Towards Adaptive Mixed-Initiative Media Recommender Systems with LLMs

Ulysse Maes
imec-SMIT, Vrije Universiteit Brussel
Brussels, Belgium
ulysse.jan.l.maes@vub.be

Abstract

Recommender systems (RS) increasingly shape how people encounter digital media, but often leave users with limited understanding of why items are recommended and few ways to influence them. Existing user interfaces (UIs) typically offer static, one-size-fits-all explanations and controls that do not reflect users' dynamic needs, limiting user agency. My research investigates how mixed-initiative recommender interfaces, enabled by large language models (LLMs), can adapt explanatory and interactive elements to users' dynamic needs. I plan to develop a conceptual model that links situational media needs to requirements for information (understanding) and interaction (control). Building on this model, I will design and experimentally evaluate adaptive UIs that combine personalized explanations with interactive controls, measuring their effects on user understanding and perceived control. Through this doctoral consortium, I seek feedback on my research plan and guidance in designing effective experiments on adaptive mixed-initiative RS.

CCS Concepts

• **Human-centered computing** → **Graphical user interfaces**; **Natural language interfaces**.

Keywords

Explainable Recommender Systems, Interactive Explanations, Adaptive User Interfaces, User Needs

ACM Reference Format:
Ulysse Maes. 2026. Towards Adaptive Mixed-Initiative Media Recommender Systems with LLMs. In *Companion Proceedings of the 31st International Conference on Intelligent User Interfaces (IUI Companion '26), March 23–26, 2026, Paphos, Cyprus.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3742414.3789233

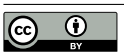
1 Motivation and Problem Statement

Media recommender systems (RS) influence the selection of digital content (e.g., news, music and video) by automatically exposing users to a personalized subset selected out of many items. A key challenge is balancing system automation with user agency, which requires interfaces that both clarify system behavior (via explanations) and allow users to influence it (through control mechanisms) [29, 33]. Yet two problems persist. First, explanations are often static and non-actionable, while available controls provide limited or opaque influence on the underlying model. Mixed-initiative RS address this by coupling explanation and control, treating recommendation as a two-way conversation in which the system exposes its assumptions and users can correct or refine them [31]. Second, most existing implementations remain generic and insensitive to context: explanations offer the same information regardless of a user's situation, and controls –such as like buttons or fixed category links– rarely align with the user's immediate intent. Viewed through the lens of Uses and Gratifications (U&G) theory, this rigidity limits current RS, as U&G posits that users' motivations for media consumption vary across contexts [25]. Consequently, static explanations and binary controls fail to capture the situational nature of user intent, creating a misalignment between the system's model and the user's current goal [8]. For instance, a user looking for a short, funny movie with their children may require different explanations and controls than the same or a different user trying to learn how a rocket engine works. Recent research on conversational recommender systems (CRS) shows that large language models (LLMs) can be used to generate contextualized, personalized explanations [23, 26] and interfaces [13]. It creates an opportunity to support mixed-initiative RS that personalize explanatory and interactive elements in response to user needs within the structured constraints of graphical user interfaces (GUIs), combining proven RS interface patterns with the flexibility of LLM-driven personalization. This approach should improve understanding and control, ultimately advancing user agency.

2 Research Goals and Questions

The goal of this dissertation is to design, operationalize, and evaluate mixed-initiative recommender interfaces that adapt explanations and interactive controls to users' dynamic needs. This requires understanding how different user needs translate into requirements for information and control, and how RS interfaces should be designed and assessed accordingly. These considerations lead to the following research questions:

- **RQ1**: *How do different types of user needs (i.e., cognitive, affective) shape users' requirements for information (understanding) and interaction (control) in media recommender interfaces?*
- **RQ2**: *How does combining personalized explanations with interactive controls in mixed-initiative recommenders influence user understanding and perceived control?*
- **RQ3**: *How can mixed-initiative recommender interfaces flexibly adapt explanatory and interactive features to align with users' dynamic needs?*



This work is licensed under a Creative Commons Attribution 4.0 International License.
IUI Companion '26, Paphos, Cyprus
© 2026 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-1985-1/26/03
https://doi.org/10.1145/3742414.3789233

3 Related Work

Dynamic User Needs in RS. U&G theory shows that people use media to satisfy different needs (i.e., cognitive, affective, and utilitarian) that vary across contexts and moments [6, 25]. Traditional RS, however, assume relatively stable preferences and therefore struggle to respond to immediate user intent [8]. Media use often involves exploratory, dynamic information needs. Models such as "Berry-Picking" [2], "Information Encountering" [5], and "Sense-Making" [22] highlight how intent unfolds iteratively. This motivates RS interfaces that adapt to shifting moods, contexts, and goals [33]. Recent work suggests that LLMs infer rich, contextualized user intent from sparse or conversational signals [8, 24, 34], yet how to translate these insights into adaptive explanations and controls in GUIs remains underexplored.

Supporting User Agency through Understanding and Control. User agency in RS comprises both understanding (transparency) and the ability to influence system behavior (scrutability) [29, 33]. Neither component is sufficient alone: understanding without control is passive [4], while control without understanding can reduce autonomy or increase frustration [11]. Explanations thus form part of an iterative loop where understanding enables corrective action and vice versa [1, 27]. Although users expect explanations to be actionable [15], current RS offer few feedback mechanisms, and existing controls often lack clarity in how they affect system behavior [7]. Research on explanatory debugging confirms that pairing explanations with feedback opportunities strengthens mental models and system alignment [12]. Mixed-initiative RS operationalize this loop by distributing initiative between user and system [31].

Mixed-Initiative, LLM-Enabled Adaptive Interfaces. Like dynamic user motivations for media use, needs for explanations and control differ [31]. LLMs offer mechanisms for generating contextualized explanations, follow-up questions, and tailored control suggestions [23, 35]. While conversational RS illustrate these benefits, most media RS still rely on proven GUI patterns, such as multiple topic-focused lists [9, 19, 28]. HCI theory provides a useful lens on this design space: explanations support users in bridging the "Gulf of Evaluation", while controls help them traverse the "Gulf of Execution" [17]. Furthermore, principles like "cognitive fit" and "recognition over recall" indicate circumstances under which graphical interfaces may be more effective than chat-based ones [16, 32]. LLMs may act as "orchestrators" coordinating adaptive explanations and controls. They enable context-rich, user-tailored narratives [23, 26] and can describe preference evolution or integrate graphical and interactive elements [13, 18]. Yet the field lacks a framework linking LLM-driven mixed-initiative interaction to dynamic user needs, motivating the focus of this PhD project.

4 Preliminary Results and Expected Contributions

My early work provides initial evidence supporting the need for and feasibility of adaptive, mixed-initiative RS interfaces. First, an analysis of heterogeneous user reading patterns in a news RS revealed substantial variation in how users engage with news content, underscoring the importance of modeling dynamic media intents and motivating RQ1 [30]. Second, we evaluated LLM-based explanations, establishing a methodological foundation for studying how explanations influence user agency (RQ2) [14]. Third, we developed a prototype demonstrating the feasibility of coupling explanations with interactive refinement controls in a unified interface, offering a proof-of-concept for both RQ2 and RQ3 [13]. In parallel, an ongoing literature review synthesizes the link between user needs and need for information and control, informing the conceptual model underlying RQ1. With the dissertation, I aim to contribute on three levels. Theoretically, it will propose a model linking user needs from U&G theory to corresponding needs for information and control in recommender interfaces. Empirically, it will provide controlled evidence on when and why combining explanations with interactive elements enhances user agency, and offer insight into how LLMs can mediate adaptive explanatory behavior. Technically, it will deliver open-source prototypes of adaptive mixed-initiative RS and derive actionable design patterns for integrating explanations and controls in media recommendation contexts.

5 Expected Next Steps

I will follow a three-stage research plan, where each phase aligns with a core RQ and progressively builds conceptual understanding, empirical validation, and interface patterns. *Phase 1: Conceptualizing Dynamic User Needs*: To address RQ1, I will conduct qualitative think-aloud interviews using early "provotypes", provocative prototypes [3], and apply thematic analysis to uncover patterns in information needs, system perceptions, and preferred forms of control. These insights will inform a conceptual model that maps dynamic user needs to explanation and control requirements, and clarifies how needs shift across contexts. *Phase 2: Evaluating Mixed-Initiative RS*: To address RQ2, I will develop functional prototypes that vary in explanation style and interactive elements. In controlled, between-subjects experiments, participants will complete representative recommendation tasks. Understanding will be measured both objectively [21] and subjectively [20], alongside perceived control, perceived usefulness [10], and interaction logs. *Phase 3: Evaluating LLM-based Adaptivity*: In a final phase, I will develop semi-functional mixed-initiative RS interfaces that use LLMs to infer users' evolving information needs from their interactions. The system will adapt its explanatory strategy and propose relevant control actions. A within-subjects study with open-ended media browsing tasks, complemented by probing questions and follow-up interviews, will assess perceived adaptivity, usefulness, and agency. Ultimately, the findings of these research steps are aimed towards constructing a framework that links situational user needs to requirements for information and control.

Acknowledgments

This research was supported by the Research Foundation Flanders (FWO) under grant number 1158225N.

References

[1] Krisztian Balog, Filip Radlinski, and Shushan Arakelyan. 2019. Transparent, Scrutable and Explainable User Models for Personalized Recommendation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Paris, France) *(SIGIR'19)*. Association for Computing Machinery, New York, NY, USA, 265–274. doi:10.1145/3331184.3331211

[2] Marcia J. Bates. 1989. The design of browsing and berrypicking techniques for the online search interface. *Online Review* 13, 5 (05 1989), 407–424.

arXiv:https://www.emerald.com/oir/article-pdf/13/5/407/2074806/eb024320.pdf doi:10.1108/eb024320

[3] Laurens Boer and Jared Donovan. 2012. Provotypes for participatory innovation. In *Proceedings of the Designing Interactive Systems Conference* (Newcastle Upon Tyne, United Kingdom) *(DIS '12)*. Association for Computing Machinery, New York, NY, USA, 388–397. doi:10.1145/2317956.2318014

[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* (Barcelona, Spain) *(FAT* '20)*. Association for Computing Machinery, New York, NY, USA, 436–445. doi:10.1145/3351095.3372866

[5] Sanda Erdelez. 1997. Information encountering: a conceptual framework for accidental information discovery. In *Proceedings of an International Conference on Information Seeking in Context* (Tampere, Finland) *(ISIC '96)*. Taylor Graham Publishing, GBR, 412–421.

[6] Yuanjun Feng, Stefan Feuerriegel, and Yash Raj Shrestha. 2025. Contextualizing Recommendation Explanations with LLMs: A User Study. arXiv:2501.12152 [cs.HC] https://arxiv.org/abs/2501.12152

[7] Muheeb Faizan Ghori, Arman Dehpanah, Jonathan Gemmell, and Bamshad Mobasher. 2025. "They Only Offer the Illusion of Choice": Exploring User Perceptions of Control and Agency on YouTube. In *Adjunct Proceedings of the 33rd ACM Conference on User Modeling, Adaptation and Personalization (UMAP Adjunct '25)*. Association for Computing Machinery, New York, NY, USA, 214–218. doi:10.1145/3708319.3733664

[8] Dietmar Jannach and Markus Zanker. 2024. A Survey on Intent-aware Recommender Systems. *ACM Trans. Recomm. Syst.* 3, 2, Article 23 (Dec. 2024), 32 pages. doi:10.1145/3700890

[9] Yucheng Jin, Bruno Cardoso, and Katrien Verbert. 2017. How do different levels of user control affect cognitive load and acceptance of recommendations?. In *Jin, Y., Cardoso, B. and Verbert, K., 2017, August. How do different levels of user control affect cognitive load and acceptance of recommendations?. In Proceedings of the 4th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems co-located with ACM Conference on Recommender Systems (RecSys 2017)*, Vol. 1884. CEUR Workshop Proceedings, 35–42.

[10] Bart P Knijnenburg, Martijn C Willemsen, Zeno Gantner, Hakan Soncu, and Chris Newell. 2012. Explaining the user experience of recommender systems. *User modeling and user-adapted interaction* 22, 4 (2012), 441–504.

[11] Pascal D König. 2024. Challenges in enabling user control over algorithm-based services. *AI & SOCIETY* 39, 1 (2024), 195–205.

[12] Todd Kulesza, Margaret Burnett, Weng-Keen Wong, and Simone Stumpf. 2015. Principles of Explanatory Debugging to Personalize Interactive Machine Learning. In *Proceedings of the 20th International Conference on Intelligent User Interfaces* (Atlanta, Georgia, USA) *(IUI '15)*. Association for Computing Machinery, New York, NY, USA, 126–137. doi:10.1145/2678025.2701399

[13] Ulysse Maes, Lien Michiels, and Annelien Smets. 2024. GenUI(ne) CRS: UI Elements and Retrieval-Augmented Generation in Conversational Recommender Systems with LLMs. In *Proceedings of the 18th ACM Conference on Recommender Systems* (Bari, Italy) *(RecSys '24)*. Association for Computing Machinery, New York, NY, USA, 1177–1179. doi:10.1145/3640457.3691697

[14] Ulysse Maes, Lien Michiels, and Annelien Smets. 2025. Mitigating Misleadingness in LLM-Generated Natural Language Explanations for Recommender Systems: Ensuring Broad Truthfulness Through Factuality and Faithfulness. In *Proceedings of the 29th Annual ACM Conference on Intelligent User Interfaces*.

[15] Eliza Mitova, Sina Blassnig, Edina Strikovic, Aleksandra Urman, Claes de Vreese, and Frank Esser. 2024. Exploring users' desire for transparency and control in news recommender systems: A five-nation study. *Journalism* 25, 10 (2024), 2001–2021. arXiv:https://doi.org/10.1177/14648849231222099 doi:10.1177/14648849231222099

[16] Jakob Nielsen. 1994. Enhancing the explanatory power of usability heuristics. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. 152–158.

[17] Donald A Norman. 1986. Cognitive engineering. In *User centered system design*. CRC Press, 31–62.

[18] Alessandro Petruzzelli, Cataldo Musto, Lucrezia Laraspata, Ivan Rinaldi, Marco de Gemmis, Pasquale Lops, and Giovanni Semeraro. 2024. Instructing and Prompting Large Language Models for Explainable Cross-domain Recommendations. In *Proceedings of the 18th ACM Conference on Recommender Systems* (Bari, Italy) *(RecSys '24)*. Association for Computing Machinery, New York, NY, USA, 298–308. doi:10.1145/3640457.3688137

[19] Behnam Rahdari, Branislav Kveton, and Peter Brusilovsky. 2022. The Magic of Carousels: Single vs. Multi-List Recommender Systems. In *Proceedings of the 33rd ACM Conference on Hypertext and Social Media* (Barcelona, Spain) *(HT '22)*. Association for Computing Machinery, New York, NY, USA, 166–174. doi:10.1145/3511095.3531278

[20] Yao Rong, Tobias Leemann, Thai-Trang Nguyen, Lisa Fiedler, Peizhu Qian, Vaibhav Unhelkar, Tina Seidel, Gjergji Kasneci, and Enkelejda Kasneci. 2023. Towards human-centered explainable ai: A survey of user studies for model explanations. *IEEE transactions on pattern analysis and machine intelligence* 46, 4 (2023), 2104–2122.

[21] Yao Rong, Tobias Leemann, Thai-Trang Nguyen, Lisa Fiedler, Peizhu Qian, Vaibhav Unhelkar, Tina Seidel, Gjergji Kasneci, and Enkelejda Kasneci. 2024. Towards Human-Centered Explainable AI: A Survey of User Studies for Model Explanations. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 46, 4 (2024), 2104–2122. doi:10.1109/TPAMI.2023.3331846

[22] Daniel M. Russell, Mark J. Stefik, Peter Pirolli, and Stuart K. Card. 1993. The cost structure of sensemaking. In *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems* (Amsterdam, The Netherlands) *(CHI '93)*. Association for Computing Machinery, New York, NY, USA, 269–276. doi:10.1145/169059.169209

[23] Alan Said. 2025. On explaining recommendations with Large Language Models: a review. *Frontiers in Big Data* 7 (2025), 1505284.

[24] Sarama Shehmir and Rasha Kashef. 2025. LLM4Rec: A Comprehensive Survey on the Integration of Large Language Models in Recommender Systems—Approaches, Applications and Challenges. *Future Internet* 17, 6 (2025), 252.

[25] Moses Sichach. 2023. Uses and gratifications theory-background, history and limitations. *History and Limitations (November 17, 2023)* (2023).

[26] Ítallo Silva, Leandro Marinho, Alan Said, and Martijn C. Willemsen. 2024. Leveraging ChatGPT for Automated Human-centered Explanations in Recommender Systems. In *Proceedings of the 29th International Conference on Intelligent User Interfaces* (Greenville, SC, USA) *(IUI '24)*. Association for Computing Machinery, New York, NY, USA, 597–608. doi:10.1145/3640543.3645171

[27] Frode Sørmo, Jörg Cassens, and Agnar Aamodt. 2005. Explanation in case-based reasoning–perspectives and goals. *Artificial Intelligence Review* 24, 2 (2005), 109–143.

[28] Ruixuan Sun, Xinyi Li, Avinash Akella, and Joseph A Konstan. 2024. Large language models as conversational movie recommenders: A user study. *arXiv preprint arXiv:2404.19093* (2024).

[29] Nava Tintarev and Judith Masthoff. 2012. Evaluating the effectiveness of explanations for recommender systems: Methodological issues and empirical studies on the impact of personalization. *User Modeling and User-Adapted Interaction* 22, 4 (2012), 399–439.

[30] Hanne Vandenbroucke, Ulysse Maes, Lien Michiels, and Annelien Smets. 2025. Not One News Recommender To Fit Them All: How Different Recommender Strategies Serve Various User Segments. In *Proceedings of the Nineteenth ACM Conference on Recommender Systems (RecSys '25)*. Association for Computing Machinery, New York, NY, USA, 643–648. doi:10.1145/3705328.3748034

[31] Katrien Verbert. 2018. Mixed-initiative Recommender Systems: Towards a Next Generation of Recommender Systems through User Involvement. In *CEUR Workshop Proceedings*, Vol. 2225. 1.

[32] Iris Vessey and Dennis Galletta. 1991. Cognitive fit: An empirical study of information acquisition. *Information systems research* 2, 1 (1991), 63–84.

[33] Mengke Wu, Weizi Liu, Yanyun Wang, Weiyu Ding, and Mike Yao. 2025. Rethinking User Empowerment in AI Recommender Systems: Designing through Transparency and Control. (2025). arXiv:2509.11098 [cs.HC] https://arxiv.org/abs/2509.11098

[34] Xiaochuan Xu, Zeqiu Xu, Peiyang Yu, and Jiani Wang. 2025. Enhancing user intent for recommendation systems via large language models. In *International Conference on Artificial Intelligence and Machine Learning Research (CAIMLR 2024)*, Jun Liu, Ankush Ghosh, Chee Wei Tan, and Haiquan Zhao (Eds.), Vol. 13635. International Society for Optics and Photonics, SPIE, 1363507. doi:10.1117/12.3060232

[35] Ziliang Zhao, Shiren Song, and Zhicheng Dou. 2025. FollowGPT: A Framework of Follow-up Question Generation for Large Language Models via Conversation Log Mining. In *Proceedings of the 34th ACM International Conference on Information and Knowledge Management* (Seoul, Republic of Korea) *(CIKM '25)*. Association for Computing Machinery, New York, NY, USA, 4412–4422. doi:10.1145/3746252.3761401