, and neutral using a pre-trained language model i.e., TimeLM [32]. As TimeLM trained on Twitter data, which includes informal language such as slang and unstructured text, so it was considered appropriate for analyzing the feedback from the questionnaire. Regarding comparative analysis, the correlation between SOTA-generated recommendations and the final ranked choices of user were calculated by applying above mentioned RCC measures. The outcomes of correlation coefficient were compared with those of SCEFR system to evaluate system effectiveness.

4. Results

This section outlines the empirical results obtained from experimentation. The primary objective of these experiments was to assess the effectiveness of the SCEFR system in terms of its capability to generate recommendations by leveraging the social circle. Furthermore, our study aimed to investigate the importance of user's shopping preferences in the generation of precise recommendations.

In order to assess the efficacy of the SCEFR system, the recommendations generated by the system were compared to the final choices made by the user to calculate the correlation coefficient. Three RCC measures were used and their results are shown in Tables 1 and 2. The findings were categorised into several buying intentions, including Home, Business meeting, Gym/Sport, and so on. Each row displays the correlation between recommendations offered by the system and the user's choices. The average correlation coefficient for all RCC metrics throughout 286 rounds of shopping was found to be around 0.20 that indicated SCEFR system has limited potential to effectively aid users in their purchasing decisions. In order to assess the influence of a user's shopping preferences shared with the user's social circle, again the correlation coefficient was computed between the ranked lists of products generated by the SCEFR System and the user's choices. The results as shown by Table 2 highlighted average correlation coefficient of around 0.56 for all RCC measures. The findings where the correlation coefficients of the recommendations provided by the system are compared with and without the inclusion of shopping preferences are shown in Figure 4. Based on these findings, it is clear that preferences enhance the correlation between recommendations given by the system and the decisions made by the user. In other words, incorporation of only social circle feedback would might incorporate a negative impact because friends have their own distinct preferences that would might not match user's preferences. Overall, by the incorporation of user's shopping prefereces the average correlation coefficient value was higher by 0.36 for all RCC measurements, indicating a considerable influence of sharing user's shopping preferences with their social circle in enhancing the recommendations generated by SCEFR system. It also highlights the significance of real-time user's shopping preferences incorporation otherwise it might not be useful because user's shopping preferences might change with time. In addition, an Independent sample t-test was conducted to assess the statistical significance of the correlation measurements obtained with and without the shopping preferences. The t-test findings for various shopping intentions are shown in Table 3. The findings indicated that user preferences had a significant impact on improving SCEFR system generated recommendations, with a significance level of 0.05. Although the impact of user preferences was found to be significantly important for all shopping intents, it was particularly predominant for the "Outdoor", "Meetup with Friends & Family", and "Party" intents. The p-values for these intents were 0.001, 0.004, and 0.006, respectively, with corresponding degrees of freedom of 89.96, 23.32, and 69.53.

In the qualitative analysis conducted, participant responses to a questionnaire were categorized based on sentiment: positive, negative, and neutral, as depicted in Figure 5. The initial query sought to assess the impact of social-circle feedback on recommendation generation. A significant majority, 87.32% (n=62), expressed positive feedback, while a minor segment, 8.45% (n=6), conveyed negative sentiments, and a small proportion, 4.22% (n=3), remained neutral. The second question, focusing on assistance in decision-making, elicited a more diverse set of responses: 49.30% (n=35) of participants provided positive feedback, 33.80% (n=24) expressed disagreement, and 16.90% (n=12) held a neutral stance. Regarding the third question, which investigated the alignment of system-generated recommendations with user preferences, 58.70% (n=37) of participants acknowledged the overlap between the system's suggestions and their personal choices. In contrast, 12.70% (n=8) disagreed with this alignment, and 28.57% (n=18) maintained a neutral position on this matter.

In addition, the evaluation outcomes of SCEFR system were comparatively analysed with other SOTA [24, 25, 26] approaches of recommender systems as shown in Table 4. The results indicate that although LLM-based recommendations provide superior performance compared to content-based and knowledge-based recommendations. However, the social-aware recommendations incorporated with user's shopping preferences outperforms the LLM-based recommendations for all RCC measures.

5. Discussion and Conclusion

We started with the given research question that investigates the contribution of a user's social-circle to generate fashion recommendations that could provide shopping decision support to the user for different shopping intents. In this regard, an SCEFR system was developed and evaluated where feedback of social-circle individuals were integrated to generate effective recommendations. The generated

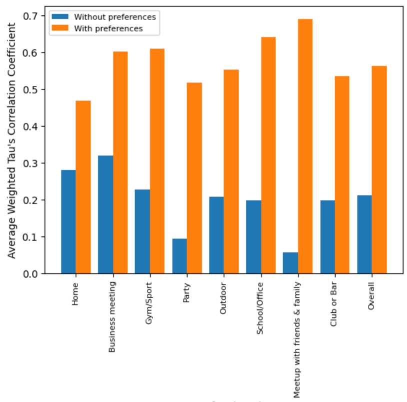


Figure 4: Impact of Shopping Preferences

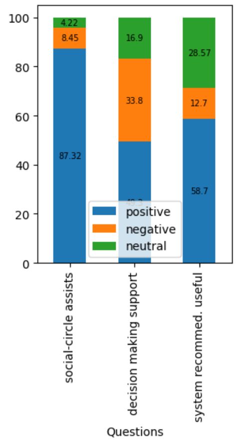


Figure 5: Users Feedback on SCEFR system Effectiveness

Table 1
Correlation Coefficients between Social-aware Recommendations (without user's shopping preferences) and User's Choices

Shopping Intent	Sample size(n)	Kendall's Tau Mean	Kendall's Tau Std.	Spearman's Correlation Mean	Spearman's Correlation Std.	Weighted Tau Mean	Weighted Tau Std.
Home	56	0.2335	0.4950	0.2338	0.5734	0.2799	0.5279
Business Meeting	44	0.3078	0.5445	0.3188	0.6167	0.3210	0.5622
Gym/Sport	26	0.2231	0.5413	0.2456	0.6300	0.2270	0.5802
Party	48	0.0931	0.5966	0.0940	0.6532	0.0942	0.6021
Outdoor	52	0.2209	0.5897	0.2150	0.6485	0.2088	0.6027
School/Office	23	0.2232	0.5961	0.2795	0.6586	0.1977	0.6067
Meetup with Friends & Family	15	0.0622	0.6678	0.0409	0.7302	0.0576	0.6971
Club or Bar	22	0.1727	0.6165	0.1981	0.67866	0.1978	0.6236
Overall	286	0.2036	0.5740	0.2119	0.6415	0.2127	0.5934

Table 2
Correlation Coefficients between Social-aware Recommendations (with user's shopping preferences) and User's Choices

Shopping Intent	Sample size(n)	Kendall's Tau Mean	Kendall's Tau Std.	Spearman's Correlation Mean	Spearman's Correlation Std.	Weighted Tau Mean	Weighted Tau Std.
Home	56	0.4716	0.5588	0.4603	0.6131	0.4699	0.5664
Business Meeting	44	0.5864	0.4811	0.6122	0.4934	0.6033	0.4869
Gym/Sport	26	0.61075	0.5167	0.6230	0.5343	0.6105	0.5289
Party	48	0.5064	0.6355	0.5157	0.6753	0.5188	0.6391
Outdoor	52	0.5535	0.4472	0.5862	0.4584	0.5543	0.4651
School/Office	23	0.6175	0.5265	0.6280	0.5618	0.6410	0.53076
Meetup with Friends & Family	15	0.6878	0.4509	0.7042	0.4913	0.6907	0.4612
Club or Bar	22	0.5434	0.5221	0.5419	0.5823	0.5365	0.5351
Overall	286	0.5569	0.5260	0.5686	0.5611	0.5623	0.5355

recommendations were analysed considering impact of user's shopping preferences to generate social-aware recommendations for a set of shopping intents. The analysis results were accessed in terms of correlation between system generated recommendations and user's choices. It was found that on one hand the feedback of a user's social circle without informed of user's shopping preferences have limited potential to generate effective SCEFR. On the other hand, the user's social circle feedback who are familiar about its shopping preferences significantly improved SCEFR system generated recommendations. The t-test results verified the significance of informed social-circle feedbak in SCEFR for all shopping intents as the null hypothesis was rejected by the significance level of 0.05. The findings revealed that by incorporating user's shopping preferences, the SCEFR system generated recommendations have latent

Table 3
Impact of shopping preferences on SCEFR system recommendations

Shopping Intent	Sample size(n)	DF	t-value	p-value	Effect Size
Home	56	101.6150	2.0323	0.0447	0.3986
Business Meeting	44	82.2449	2.3611	0.0206	0.5092
Gym/Sport	26	49.8870	2.0018	0.0507	0.5552
Party	48	69.5265	2.7946	0.0067	0.6587
Outdoor	52	89.9556	3.3627	0.0011	0.6794
School/Office	23	43.5357	2.2762	0.0278	0.6712
Meetup with Friends & Family	15	23.3164	3.1581	0.0043	1.1531
Club or Bar	22	41.6386	1.3114	0.0196	0.3954

Table 4
Comparative Analysis of Recommender Systems

Recommendation Systems	Kendall's Tau (Mean)	Spearman's Correlation (Mean)	Weighted Tau (Mean)
LLM-based Recommender System [24]	0.4634	0.4881	0.4874
Knowledge-based Recommendations [25]	0.3823	0.3973	0.3866
Content-based Recommendations [26]	0.4301	0.4483	0.4454
SAFRS (Based on weak ties)	0.2036	0.2119	0.2117
SAFRS (Based on strong ties)	0.5569	0.5686	0.5623

ability to assist users in making their decisions for shopping selection.

To further analyse the incorporation of user's shopping preferences to the SCEFR system, the qualitative and comparative analyses were performed. The qualitative analysis results about user's opinions revealed the significant positive feedback regarding system support for decision making, recommendation generation, and social-circle incorporation. Similarly, the comparative analysis with SOTA recommendation approaches highlighted the prevalent superiority of social-context for recommendations and encouraged the social-circle feedback incorporation in recommendation generation process. Our findings indicate that this study has some implications for the online shoppers, for example, systems can assist them in making informed shopping decisions by providing recommendations based on social circle feedback. This support facilitates shoppers to get rid of over-thinking while selecting of items and speed up the decision making by enhancing their confidence in the selected items. Furthermore, the friends in the social circle that are already aware of user's preferences could be more effective members to assist the user in making his/her shopping selection as they leverage the potential of trust relation and could be perceived as more trustworthy and credible by the user. In addition, as the developed system provides an established way of communicating users with their friends so it facilitates user shopping in an integrated and practical way.

5.1. Limitations and Future Directions

The study acknowledges limitations and plans future improvements: adding conversational features to the system, expanding research to a more diverse and larger participant group, incorporating hierarchical social networks like friends of friends, prioritizing feedback based on relationship strength and shared interests, and developing hybrid approaches that combine social-contextual data with advanced techniques for better recommendations.

6. Acknowledgments

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