Check for updates

Latest updates: https://dl.acm.org/doi/10.1145/3640794.3665881

PDF Download
3640794.3665881.pdf
23 March 2026
Total Citations: 1
Total Downloads: 402

Published: 08 July 2024

Citation in BibTeX format

CUI '24: ACM Conversational User Interfaces 2024
July 8 - 10, 2024
Luxembourg, Luxembourg

Conference Sponsors:
SIGCHI

EXTENDED-ABSTRACT

You Today, Better Tomorrow: Envisioning the Role of Conversation in Recommender Systems of the Future

MANVEER KALIRAI, University of Toronto, Toronto, ON, Canada

ANASTASIA KUZMINYKH, University of Toronto, Toronto, ON, Canada

Open Access Support provided by:

University of Toronto

CUI '24: Proceedings of the 6th ACM Conference on Conversational User Interfaces (July 2024)
https://doi.org/10.1145/3640794.3665881
ISBN: 9798400705113

You Today, Better Tomorrow: Envisioning the Role of Conversation in Recommender Systems of the Future

Manveer Kalirai
University of Toronto
Toronto, Canada
manveer.kalirai@mail.utoronto.ca

Anastasia Kuzminykh
University of Toronto
Toronto, Canada
anastasia.kuzminykh@utoronto.ca

ABSTRACT

Recommender systems could evolve from traditional models of recommendation that largely harness data on past interactions to predict what a user might want in a given moment, towards systems that also support and nurture user self-actualization. This shift could guide users in exploring and fulfilling the needs of their future potential selves, untethered from their past and current identities. In this provocation, we suggest that interactive conversational recommendation is a suitable means to rouse this vision. Conversational recommendation is capable of eliciting real-time and layered preferences, and can enable systems to take on a more proactive role in dialoguing with users about their aspirational needs—particularly in helping users navigate the intricacies that often surround these needs. We also examine the potential challenges associated with the realization of such recommender systems—for instance, the complexities in transitioning from past-based patterns of personalization to those that accommodate present-oriented and future-oriented personalization, and the preservation of user agency whilst broadening the scope of roles recommender systems can play. Overall, this paper advocates for a necessary progression in recommender systems, one propelled by conversational recommendation, towards designs that not only avail present-day user needs, but also actively stimulate pathways toward the actualization of their potential and aspirational future selves.

CCS CONCEPTS

• **Human-centered computing → Natural language interfaces**; **HCI theory, concepts and models**.

KEYWORDS

Conversational Recommendation, Recommender Systems, Self-Actualization

ACM Reference Format:
Manveer Kalirai and Anastasia Kuzminykh. 2024. You Today, Better Tomorrow: Envisioning the Role of Conversation in Recommender Systems of the Future. In *ACM Conversational User Interfaces 2024 (CUI '24), July 08–10, 2024, Luxembourg, Luxembourg*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3640794.3665881

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
CUI '24, July 08–10, 2024, Luxembourg, Luxembourg
© 2024 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-0511-3/24/07
https://doi.org/10.1145/3640794.3665881

1 INTRODUCTION

People worldwide are increasingly turning to recommender systems to assist, advise, inform, and inspire them. These systems have a growing influence in shaping how people manage their time, money, energy, and efforts in pursuit of a better, more enriching life. Current recommender systems typically operate by harnessing vast amounts of user and item data from a range of sources to create personalized suggestions through algorithms that identify and exploit patterns—often similarities—between these entities [21]. They do so by leveraging techniques such as content-based filtering, collaborative filtering, or a blend of both (i.e., hybrid techniques) to predict what users are likely to favour next, usually based on their historical interactions with a system [1]. Although these proactive techniques may impose a lighter cognitive and time load on users than other more reactive techniques, basing future recommendations on past data can culminate in the formation of 'filter bubbles'. These bubbles form when systems continually recommend options that resemble users' earlier choices, markedly limiting their exposure to novel or different information [19]. Not only does this curtail users' opportunities to discover new interests and ideas, but it also potentially stunts their personal and intellectual growth [3]. Over time, users may find themselves in an 'information cocoon', where the scope of their experiences and knowledge whilst interacting with recommender systems is narrowly defined by an algorithmic interpretation of their past interests and choices.

One vision articulated in the literature regarding the future of recommender systems proposes a shift from merely amplifying current preferences towards fostering the actualization of users' potential selves [16][8][22][7]. This involves designing recommender systems that not only reflect users' present selves, but also support their growth towards future goals and identities; extending the breadth of recommendations to include pathways that nurture personal and intellectual development. Developing this vision further, we argue that while current approaches to recommender systems predominantly adhere to a practice of predicting user preferences based on past interaction data—a concept we term '*past-based predictive precedent*'—conversational interactions through recommender systems can—and indeed *should*—serve as a cornerstone in advancing towards this new paradigm of recommendation patterns.

Conversational recommendation, i.e., the use of interactive, natural language dialogue within the recommendation process [17], opens up opportunities to develop systems that support user self-actualization needs. It is able to do so by leveraging its capacity to: (i) elicit real-time, active preferences directly from users, (ii) engage with preferences as negotiated dialogues, and (iii) expand the social dimensions of system-generated recommendations. First, unlike traditional systems that infer preferences from historical data, conversational interactions can capture preferences in-situ, providing a more immediate and precise reflection of what users may want in a given moment [20]. Second, conversational interactions can challenge the 'static' view of user preferences in traditional systems; recognizing that preferences emerge from the interplay between a decision-maker and their decision context. By engaging in dialogue and, more importantly, *negotiation*, these systems can adapt to evolving user circumstances, and consider broader individual and situational factors when offering recommendations [26][11]. Third, conversational interactions can deepen the sociality of the recommendation process through the intrinsic social properties of conversation itself, and by helping to navigate the social nuances that span intermediate negotiations between the user's internal decision context and their external one [10][27].

However, critical considerations must be taken into account for recommender systems and conversational recommendation to evolve further in this space.

Firstly, there is the lofty challenge of transitioning from solely *past-based* personalization (i.e., recommendations generated based on a user's historical interactions with a system) to *present-based* (i.e., focusing on the user's current context and immediate preferences which can vary significantly from past behaviours), and *future-based* personalization (i.e., catering to the future needs, aspirations, and potential identities of the user, not just reacting to past or present behaviours) as well. While current recommender systems predominantly focus on personalizing recommendations based on past user interactions, the challenge is in expanding their ability to account for preferences over a broader range of temporalities [21]. This involves refining how these systems capture, elicit, interpret, and predict user preferences; this calls for bolstering the modelling capabilities of these systems to accommodate, and productively handle this extended temporal range.

Secondly, conversational recommender systems may further erode user agency, and amplify vulnerabilities to manipulation and exploitation, particularly in future systems that emphasize social aspects. The ongoing issue with current recommender systems is the concern that algorithmic recommendations could undermine user agency by unduly influencing users' choices [2]. In the context of advanced recommender systems, especially ones designed to nurture user aspirations and self-actualization, this concern might become intensified. For instance, the input of personal information in these advanced conversational systems is arguably more intimate, and directly related to the user's current self and their future trajectory. As a result, these systems will likely require a considerably higher level of trust than what is common today. With the potential of recommender systems to diffuse more widely and seep more deeply into quotidien life, the stakes of diminished agency can be considered even higher, as users' vulnerability to harms such as manipulation and exploitation increases (e.g., marketing manipulations, privacy violations, and breaches of confidentiality). The potential risks may become more pronounced by enhancing the social aspects of the recommendation process, as this could inadvertently foster social conformity among users.

Moving forward with this paper, we examine the arguments introduced here in greater depth to demonstrate how conversational interactions in recommender systems can unlock new opportunities for supporting user self-actualization needs. We will explore how these systems transcend the past-based predictive precedent observed in current recommender systems, which can inadvertently confine users within filter bubbles. Additionally, we will discuss the considerations that need to be addressed before ushering in a new paradigm for recommendation.

2 LIMITATIONS OF THE CURRENT STATE OF RECOMMENDER SYSTEMS

Today's recommender systems predict and present personalized options to users primarily by leveraging past interaction data. This data models relationships and dynamics between users and items. Combined, this data helps define user profiles, item representations, and the dynamics between users and items [22]. Algorithms play a crucial role in processing and analyzing this data, employing methods like content-based filtering (i.e., using item attributes to suggest similar items), collaborative filtering (i.e., matching users with similar preferences to recommend items), and hybrid approaches that combine multiple techniques to enhance recommendation accuracy. The algorithm's ability to personalize and determine relevance, and therefore the options it proactively recommends, is guided by analyzing data on users' previous interactions and known preferences.

However, traditional algorithms in recommender systems, although effective at tailoring choices to known user preferences, can also create the unintended side effect of filter bubbles. These bubbles occur when algorithms limit exposure to information and options that diverge from the user's established interests, thus reinforcing their existing preferences [19]. As a result, users could find themselves in a loop of similar options, which restricts their opportunity to discover diverse and potentially enriching new experiences. This phenomenon not only constricts the user's exploration but also hampers personal growth and broader understanding by filtering out materials that could challenge their viewpoints or contrast with their current beliefs. It also prevents exposure to options they might never have considered—options that could precipitate new interests and preferences [23].

There is a maxim coined by American architect Louis Sullivan—"*form ever follows function*"—which stresses that the design of a structure should be based on its intended function [24]. It contrasts the notions of "form follows precedent" the idea that design ought to be determined by historical or traditional examples, or established practices. Over the years, this axiom has extended to the design conceptualization of all spectra of structures—for example: the biological organization of our bodies to the ergonomic structure of a computer mouse. We believe this maxim can also poignantly be extended to the design of recommender systems and their choice architectures. Rather than solely relying on the past-based predictive precedent of traditional recommender systems, there is an opportunity to explore new forms of recommendations, new design patterns for recommendations that better accommodate the evolving, complex needs of users in the dynamic world they inhabit and new functions therein. There are choice support functions that remain under-explored today, each embodying new possibilities for future recommender systems.

One such function involves orienting recommender systems to support human self-actualization needs. '*Self-actualization*' is the pinnacle of Maslow's hierarchy of needs, where individuals strive to reach their highest potential, pursue personal growth, and achieve a deep sense of fulfillment in life. This perspective on the role of future recommender systems has been touched upon in existing literature [16] [22][8][7]. To implement this vision, practically, robust interactive elements are needed in recommender systems to facilitate a productive dialogue between the system and the user. This approach sets the stage for conversational recommendation systems, which stand out as a particularly effective technique as it can leverage natural language dialogue to actively and meaningfully engage users, allowing the system to better understand and respond to their individual needs and aspirations.

3 A PROGRESSION ENABLED THROUGH CONVERSATIONAL RECOMMENDATION

We will now take a closer look at why conversation-based interaction, with its unique properties, is ideally positioned to achieve the goal of recommender systems aiding in self-actualization. These properties include being able to: (i) directly capture active user preferences in real-time, (ii) treat user preferences as dynamic, layered, and subject to negotiation, and (iii) deepen social aspects that support the recommendation process.

3.1 Real-Time Capture of User Preferences

In conversational recommender systems, preference elicitation is a dynamic process that involves a back-and-forth exchange of information between the user and the system [20]. The design of this interaction involves asking questions that elucidate and grasp what the user wants, thereby enabling the system to select down the most appropriate option(s) from the available search space based on real-time feedback. Preference modelling in traditional predictive recommender systems relies heavily on analyzing previous interaction data to deduce the user's preference. The problem with this type of modelling is that it often fails to reflect the user's actual, immediate interests, and does not account for 'preference shift', i.e., the gradual or sudden change in one's proclivities over time. Historical data can also make it difficult to pinpoint precise reasons for recommendations, as past preferences might not align with current needs [18].

Moreover, preference elicitation becomes particularly beneficial in scenarios where users may not have a clear understanding of what they want or when their preferences are unstable or complex [17][18]. In such cases, the interactive, conversational approach helps guide users through the preference construction or elicitation process, gradually helping them to articulate and clarify their preferences [13][12]. This structured dialogue is advantageous because it facilitates the incremental capture of user preferences, allowing the system to gather more detailed insight into what the user is seeking to progressively refine option candidates for recommendation. This method ensures that recommendations are not only relevant but also timely, reflecting the user's most current desires and needs. This method can similarly recalibrate recommendations as often as necessary to align with the user's evolving self-trajectory.

3.2 Dynamic Negotiation of User Preferences

In exploring the complexity of human preferences, it becomes clear that they are neither static nor simple constructs but rather layered and mutable, involving internal, external, and intermediate negotiations, as well as multiple levels of desires [11]. Preferences encompass first-order desires, such as everyday choices between options for what to eat for lunch or what to do in the evening, as well as higher-order preferences, where individuals reflect on and desire to modify their instinctual impulses based on deeper values or long-term goals. This multi-tiered nature suggests that preferences are continuously shaped and reshaped through internal dialogues, where conflicting desires and goals are negotiated and reconciled. Additionally, this negotiation extends beyond one's internal sphere to include interactions between the decision-maker and the decision environment [27]. Preferences are influenced by external factors such as social pressures, cultural norms, available information, and even the way choices are presented, making the construction of preferences a fluid negotiation between personal desires and environmental realities. For instance, someone might enjoy reading lightweight, entertaining, popular fiction novels as a first-order preference, but also simultaneously possess a higher-order preference for engaging with more dense, challenging, erudite literature that requires careful reading and pushes the reader to think beyond their comfort zone—this reflects a negotiation between seeking immediate enjoyment and aspiring towards the more trying pursuit of intellectual enrichment.

Given the intricate and unstable nature of human preferences, future recommender systems could greatly benefit from incorporating conversation-based interactions that are capable of engaging with users on multiple levels of preferences. Such interactions, which are built on the principle of interchange, enable the system to probe beyond mere surface-level desires, engaging users in a dialogue that progressively clarifies and adapts to their higher-order preferences and the contextual factors influencing their decision-making. This approach would effectively attune to the flux in preferences, recognizing their inherent variability.

3.3 Deepening Recommendation Sociality

Recommender systems increasingly mobilize social elements to deliver compelling and contextually-relevant suggestions—further demonstrating the complex dynamics of human interactions and preferences. This is accomplished through strategies such as leveraging social connections and behavioural patterns [22][25][15]. Recommender systems employing techniques such as collaborative filtering use data from users' social networks, representative user groups, and observed behaviours to suggest options that friends or similar users have liked or used [21]. For instance, if a user's social group shows a preference for certain books or authors, these might be recommended to the user, assuming shared tastes and literary interests. The effectiveness of these recommendations can be augmented by incorporating social signals like trust connections (i.e., relationships where users have demonstrated reliance on each other's choices in various contexts), and social tags (i.e., keywords or labels that users assign to content to describe and categorize it), which helps refine the accuracy of recommendations. User-based collaborative filtering predicts a user's interest in an item based on the preferences of other users who have similar tastes, item-based collaborative filtering predicts a user's interest in an item based on the similarities between items, and hybrid recommendation models combine these with other techniques like content-based filtering to improve recommendation accuracy.

What is generally lacking in current recommender systems is the recognition of heterogeneity in social relationships, as they often treat all types of social connections uniformly, disregarding the varied influence of different relationship types [25]. For example, these systems might give the same weight to recommendations generated by looking at close friends as they do to those coming from acquaintances, failing to recognize that recommendations from close friends often carry more weight due to the stronger social bond and shared interests. Relatedly, by neglecting to incorporate the potential of 'weak ties' (i.e., connections beyond the user's immediate social circles), these systems miss out on chances to introduce users to diverse and unexpected content or products. Moreover, the failure to differentiate between general trends and individual tastes results in recommendations that may be popular overall but lack personal relevance for the user.

Natural language conversation is inherently social because it is familiar in the sense that we use it in everyday human-human dialogue, and because it is interactive in nature—the active sharing of information which is typically how we build shared understanding and rapport in our regular human-human conversations. Social dynamics span external and intermediate negotiations between the decision-maker's internal decision context and the external one.

By engaging in natural language dialogue, conversational recommendation can more actively participate in the social dynamics that influence decision-making processes. Conversational recommendation systems extend the traditional use of social dynamics in existing recommender systems, which often rely on observing patterns within social networks or leveraging the preferences of similar users or looking at similar items. By integrating natural language dialogue, these advanced systems gain the capability to explore and utilize social influences in real-time, providing a richer, more contextual understanding of the user's social environment. This approach allows them to not only draw from existing social relationships but also dynamically respond to new social contexts as they emerge. For example, a conversational recommender systems might adapt its recommendations based on a user's reactions during discussions about recent social interactions or general current trends among peers, thereby capturing subtle shifts in social dynamics. This dynamic interaction deepens the personalization of recommendations, fostering a stronger connection with the user's social realities and aspirations. Such capabilities make conversational recommendation systems uniquely positioned to transform how users interact with and are influenced by their social circles, pushing the boundaries of how social relationships are leveraged to facilitate not just preference satisfaction, but also personal growth and social exploration.

4 THE COMPLEXITIES OF FUTURE-ORIENTED RECOMMENDATION

As we advance the integration of conversational interactions into future recommender systems, like those discussed previously, several critical aspects require careful consideration. These include: (i) navigating the complexities of advanced personalization, and (ii) understanding the potential unintended consequences of these systems, such as implications for and risks to user autonomy.

4.1 The Challenges of Evolving Personalization

The transition in personalization strategies presents a complex challenge. Current, conventional recommender systems rely on *past*-based personalization, i.e, deriving recommendations from a user's historical engagements with the system. The shift to *present*-based personalization requires a focus on the user's current internal psychological state and immediate needs, which may deviate notably from historical patterns due to situational factors [18]. Moreover, there is the ambitious goal of *future*-based personalization, which aims to anticipate and meet the future needs and aspirations of the user, rather than merely reacting to past or present behaviours [14].

The implementation of present-based personalization alone faces significant hurdles. Firstly, accurately gauging a user's current psychological state and immediate needs demands advanced real-time data collection and analysis capabilities [21]. This involves leveraging sophisticated technologies such as natural language processing, emotion recognition, and contextual awareness, which are still in developmental stages [21], and present substantial privacy concerns. Secondly, present-based personalized systems must dynamically adapt to rapid changes in user behaviours and circumstances, which necessitates constant system updates and agile algorithms that can quickly interpret and respond to new data inputs. Furthermore, balancing user privacy with the need for continuous data collection poses ethical and technical challenges that must be addressed to sustain user trust and safety. Current systems grapple with the challenge of maintaining a delicate balance between personalization and privacy. This challenge will likely extend to future generations of recommender systems, requiring ongoing research and innovation in both technological and ethical domains.

4.2 Risks to User Agency in Recommender Systems

Recommender systems, particularly those leveraging social elements, present significant concerns regarding user autonomy and susceptibility to manipulation and exploitation [6][4][5]. The core issue with contemporary recommender systems lies in their potential to subtly guide user choices, thereby diminishing personal agency. For example, by filtering the information to which users are exposed, these systems can significantly influence users' understanding of reality and their ability to make truly informed decisions. Advanced systems that focus on fostering personal growth and self-actualization intensify these concerns. The exchange of deeply personal information with such systems, information that is closely linked to a user's present self and their envisioned future, demands a higher level of user involvement—and thus, trust—than currently prevalent. This raises the stakes as reduced agency can lead to increased risks, such as aggressive marketing strategies, privacy breaches, concerns over surveillance, and the inappropriate use of personal data, which may not be fully understood or consented to by users.

The nuanced relationship between user agency and algorithmic recommendations can be quite fragile if not managed appropriately; as these systems could amplify existing vulnerabilities by promoting social conformity. As recommender systems evolve, the dynamics of user interactions with these systems must be scrutinized to prevent adverse effects, and fulfill an expectation for transparent and adjustable recommender systems—ones that respect user sensibilities while providing diverse content options needs to be paid heed. Empirical studies, such as the one by Harper et al. [9], highlight the importance of allowing users to exert greater control over their recommendations. Studies in this area suggest that user agency can significantly enhance the efficacy and fairness of recommender systems. Interactive conversational recommendation, by engaging users in a dialogue about their preferences and choices, effectively keeps the user in the decision-making loop, thus enhancing transparency and encouraging the individual's control over what options they are recommended, and how.

5 CONCLUSION

In closing, conversational recommender systems hold great promise for supporting user self-actualization, and stimulating dynamic engagement with both present and future user identities. By transitioning from traditional predictive models that rely on past behaviours towards systems that can actively capture real-time preferences and negotiate them in the context of users' internal and external decision environments, we can address the limitations of contemporary systems that often confine users within filter bubbles. Conversational recommendation, by leveraging natural language dialogue, is not only able to adjust suggestions to match users' current interests; it can also lay out paths that align with their evolving aspirations. However, as we advance these systems, it remains critical to navigate the complexities of personalization, and address potential risks to user agency and privacy, ensuring that these innovative systems enhance rather than undermine the very agency they seek to support.

REFERENCES

[1] Charu C Aggarwal et al. 2016. *Recommender systems*. Vol. 1. Springer.

[2] Sofia Bonicalzi, Mario De Caro, and Benedetta Giovanola. 2023. Artificial intelligence and autonomy: on the ethical dimension of recommender systems. *Topoi* 42, 3 (2023), 819–832.

[3] Engin Bozdag and Jeroen Van Den Hoven. 2015. Breaking the filter bubble: democracy and design. *Ethics and information technology* 17 (2015), 249–265.

[4] Sarah Dean, Sarah Rich, and Benjamin Recht. 2020. Recommendations and user agency: the reachability of collaboratively-filtered information. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 436–445.

[5] Lior Fink, Leorre Newman, and Uriel Haran. 2024. Let me decide: Increasing user autonomy increases recommendation acceptance. *Computers in Human Behavior* (2024), 108244.

[6] Sergio Genovesi, Katharina Kaesling, and Scott Robbins. 2023. *Recommender Systems: Legal and Ethical Issues*. Springer Nature.

[7] Mouadh Guesmi, Clara Siepmann, Mohamed Amine Chatti, Shoeb Joarder, Qurat Ul Ain, and Rawaa Alatrash. 2023. Validation of the EDUSS Framework for Self-Actualization Based on Transparent User Models: A Qualitative Study. In *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization*. 229–238.

[8] Lijie Guo. 2018. Beyond the top-n: algorithms that generate recommendations for self-actualization. In *Proceedings of the 12th acm conference on recommender systems*. 573–577.

[9] F Maxwell Harper, Funing Xu, Harmanpreet Kaur, Kyle Condiff, Shuo Chang, and Loren Terveen. 2015. Putting users in control of their recommendations. In *Proceedings of the 9th ACM Conference on Recommender Systems*. 3–10.

[10] Dietmar Jannach, Ahtsham Manzoor, Wanling Cai, and Li Chen. 2021. A survey on conversational recommender systems. *ACM Computing Surveys (CSUR)* 54, 5 (2021), 1–36.

[11] Richard C Jeffrey. 1974. Preference among preferences. *The Journal of Philosophy* 71, 13 (1974), 377–391.

[12] Manveer Kalirai and Anastasia Kuzminykh. 2022. What Can You Do For Me? The Discoverability of Intelligent Assistant Skills. In *Adjunct Proceedings of the 2022 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2022 ACM International Symposium on Wearable Computers*. 57–59.

[13] Manveer Kalirai, Alex C Williams, and Anastasia Kuzminykh. 2024. Toward Faceted Skill Recommendation in Intelligent Personal Assistants. In *Proceedings of the 29th International Conference on Intelligent User Interfaces*. 640–649.

[14] Judy Kay and Bob Kummerfeld. 2009. Lifelong user modelling goals, issues and challenges. In *Proceedings of the Lifelong User Modelling workshop at UMAP*, Vol. 9. Citeseer, 27–34.

[15] Irwin King, Michael R Lyu, and Hao Ma. 2010. Introduction to social recommendation. In *Proceedings of the 19th international conference on World wide web*. 1355–1356.

[16] Bart P Knijnenburg, Saadhika Sivakumar, and Daricia Wilkinson. 2016. Recommender systems for self-actualization. In *Proceedings of the 10th acm conference on recommender systems*. 11–14.

[17] Wenqiang Lei, Xiangnan He, Maarten de Rijke, and Tat-Seng Chua. 2020. Conversational recommendation: Formulation, methods, and evaluation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2425–2428.

[18] Wenqiang Lei, Xiangnan He, Yisong Miao, Qingyun Wu, Richang Hong, Min-Yen Kan, and Tat-Seng Chua. 2020. Estimation-action-reflection: Towards deep interaction between conversational and recommender systems. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 304–312.

[19] Tien T Nguyen, Pik-Mai Hui, F Maxwell Harper, Loren Terveen, and Joseph A Konstan. 2014. Exploring the filter bubble: the effect of using recommender systems on content diversity. In *Proceedings of the 23rd international conference on World wide web*. 677–686.

[20] Bilih Priyogi. 2019. Preference elicitation strategy for conversational recommender system. In *Proceedings of the twelfth ACM international conference on web search and data mining*. 824–825.

[21] Francesco Ricci, Lior Rokach, and Bracha Shapira. 2021. Recommender systems: Techniques, applications, and challenges. *Recommender systems handbook* (2021), 1–35.

[22] Michael Schrage. 2020. *Recommendation engines*. MIT press.

[23] Daniel Stegmann, Melanie Magin, and Birgit Stark. 2022. Filter bubbles. *Elgar Encyclopedia of Technology and Politics* 37, 2 (2022), 220.

[24] Louis H Sullivan. 1922. *The tall office building artistically considered.*

[25] Jiliang Tang, Suhang Wang, Xia Hu, Dawei Yin, Yingzhou Bi, Yi Chang, and Huan Liu. 2016. Recommendation with social dimensions. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 30.

[26] Cynthia A Thompson, Mehmet H Goker, and Pat Langley. 2004. A personalized system for conversational recommendations. *Journal of Artificial Intelligence Research* 21 (2004), 393–428.

[27] W Zachary, R Wherry, F Glenn, and J Hopson. 1982. Decision situations, decision processes, and decision functions: Towards a theory-based framework for decision-aid design. In *Proceedings of the 1982 Conference on Human Factors in Computing Systems*. 355–358.