Proponents as the Means to Increase the Uptake of Recommendations

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ABSTRACT

While much research in recommender systems focused on improving the accuracy of recommendations, issues pertaining to their presentation have been under-explored. Considering the uptake of recommendations as one of their success indicators, we investigate the role of proponents in affecting user's decision to accept a recommendation. We refer to proponent as a person or avatar, advocating in favor of the recommended item. This paper reports on a user study that evaluated the impact of including several types of proponents in the recommender interface and their impact on the uptake of recommendations. We observe that out of the studied proponents, real-world contacts have the strongest impact on the uptake of recommendations, which can inform the design recommender system interfaces.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Empirical studies in HCI.

KEYWORDS

Proponents, recommendations, explanations user study

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1 INTRODUCTION

Much work in recommender systems has traditionally focused on algorithmic methods for improving the recommendation accuracy [1]. The algorithmic work incorporated social and semantic factors into the recommendation process [2], to supplement the user similarity notion underpinning the reasoning of collaborative recommenders. However, it has been shown that the recommendation accuracy alone did not necessarily lead to a better user experience [3]. Recently, research also turned to improving the user experience when interacting with recommenders, including intuitive user interfaces [4], affecting decision-making processes [5], and persuading users to follow recommendations [6].

One of the contributors of user experience in recommender systems is *explanations* [7]. Traditionally, recommenders have presented their outputs as recommendation lists, sometimes accompanied by limited information about the items, such as their feature descriptors or match for the user [8]. However, it was suggested that enriching the recommendation lists with explanations may contribute to user experience and the uptake of recommendations. The seminal work on explanation of recommendations highlighted four potential benefits of explanatory interfaces [9]: (i) help users understand the reasoning behind recommendations, (ii) increase user engagement with the recommender, (iii) educate users about the recommendation generation, and (iv) boost the acceptance of recommendations.

However, the questions of associating the recommended items with certain people and agents as a form of social influence in explanations have not been studied in depth. Specifically, conclusive comparison of real-world contacts and established authorities on the uptake of movie recommendations has been limited. Hence, this paper sets out to investigate two *research questions*: (RQ1) how does adding a proponent to the recommendation interface impact the uptake of recommendations, and (RQ2) which proponents have the strongest impact on the uptake of recommendations. To this end, we report on a study measuring how associating a recommended item with a person or avatar, who already experienced the recommended item and advocates in favor of its consumption (referred to as the recommendation *proponent*), affects the uptake of the recommendation. In more detail, we focus on the movie recommendation task and enrich the traditional ranked list recommendation interface by including a proponent for each item. We experiment with three proponents: real-world contacts, movie experts, and recommender robots, and compare them to a baseline interface with no proponent.

The obtained results show that including the proponent in the recommendation interface slightly increases the uptake of the recommendations. We also observe that a real-world contact proponent increases the uptake of recommendations, expert and robot proponents do not have a significant impact, while having no proponent decreases the uptake. Hence, the contribution of this work is two-fold: we show that (i) adding proponents can increase the uptake of recommendations, and (ii) real-world people lead to the highest uptake. Our results bear practical implications for designers of recommendation interfaces and raise intriguing questions around the responsible deployment of proponents in recommender systems.

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2 RELATED WORK

Recommender systems have been harnessing social relationships between users since their conception, e.g., the social nature of collaborative filtering. The advent of online social networks facilitated the expansion of the notion of similarity to offline familiarity or other indicators of personal, social, or professional relationships [10]. This fueled a spike of interest in social recommender systems and led to the development of movie [2], music [11], publication [12], and many other recommenders. These recommenders relied on the assumption that similarity and familiarity span the online and offline worlds [13]. In addition, social relationships between users can be used for recommendation explanation purposes. Such explanations can support all the benefits outlined by [9]: justify recommendations by showing ratings of familiar users, increase engagement by providing argumentation, demonstrate the intelligence of the recommendation engine, and increase the willingness to consume the recommended items. The last one is the key objective addressed in this paper.

Many works investigated the output interfaces of recommender systems. The communication between the user and recommender system was studied in [14], which compared the acceptance of recommendations made by a smartphone and a humanoid robot. While the results demonstrated no significant differences, interaction with the robot was considered more attractive. The work also investigated the effects of incorporating human images and voices in the recommendation interface and observed that such recommendations improved user experience by increasing trust and the perceived user enjoyment. The look-and-feel of recommendation agents also attracted attention and [15] focused on the relationship between the appearance of the recommendation agent and user willingness to purchase the recommended items. The results showed that users were most willing to purchase products recommended by a humanoid agent.

The value of explanations in music recommendations was investigated in [16] that considered item and social factors. The perceived persuasiveness of recommendations was measured and it was found that item factors were more persuasive than social factors. The social aspects of recommendation and explanation were successfully intertwined in [11] by integrating data from multiple sources into the recommendation process. Differently from our work, the explanations did not reflect the social connections of users, but were seen as the means to make the recommender more transparent. The problem of social recommendations was targeted in [17]. The generated recommendations harnessed similarity and familiarity networks and were accompanied by explanations showing the names of users related to the recommended items. The study showed that the explanations improved the ratio of relevant items in the recommended lists and the click-through rate. Unlike our study, neither diverse proponents nor the optimal recommendation uptake conditions were analyzed.

The most closely related research to ours is [18]. This work reported on a user study of social explanations in a music recommender and developed a framework for quantifying the impact of explanations on users' decision-making processes. It was found that social explanations exploiting close friends in a social network increased item examination likelihood. Despite this, the friends' opinions did not affect the post-consumption ratings. The name of the friend and the degree of their closeness were identified as confounding factors. Considering the key stages of interaction with the recommended items –examination, consumption, and rating – we highlight that our work focusses on the impact of explanations on the consumption decisions, complementing the examination and rating decisions studied by [18].

3 METHODS

We present a user study evaluating the impact of proponents on the uptake of recommendations. In this between-group study, the subjects are partitioned into two groups interacting with different movie recommendation interfaces: subjects in the *control group* can only see the titles and thumbnails of the recommended movies, while subjects in the *intervention group* are also shown a brief explanation mentioning the movie proponent that argues in favor of watching the movie. We measure the impact of including the proponents on the uptake of recommendations.

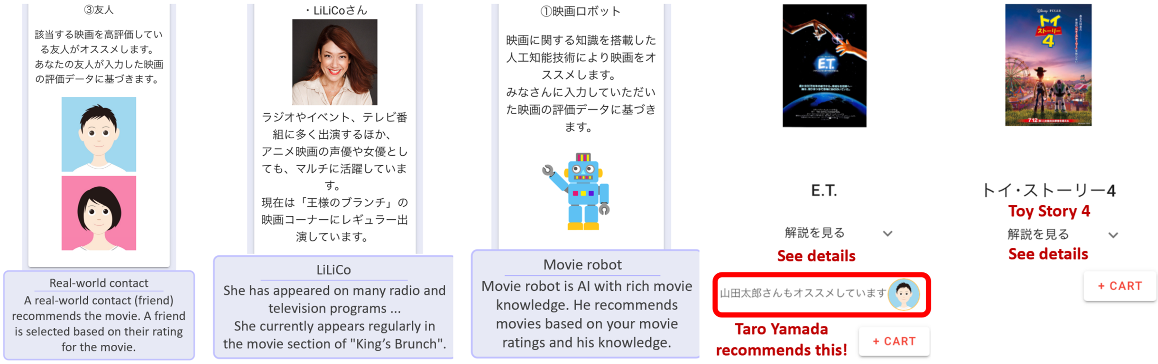
3.1 Procedure

The study was conducted at Kwansei Gakuin University (KGU) in groups of 10-20 students, whose members knew each other offline, as the students within a group were enrolled to the same seminar. We invited students of nine seminars to participate and randomly assigned them to the control and intervention groups. The total number of subjects recruited was 134 (62 males, 72 females): 74 (35 males, 39 females) were in the intervention group and 60 (27 males, 33 females) – in the control group. This study was reviewed and approved by the Behavioral Sciences Ethics Committee of KGU.

At the beginning of the study, the subjects provided data about their movie preferences. First, they were asked how often they watched movies. Next, subjects rated 14 movie genres (action, adventure, animation, comedy, crime, drama, family, horror, history, musical, mystery, romance, science fiction, thriller) and 10 movies they already watched, out of a pre-compiled list of popular movies. Genre preferences were harnessed to generate recommendations, while specific movie scores were collected to create an impression of an underlying recommender. Finally, the subjects were asked to set an avatar image showing how they would be visualized for other group members.

We deployed a simplistic content-based recommendation algorithm. The only content feature considered by the recommender was the movie genre. At the outset, each user u assigned each genre g an explicit rating $R_{u,g}$ on a 4-point scale ranging from 0 ("don't like at all") to 3 ("like a lot"). Given T movies to be recommended, the number of movies $N_{u,g}$ of genre g in u's recommendation list was proportional to $R_{u,g}$, i.e., $N_{u,g} = T \frac{R_{u,g}}{\sum_g R_{u,g}}$. While this recommendation method is inferior to smore accurate state-of-the-art methods, it mitigates several risks of lab-based user studies, such as profile bootstrapping and noises, observed even within repetitive ratings [19]. We also highlight that our work focuses on the presentation of recommendations, whereas the recommendation algorithm can be replaced by any other method.

Once the number of movies for every genre was determined, specific movies to be recommended were randomly selected from a list of movies pre-classified into genres. Movies that had been marked



(a) (b) (c) (d) (e)

Figure 1: (a) real-world contact proponent; (b) movie expert proponent; (c) robot proponent; (d) intervention group interface, proponent highlighted; (e) control group interface, no proponent.

by the subject as watched, were excluded. A total of 32 movies were selected for every subject and randomized into four recommendation lists of eight movies. Splitting the 32 recommendations into four lists allowed us to adjust the size of recommendation lists to 5-10 items typically offered by commercial recommenders and formed a more controlled experimental setting. The distribution of genres in each list reflected as accurately as possible the overall distribution of genre preferences. The order of the eight movies in each list was also randomized.

3.2 Proponents

In the intervention group, three types of proponents were studied: real-world contact, movie expert, and recommender robot. *Contact* is a real-world acquaintance of the subject. As the subjects were recruited as groups of students taking the same seminars at KGU, they were expected to know each other in person. Thus, recommendations could be associated with specific people from the group, which could instill trust in the recommendations. Movie *experts* were Kon Arimura and LiLiCo – well-known movie commentators in Japan. They regularly appear in TV shows and feature new movies, such that they were expected to be known to the subjects and their opinions could add credibility to the recommendations. Recommendation *robots* can be perceived as AI technologies having a rich knowledge of the movie domain and exploiting sophisticated AI to recommend items. Recommendations supported by the opinions of robot proponents could also influence the subjects' decisions due to the perceived intelligence of AI.

The proponents were implemented in form of a name and avatar of the person or robot recommending the subject to watch the movie. Descriptions of the proponents were explained to the subjects as follows. Figure 1a exemplifies the real-life contact proponent and the text translates as "*real-world friend recommending their highly-rated movies considering the ratings the friend gave to the movies*". Figure 1b shows an expert recommendation by LiLiCo, who presents herself as "*participant of radio and TV shows with many actors and actresses, currently performing as actress at movies and voice actress at anime, and also appears on TVs show as movie commentator*". Description of the movie robot recommender is given in Figure 1c. It is stated that the robot "*recommends movies based on movie evaluation data and knowledge of the movies*". An example contact proponent is shown in Figure 1d, with the text in the red frame advocating for the recommended item. The translation of the framed text is "*this movie is recommended because [friend's name] gave high evaluation to it*", with the name and avatar of the friend appearing alongside the text.

In the recommendation lists of the intervention group subjects, the three types of proponents as well as the no-proponent items were randomized, such that each list included two items with a contact proponent, two with an expert proponent, two with a robot proponent, and two with no proponent. Thus, each proponent was included twice in each recommendation list of eight movies and their order varied across the lists. Note that proponents were neither matched to the subject preferences nor to the recommended movies. While we considered an alternative design of one type of proponent per recommendation list, this would have required a substantially larger number of subjects for a between-subjects experiment than the current within-subject setting. Thus, we adopted the method of including all proponents in one recommendation list.

The assignment of Kon Arimura or LiLiCo as the expert proponent was randomized. Likewise, the real-world contact to be used as a proponent was selected at random out of the subject's group members. Considering that the size of the groups was 10-20 students and each was presented with a total of eight recommendations with the contact proponent, each of these likely used a different real-world contact. Conversely, no proponent was presented in the *control* group, and only the standard ranked recommendation list of eight movies, including their titles and thumbnail icons, was provided (see Figure 1e, lacking the proponent text framed in Figure 1d). Thus, control group subjects received no proponent support for the recommendations, equivalent to the baseline recommendation lists deployed by many recommender systems.

3.3 Data and metrics

Following the above setup, recommendation generation, and assignment of proponents, the subjects interacted with four recommendation lists of eight movies each. The subjects were instructed to select movies they would like to watch, with a fictitious price of 300 Yen per movie. Note that neither the budget nor the number of selected movies was limited, such that the subjects could select as many recommended items as they liked or, alternatively, select none. The selected movies were added to the shopping cart and we refer to these as taken up (or accepted) recommendations.

For each movie in the recommendation list, we asked if the subject has already watched the movie and to what extent the movie matched their taste. The latter was rated on a 3-point scale: does not match, cannot decide, and matches. Upon interacting with all four recommendation lists, intervention group subjects were asked to rate on a 5-point scale the perceived usefulness of every proponent. In the analysis, we compare the distribution of data across different interfaces (with vs without proponent) and types of proponents (contact, expert, robot, none). To establish whether the differences are statistically significant, we compare the distributions of the observed behavioral responses using the Pearson's Chi-squared test with Yates' continuity correction. We also report the adjusted residuals, using the conventional threshold of $Res \geq 1.96$ for the Chi-squared significance threshold of p=.05 [20]. Since the contact and expert proponents change across the delivered recommendations, no correction for repeated measures was deemed necessary.

4 RESULTS

Subjects who reported that they never watched movies were excluded from the analysis. For data sanitation purposes, we also excluded three intervention group and two control group subjects, who reported the same match level for more than 80% of the recommended movies. Hence, in the following analyses we use the data of 71 subjects in the intervention group and 58 subjects in the control group. Also, we limit the analyses to *unseen* movies that have not been watched by the subject receiving the recommendation. This is due to the observation that if a recommended movie has already been watched, the decision to accept or reject the recommendation relies on the subject's personal opinion for the movie, rather than influenced by the recommender, its interface, or the proponent.

The 71 subjects in the intervention groups received a total of 2272 recommendations across the four lists of eight movies each and the 58 subjects in the control group – 1856 recommendations. Out of all the delivered recommendations, in the intervention and control groups, 1993 (87.7%) and 1595 (85.9%), respectively, were marked by the subjects as unseen. We use these recommendation sets in the analyses reported below. The first analysis focuses on the impact of including the proponent in the recommendation interface and we compare the uptake of the recommendations with a proponent in the intervention group (all the proponents combined) with recommendations without proponents in the control group.

In the intervention group, 427 recommendations were taken up and added to the shopping cart, whereas 1566 were rejected, yielding an acceptance rate of 21.4%. In the control group, 310 recommendations were taken up, resulting in a lower acceptance rate of 19.4%. However, the difference between the groups was not statistically significant, χ^2 *(1,N=3588)=2.03, p=.1544*. Revisiting RQ1, we note that including a proponent in the recommendation interface slightly increased the overall uptake of the recommended movies, while this increase was not statistically significant.

To refine this finding, we compare the four studied types of proponents and conduct an intra-group analysis in the intervention group. Recall that each recommendation list in the intervention group included eight recommendations: two with a contact proponent, two with an expert proponent, two with a robot proponent, and two with no proponent. Thus, intra-group analysis within the intervention group allows us to compare the impact of different proponents. Of the 1993 unseen recommendations in the intervention group, 492 were associated with a contact, 503 – with an expert, 500 – with a robot, and 498 had no proponent. We use these sets in this analysis.

As shown in Table 1, the highest uptake of recommendations, 27.2%, was observed for the contact proponent. Robot and expert proponent recommendations scored similarly, with 20.6% and 20.5% uptake, respectively. The lowest uptake of 17.5% was observed for recommendations with no proponent. Notably, this uptake level is lower than the 19.4% observed in the control group, presumably due to the low attractiveness of recommendations having no proponent, compared to recommendations with all other types of proponents included in the same recommendation interface of the intervention group.

The differences between these types of proponents were statistically significant, χ^2 *(3,N=1993)=14.97, p=.0018*. Residual analysis shows that for recommendations with a contact proponent, the acceptance rate was significantly higher than the expected one, with *Res=3.62*. On the contrary, for recommendation with no proponent, we obtained *Res=-2.48*, which shows that their uptake was significantly lower than the expected uptake and reaffirms our earlier findings related to RQ1. Since the observed differences were significant overall, in this analysis we do not repeat the above breakdown of the match scores.

Finally, we analyze the perceived usefulness of the proponents, reported by the 71 intervention group subjects. The average usefulness score was 3.13 for the contact proponent, 2.72 for expert, and 2.38 for robot. As the Shapiro-Wilk test did not show normal distributions, we conducted a non-parametric significance test. The Kruskal-Wallis test for differences in representative values confirmed a significant difference, *p<.001*. Furthermore, a Wilcoxon rank sum test using the Holm's method confirmed significant differences for all combinations: *p=0.0033* for contact vs expert, *p<.001* for contact vs robot, and *p=0.0200* for expert vs robot. Thus, the subjects perceived the contact proponent to be the most useful, followed by the expert proponent, and then by the recommendation robot.

In summary, revisiting RQ2, we note that the studied proponents differed in their impact on the uptake of recommendations and their perceived usefulness. Real-world contact proponents were found to increase the uptake of recommendations, expert and robot had no significant impact, whereas including no proponent decreased the recommendation uptake. This result corresponded to the usefulness of the proponents, where real-world contact was appreciated most

Table 1: Uptake of recommendations with various proponents (denotes p-value<.01).**

	contact **	expert	robot	no proponent **
Accepted	134 (27.2%)	103 (20.5%)	103 (20.6%)	87 (17.5%)
Rejected	358 (72.8%)	400 (79.5%)	397 (79.4%)	411 (82.5%)
Total	**492**	**503**	**500**	**498**

by the users, likely highlighting the projection of offline trust into the digital realm.

5 SUMMARY

In the comparison of recommendation interfaces with and without proponents, no conclusive differences were observed. This may be due to the recommendation interface in the intervention group including three different proponents and two items with no proponent, which blurred the proponents' impact. Comparing the proponents, real-world contacts increased the recommendation uptake and received the highest usefulness ratings. Prior research showed strong influence of real-life friends on online purchases [21] and music recommendations [18]. Our results reaffirm this for movies, even with simple explanation including the proponent's name and avatar only. Real-life connections were established by recruiting students enrolled in the same seminar, ensuring that the subjects knew each other, which is a strength of our work.

Surprisingly, expert recommendations did not show a significant impact, although their usefulness was perceived mildly positive. This contrasts with previous results showing that expert recommendations are beneficial [22], product purchases correlate with the number of expert reviews [23], and hIndex of authors is a predictor of click-through rate [24]. We posit that this effect was not observed due to the intervention group interface including the contact proponents, which leveraged offline familiarity and dominated the expert proponents. Also, the impact of robot proponent was minor, likely due to their perceived similarity with a standard recommender, which can be seen as a decision-support tool.

An important finding for designers of future recommender systems is the superiority of real-life contact proponents. Information about real-life contacts may be readily available in online social networks or communities mirroring offline relationships. While endorsement-based mechanisms for content sharing are common in social networks [25], obtaining this information and harnessing it for recommendation purposes may be challenging for online recommenders. This brings forward another argument in favor of linking online recommendation services with social networking services, to leverage each other's strengths. As our work suggests, this has the potential to elevate the uptake of recommendations.

When information about real-life contacts is unavailable, recognizable public figures, e.g., experts, TV personalities, or influencers, offer a weaker alternative. However, it is critical to highlight that the use of human proponents poses substantial challenges. The use of real-life contacts may compromise user privacy and leak sensitive information, whereas the use of public figures opens the door for manipulation or deception, lending itself to the realm of responsible AI [26]. For instance, providers may want to boost item consumption by using proponents not actually endorsing them, which may undermine user trust and cause reputational damage [27]. Designers of future recommenders need to consider such risks and integrate verification methods to safeguard their users.

While raising findings with important implications for the design of future recommender systems, this work is not without limitations. The first refers to the design of the recommendation interface in the intervention group, which combined three types of proponents and included items without proponents. While this design allowed to conduct both intra- and inter-group comparisons, it also blurred the impact of proponents, so that the sample size was not sufficiently large to obtain significant differences at the group level. We believe that commercial recommenders may not need to combine diverse proponents, but rather implement the most influential or appropriate proponent for every user or task.

Despite clearly showing the potential of proponents in recommendation explanations, the work has limitations. Future larger-scale studies are needed to re-affirm our findings with different segments of users and in a broader range of recommendation domains and tasks. That said, our work raises intriguing questions and highlights the value of proponents for designers of future recommendation interfaces, since associating the recommended items with proponents may boost the uptake of recommendations, strengthen user engagement, and improve user experience.

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REFERENCES

[1] Lekakos, G., Giaglis, G.M.: Improving the prediction accuracy of recommendation algorithms: Approaches anchored on human factors. Interacting with computers, vol. 18(3), 410-431, 2006.
[2] Carrer-Neto, W., Hernández-Alcaraz, M.L., Valencia-García, R., García-Sánchez, F.: Social knowledge-based recommender system. Application to the movies domain. Expert Systems with applications, vol. 39(12), pp. 10990-1000, 2012.
[3] Konstan, J.A., Riedl, J.T.: Recommender Systems: from Algorithms to User Experience. User Modeling and User-Adapted Interaction, vol. 22(1-2), pp. 101-123, 2012.
[4] Murphy-Hill, E., Murphy, G.C.: Recommendation delivery: Getting the user interface just right. In Recommendation systems in software engineering, pp. 223-242, Springer, 2013.
[5] Jameson, A., Willemsen, M.C., Felfernig, A.: Individual and group decision making and recommender systems. In Recommender systems handbook, pp. 789-832, Springer, 2022.
[6] Sakuma, H., Hori, A., Murashita, M., Kondo, C., Hijikata, Y.: YouTubers Versus VTubers: Persuasiveness of human and virtual presenters in promotional videos. Frontiers in Computer Science, vol. 5(17), 2023.
[7] Tintarev, N., Masthoff, J.: Explaining recommendations: Design and evaluation. In Recommender systems handbook, pp. 353-382. Springer, 2015.
[8] Nanou, T., Lekakos, G., Fouskas, K.: The effects of recommendations' presentation on persuasion and satisfaction in a movie recommender system. Multimedia systems, vol. 16, pp. 219-230, 2010.
[9] Herlocker, J.L., Konstan, J.A., Riedl, J.: Explaining collaborative filtering recommendations. In Proceedings of CSCW, pp. 241-250, 2000.

[10] Guy, I.: Social recommender systems. In Recommender systems handbook, pp. 835-870, Springer, 2022.
[11] Bostandjiev, S., O'Donovan, J., Höllerer, T.: TasteWeights: a visual interactive hybrid recommender system. In Proceedings of RecSys, pp. 35-42, 2012.
[12] Tsai, C.H., Brusilovsky, P.: The effects of controllability and explainability in a social recommender system. User Modeling and User-Adapted Interaction, vol. 31, pp. 591-627, 2021.
[13] Tiroshi, A., Berkovsky, S., Kaafar, M.A., Chen, T., Kuflik, T., 2013: Cross social networks interests predictions based ongraph features. In Proceedings RecSys, pp. 319-322, 2013.
[14] Qiu, L., Benbasat, I.: Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems, Journal of Management Information Systems, vol. 25, pp. 145-182, 2009.
[15] Jing, L., Yamada, S., Terada, K.: Effects of agents' appearance on customer's buying motivations at online shopping site. Transactions of Human Interface Society, vol. 17(3), pp. 307-316, 2015.
[16] Berkovsky, S., Taib, R., Hijikata, Y., Braslavski, P., Knijnenburg, B.: A cross-cultural analysis of trust in recommender systems. In Proceedings of UMAP, pp. 285-289, 2018.
[17] Guy, I., Zwerdling, N., Carmel, D., Ronen, I., Uziel, E., Yogev, S., Ofek-Koifman, S.: Personalized recommendation of social software items based on social relations. In Proceedings of RecSys, pp. 53-60, 2009.
[18] Sharma, A., Cosley, D.: Do social explanations work? Studying and modeling the effects of social explanations in recommender systems. In Proceedings of WWW, pp. 1133-1144, 2013.
[19] Said, A., Jain, B.J., Narr, S., Plumbaum, T.: Users and noise: The magic barrier of recommender systems. In Proceedings of UMAP, pp. 237-248, 2012.
[20] Sharpe, D.: Chi-square test is statistically significant: Now what?. Practical Assessment, Research, and Evaluation, vol. 20(1), e. 8, 2015.
[21] Gellerstedt, M., Arvemo, T.: The impact of word of mouth when booking a hotel: Could a good friend's opinion outweigh the online majority? Information Technology Tourism, vol. 21, pp. 289-311, 2019.
[22] Bonhard, P., Sasse, M.A.: "I thought it was terrible and everyone else loved it" - A new perspective for effective recommender system design. In People and Computers XIX - The Bigger Picture, Springer, 2006.
[23] Zhou, W., Duan, W.: Do professional reviews affect online user choices through user reviews? An Empirical Study. Journal of Management Information Systems, 2016.
[24] Kang, H.B., Kocielnik, R., Head, A., Yang, J., Latzke, M., Kittur, A., Weld, D.S., Downey, D., Bragg, J.: From who you know to what you read: augmenting scientific recommendations with implicit social networks. In Proceedings CHI, 2022.
[25] Berkovsky, S., Freyne, J., Smith, G.: Personalized network updates: increasing social interactions and contributions in social networks. In Proceedings of UMAP, 2012.
[26] Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R.: Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, vol. 58, pp. 82-115, 2020.
[27] Cheah, J.H., Ting, H., Cham, T.H., Memon, M.A.: The effect of selfie promotion and celebrity endorsed advertisement on decision-making processes: A model comparison. Internet Research, vol. 29(3), pp. 552-577, 2019.