Jan 17th, 12:00 AM

The Acceptance of AI-based Recommendations: An Elaboration Likelihood Perspective

Leonard Michels
Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, leonard.michels@fau.de

Jessica Ochmann
Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, jessica.ochmann@fau.de

Verena Tiefenbeck
Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, verena.tiefenbeck@fau.de

Sven Laumer
Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, sven.laumer@fau.de

The Acceptance of AI-based Recommendations: An Elaboration Likelihood Perspective

Leonard Michels, Jessica Ochmann, Verena Tiefenbeck, and Sven Laumer

Institute for Information Systems, Friedrch-Alexander-Universität Erlangen-Nürnberg, Germany
{leonard.michels, jessica.ochmann, verena.tiefenbeck, sven.laumer}@fau.de

Abstract. Algorithmic advice has been shown to outperform human reasoning in various domains. However, prior research suggests that humans might be reluctant to accept it and proposed multiple avenues to increase the acceptance. To structure these approaches and potentially shed light on inconclusive results of prior studies, we propose a novel perspective on the acceptance of AI-based recommendations based on the elaboration likelihood model (ELM). This research in progress paper introduces our perspective on AI-based recommendations as persuasive messages, suggests the ELM as a promising approach to guide interventions aiming to increase their acceptance, and develops testable hypotheses to evaluate the model. We, thereby, include the moderating effects of individual and situational variables.

Keywords: Elaboration likelihood model, Algorithmic advice, Algorithmic recommendation

1 Introduction

In the recent past, artificial intelligence (AI) and AI-based systems have become ubiquitous in supporting humans in various decision tasks [1]. The growing reliance on algorithmic advice is, at least partly, rooted in the capability of computational and statistical models, that underlie, AI to reliably outperform human reasoning in many domains – regarding both speed and accuracy [2]. In addition, such systems, when carefully developed, can be designed to actively combat biases in human decision processes, leading to more ethical decisions [3, 4].

One area in which humans can benefit particularly from the valuable and novel insights AI-based systems and their advanced analysis of large, complex data sets provide, is decision-making. This potential has led to the wide distribution of AI-based recommendations in the consumer domain that support individuals in their daily decision-making processes [1]. Based on thorough analyses of the choice set and the individual's preferences, AI-based systems point out particularly promising or beneficial alternatives [5]. Building upon this principle, AI-based recommendations are also receiving increasing attention in the organizational and professional context [6, 7]. While organizations invest substantial resources in the development of systems that support their employees' and customers' decisions by giving algorithmic advice [1, 6], prior research has raised doubt on the question whether the destined end-users would adopt such novel technology and accept its recommendations [7–11]. Recent scholarly investigations have, indeed, shown that multiple factors might drive a certain reluctance of humans to accept AI-based

17th International Conference on Wirtschaftsinformatik
February 2022, Nürnberg, Germany

recommendations [7, 8]. Among them is the tendency of human decision-makers to perceive themselves superior to algorithms [8, 12–14] and a preference to follow their own instincts [8]. In addition, algorithmic advice might suffer from a lack of trust among users and could even be actively resisted and perceived as a control approach [7, 15, 16].

To counteract such potential obstacles in the acceptance of AI-enabled technology in general and AI-based recommendations in particular, different avenues have been proposed [15, 17, 18]. So far, however, the results of empirical studies investigating their effects have been inconclusive and no clear strategy guiding the development of future approaches exists [15, 18]. Anthropomorphizing artificial intelligence, for example, can lead to increased as well as reduced adoption of AI-enabled technology [18].

We aim to contribute to current research regarding the acceptance of AI-based recommendations by proposing a perspective based on the elaboration likelihood model of persuasion (ELM) [19–22]. We, therefore, consider the underlying recommending systems as technological artifacts transmitting their recommendations as persuasive messages [15, 23, 24] and add the individual's elaboration likelihood as an important moderator for the users' general acceptance and the effects of interventions aiming to increase the acceptance of AI-based recommendations. We believe that investigating the acceptance of AI-based recommendations from an elaboration likelihood perspective will provide a contribution to the literature as it could explain the different and to some extent contradicting results of research regarding the acceptance of AI-based recommendations, such as algorithm aversion and algorithm appreciation [15, 16, 25]. Thus, we intend to answer the following research question:

RQ_1**:** How does the individual's elaboration likelihood affect the effectiveness of measures aiming to increase the acceptance of AI-based recommendations?

In this research in progress manuscript, we describe the theoretical underpinnings of our approach and further outline the expected contributions of the proposed project.

2 Related work and development of hypotheses

2.1 Acceptance of algorithmic advice

Individualized recommendations have been of broad scholarly interest since their first introduction in the late 1990s [26]. From an IS perspective, prior research regarding their acceptance had a strong focus on the technology acceptance model [27] and unveiled various cognitive, environmental, and relational constructs [28–30] as influential factors in a large spectrum of application domains such as e-commerce, media, human resources, finance, and the medical field [5].

While early investigations in this research domain focused on individuals' acceptance of personalized recommendations highlighting decision alternatives in line with the user's preferences, today's sophisticated AI-based recommendations incorporate the whole decision process up until the final decision to disencumber the human decision-maker [31]. Driven by this change, it remains unclear how prior findings in the recommendation context can be transferred to understand the acceptance of such sophisticated algorithmic advice. Individuals, for example, often have a zero error tolerance towards algorithms [32], reject algorithmic advice due to the lack of perceived control over the recommendation's underlying reasoning [13], or are reluctant to use it in the medical domain [33] – this phenomenon of preferring human to algorithmic advice is commonly referred to as *algorithm aversion* [12, 15, 16, 34]. Recent research, however, suggests a two-sided character of this phenomenon, showing that individuals indeed rely on AI-based recommendations for specific tasks with an objectively correct answer [12, 15, 25].

So far, prior scholarly research investigated various factors such as expertise of the decision-maker, task-dependence, algorithm characteristics (transparency, explainability, or performance information), and agent design (e.g., anthropomorphism) to explain and increase the acceptance of algorithmic advice [12, 15, 25, 32] – with inconclusive results. Some studies, for example, report a positive and others a negative influence of performance information on the acceptance of AI-based recommendations [35–39]. It has further been shown that anthropomorphic agent design can have both positive and negative effects [18], and that a higher degree of algorithm transparency and explainability does not necessarily increase acceptance [13, 17, 40].

These controversial findings reflect the need for a novel perspective on the acceptance of AI-based recommendations that can structure future approaches and might be able to provide explanations for the findings of prior research. To address this research gap, we apply the elaboration likelihood model of persuasion to the acceptance of AI-based recommendations, consider the recommendations as persuasive messages, and investigate the effects of central and peripheral persuasion appeals on their acceptance.

2.2 Elaboration likelihood model of persuasion

The elaboration likelihood model of persuasion (ELM) structures how persuasive messages are processed by individuals and affect their attitudes and behavior [19]. It assumes that there are two routes of persuasion and information processing: a central and a peripheral route. According to the model, the extent to which individuals rely on either of the two routes depends on their elaboration likelihood, which refers to "the extent to which a person scrutinizes the issue-relevant arguments contained in the persuasive communication" [19].

If individuals have a high elaboration likelihood (e.g., sufficient motivation and ability) to assess an attitude object (i.e., the AI-based recommendation), they will process information and persuasive messages using the central route. Here, a detailed processing or elaboration of the information in the message will take place, involving critical thinking and careful consideration of the argument's quality – resulting in a reasoned attitude that is bolstered by supporting information [41].

Individuals who either lack the necessary motivation or ability (i.e., have a low elaboration likelihood) to assess an attitude object (i.e., the AI-based recommendation) process information via the peripheral route. They rely on simple cues, undertake less thoughtful processes, and use heuristic rules to come to their final attitude and behavior [21, 41, 42].

While the ELM offers a compelling approach to persuasion that can account for various phenomena in different disciplines, such as psychology [43], marketing [44], and IS [21, 22, 42, 45], it has not yet been applied to the acceptance of algorithmic advice.

Prior research has shown, however, that central and peripheral information processes can indeed drive individual attitudes towards technology, its related acceptance behavior, and the effectiveness of persuasion approaches such as online reviews – depending on individual and situational characteristics [21, 22, 42, 45]. Applying the model to the acceptance of AI-based recommendations, therefore, offers a novel approach and explanation that could help to shed light on inconclusive results of prior research and guide further approaches to increase the acceptance in this realm. Based on the ELM, we propose that both central and peripheral persuasion appeals can increase the acceptance of AI-based recommendations. Their effectiveness, however, depends on individual and situational factors, affecting the individual's elaboration likelihood.

2.3 Research model

Based on the theoretical foundations outlined above, we consider an AI-based system's recommendations as persuasive appeals aiming to convince its users to select the recommended option. According to the ELM, this persuasion can occur via two different routes.

Central persuasion appeals persuade individuals by providing rational arguments pointing out the relative merits and benefits of an attitude object. The higher the perceived quality of the arguments, the more likely users will change their attitude [21, 22, 41, 42]. In the context of AI-based recommendations, such qualitative arguments are commonly explanations of how the AI derived its recommendations [34, 46] or performance information [15]. While giving such information has been shown to increase the acceptance of AI-based recommendations [15, 17, 34, 47], it can also lead to adverse effects such as algorithm aversion and reduced acceptance of the recommendations [16, 48].

The persuasiveness of central persuasion appeals depends strongly on an individual's elaboration likelihood. This likelihood is influenced by multiple factors. Among them is the person's need for cognition [42, 49] as well as their task involvement and the relevance of the task [21, 22, 45]. Prior research in this realm has shown that both factors are important moderators for the effects of persuasive messages on subsequent attitudes and behaviors [21,22,42,45,49]. The higher the individual's need for cognition, the more likely they are to elaborate on a persuasive message and scrutinize its key arguments and the greater the expected persuasive effect of central persuasion appeals such as argument quality [20, 49]. The same line of reasoning holds the more a person is involved in a task and the more relevant the task, for which the AI-based recommendation is provided, is for them [21, 22, 45]. We, therefore, assume that the effect of providing qualitative arguments regarding an AI-based recommendation on its acceptance is moderated by an individual's need for cognition and task involvement and hypothesize:

H_1**:** *The effect of providing qualitative arguments regarding an AI-based recommendation on its acceptance is greater for individuals with a high need for cognition (H_{1a}) and high task involvement (H_{1b}).*

In contrast, *peripheral persuasion appeals* do not provide any rational argumentation, but rather heuristic cues, such as the position or rank of the recommended option in the choice set [50] or appealing design features [18, 45]. However, the potential attitude changes evoked by these persuasive appeals are predicted to be weak and do not necessarily result in behavior change [19, 41, 42, 51]. Especially for individuals with a high elaboration likelihood, these peripheral cues are unlikely to induce behavior change [21, 50]. Individuals with a low elaboration likelihood, however, are more likely to be persuaded by these approaches as they commonly rely on simple cues to guide their behavior and decisions. We, therefore, assume that the effect of peripheral persuasion appeals regarding an AI-based recommendation on its acceptance is also moderated by an individuals need for cognition and task involvement and hypothesize:

H_2**:** *The effect of accompanying an AI-based recommendation with simple peripheral cues on its acceptance is greater for individuals with a low need for cognition (H_{2a}) and low task involvement (H_{2b}).*

3 Discussion and next steps

We aim to provide a first step towards incorporating the elaboration likelihood model as a perspective that gives guidance and structures interventions to increase the acceptance of AI-based recommendations and might help to align the different, inconclusive results of prior research in this realm. We assume that the effectiveness of measures to increase the acceptance of AI-based recommendations depends on whether they address either the central or peripheral route of persuasion and, therefore, also on individual and situational characteristics, such as the individual's need for cognition or the relevance and involvement of the task, for which the recommendation is provided.

In prior studies, the perception and use of algorithms was often attributed to external factors (e.g., task characteristics) and personal variables (e.g., task motivation) were not taken into account. In addition, the relevance of the task and the individual's involvement in the task were often disregarded. By following our elaboration likelihood approach, we extend prior research and highlight the importance of information processing routes for the acceptance of algorithmic advice. Studies focusing on algorithm characteristics (transparency, explainability, or performance information) [15] target the central route as they focus on arguments about recommendations explaining the performance of the algorithms or the way recommendations have been derived. Based on our model, we would expect that this way of influencing the acceptance of AI-based recommendations is more appropriate for individuals with a high need for cognition and for whom the task is very relevant. Hence, the different results regarding the influence of algorithm characteristics on the acceptance of AI-based recommendation [35–38] might be explained by the individual elaboration likelihood. On the other hand, peripheral cues such as the position of the recommendation in the choice set steer individuals without further consideration of the quality of the argument itself. According to our model, their effect should be greater for individuals with a low elaboration likelihood. Again, as studies in the literature have reported varying results [18], we conclude that the difference in terms of the individual elaboration likelihood in the respective studies might explain why either positive, negative, or no effects were observed. We plan to evaluate the validity of our ELM perspective by testing our hypotheses in an incentive compatible between-subject experiment.

References

1. Duan, Y., Edwards, J.S., Dwivedi, Y.K.: Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda. International Journal of Information Management 48, 63–71 (2019)
2. Lecun, Y., Bengio, Y., Hinton, G.: Deep Learning. Nature 521(7553), 436–444 (2015)
3. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., Vayena, E.: AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. Minds and Machines 28(4), 689–707 (2018)
4. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., Galstyan, A.: A Survey on Bias and Fairness in Machine Learning. arXiv:1908.09635 [cs] (2019)
5. Lu, J., Wu, D., Mao, M., Wang, W., Zhang, G.: Recommender System Application Developments: A Survey. Decision Support Systems 74, 12–32 (2015)
6. Jarrahi, M.H.: Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons 61(4), 577–586 (2018)
7. Kellogg, K.C., Valentine, M.A., Christin, A.: Algorithms at work: The new contested terrain of control. Academy of Management Annals 14(1), 366–410 (2020)
8. Burton, J.W., Stein, M., Jensen, T.B.: A systematic review of algorithm aversion in augmented decision making. Journal of Behavioral Decision Making 33(2), 220–239 (2020)
9. Juma, C.: Innovation and its enemies: why people resist new technologies. Oxford University Press, New York, NY, 1st edn. (2016)
10. Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R.: Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management 49, 157–169 (2019)
11. Leung, E., Paolacci, G., Puntoni, S.: Man Versus Machine: Resisting Automation in Identity-Based Consumer Behavior. Journal of Marketing Research 55(6), 818–831 (2018)
12. Castelo, N., Bos, M.W., Lehmann, D.R.: Task-Dependent Algorithm Aversion. Journal of Marketing Research 56(5), 809–825 (2019)
13. Dietvorst, B.J., Simmons, J.P., Massey, C.: Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. Management Science 64(3), 1155–1170 (2018)
14. Webb, N.: AI adoption advances, but foundational barriers remain (2018)
15. Jussupow, E., Benbasat, I., Heinzl, A.: Why Are We Averse Towards Algorithms ? A Comprehensive Literature Review on Algorithm Aversion. pp. 1–16 (2020)
16. Dietvorst, B.J., Simmons, J.P., Massey, C.: Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General 144(1), 114–126 (2015)
17. Shin, D.: The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies 146, 102551 (2021)
18. Li, M., Suh, A.: Machinelike or Humanlike? A Literature Review of Anthropomorphism in AI-Enabled Technology. In: Proceedings of the 54th Hawaii International Conference on System Sciences (2021)
19. Petty, R.E., Cacioppo, J.T.: The elaboration likelihood model of persuasion. Advances in Experimental Social Psychology 19(C), 123–205 (1986)
20. Tam, K.Y., Ho, S.Y.: Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes. MIS Quarterly 30(4), 865–890 (2006)
21. Bhattacherjee, A., Sanford, C.: Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model. MIS Quarterly 30(4), 805–825 (2006)

22. Cheung, C.M.y., Sia, C.l., Kuan, K.K.Y.: Is This Review Believable? A Study of Factors Affecting the Credibility of Online Consumer Reviews from an ELM Perspective. Journal of the Association for Information Systems 13(8), 618–635 (2012)
23. Gretzel, U., Fesenmaier, D.R.: Persuasion in recommender systems. International Journal of Electronic Commerce 11(2), 81–100 (2006)
24. Cremonesi, P., Garzotto, F., Turrin, R.: Investigating the persuasion potential of recommender systems from a quality perspective: An empirical study. ACM Transactions on Interactive Intelligent Systems 2(2), 1–41 (2012)
25. Logg, J.M., Minson, J.A., Moore, D.A.: Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes 151, 90–103 (2019)
26. Resnick, P., Varian, H.R.: Recommender systems. Communications of the ACM 40(3), 56–58 (1997)
27. Venkatesh, Morris, Davis, Davis: User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly 27(3), 425 (2003)
28. Komiak, S.Y.X., Benbasat, I.: The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. MIS Quarterly 30(4), 941–960 (2006)
29. Karahanna, E., Straub, D.W., Chervany, N.L.: Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. MIS Quarterly 23(2), 183–213 (1999)
30. Kim, H.W., Chan, H., Chan, Y., Gupta, S.: Understanding the balanced effects of belief and feeling on information systems continuance. In: Proceedings of the 25th International Conference on Information System (2004)
31. Venkatesh, V.: Adoption and use of AI tools: a research agenda grounded in UTAUT. Annals of Operations Research (2021)
32. Dietvorst, B.J., Simmons, J.P., Massey, C.: Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General 144(1), 114–126 (2015)
33. Longoni, C., Bonezzi, A., Morewedge, C.K.: Resistance to Medical Artificial Intelligence. Journal of Consumer Research 46(4), 629–650 (2019)
34. Burton, J.W., Stein, M., Jensen, T.B.: A systematic review of algorithm aversion in augmented decision making. Journal of Behavioral Decision Making 33(2), 220–239 (2020)
35. Bigman, Y.E., Gray, K.: People are averse to machines making moral decisions. Cognition 181, 21–34 (2018)
36. Beck, H.P., McKinney, J.B., Dzindolet, M.T., Pierce, L.G.: Effects of Human—Machine Competition on Intent Errors in a Target Detection Task. Human Factors: The Journal of the Human Factors and Ergonomics Society 51(4), 477–486 (2009)
37. Goodyear, K., Parasuraman, R., Chernyak, S., Madhavan, P., Deshpande, G., Krueger, F.: Advice Taking from Humans and Machines: An fMRI and Effective Connectivity Study. Frontiers in Human Neuroscience 10 (2016)
38. Boorman, E., O'Doherty, J., Adolphs, R., Rangel, A.: The Behavioral and Neural Mechanisms Underlying the Tracking of Expertise. Neuron 80(6), 1558–1571 (2013)
39. Dzindolet, M.T., Pierce, L.G., Beck, H.P., Dawe, L.A.: The Perceived Utility of Human and Automated Aids in a Visual Detection Task. Human Factors: The Journal of the Human Factors and Ergonomics Society 44(1), 79–94 (2002)
40. Newman, D.T., Fast, N.J., Harmon, D.J.: When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. Organizational Behavior and Human Decision Processes 160(April 2018), 149–167 (2020)
41. Petty, R.E., Briñol, P.: The Elaboration Likelihood Model. In: Handbook of Theories of Social Psychology: Volume 1, pp. 224–245. SAGE Publications Ltd, London, UK (2012)

42. Tam, K.Y., Ho, S.Y.: Web personalization as a persuasion strategy: An elaboration likelihood model perspective. Information Systems Research 16(3), 271–291 (2005)
43. Yang, S.C., Hung, W.C., Sung, K., Farn, C.K.: Investigating initial trust toward e-tailers from the elaboration likelihood model perspective. Psychology and Marketing 23(5), 429–445 (2006)
44. Batra, R., Ray, M.L.: Situational Effects of Advertising Repetition: The Moderating Influence of Motivation, Ability, and Opportunity to Respond. Journal of Consumer Research 12(4), 432 (1986)
45. Cyr, D., Head, M., Lim, E., Stibe, A.: Using the elaboration likelihood model to examine online persuasion through website design. Information and Management 55(7), 807–821 (2018)
46. Ribeiro, M.T., Singh, S., Guestrin, C.: "Why Should I Trust You?": Explaining the Predictions of Any Classifier. arXiv:1602.04938 [cs, stat] (2016)
47. Ben David, D., Resheff, Y.S., Tron, T.: Explainable AI and Adoption of Financial Algorithmic Advisors: An Experimental Study. In: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society. pp. 390–400 (2021)
48. Lehmann, C., Haubitz, C., Fügener, A., Thonemann, U.: Keep It Mystic? – The Effects of Algorithm Transparency on the Use of Advice. In: Proceedings of the 41st International Conference on Information Systems (2020)
49. Cacioppo, J.T., Petty, R.E., Morris, K.J.: Effects of need for cognition on message evaluation, recall, and persuasion. Journal of Personality and Social Psychology 45(4), 805–818 (1983)
50. Tam, K.Y., Ho, S.Y.: Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective. Information Systems Research 16(3), 271–291 (2005)
51. Droge, C.: Shaping the Route to Attitude Change: Central versus Peripheral Processing through Comparative versus Noncomparative Advertising. Journal of Marketing Research 26(2), 193 (1989)