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AI-assisted Decision-making and Consumers' Trust in AI Recommendations

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Abstract

With the development of artificial intelligence (AI) in recent years, intelligent recommendation systems have become popular in daily life and are used to help people make decisions. AI recommendation systems will be of use only if consumers are willing to be guided by them. This paper studies consumers' trust in AI-generated recommendations under conditions of AI-assisted decision-making. Based on the literature of algorithm aversion, algorithm appreciation and trust in automation, this paper will present various psychological and cognitive reasons for changes in people's perceptions of algorithms. Research has shown that a sense of personalisation, relatively simple tasks and good explanations (explainable AI) can make people feel more trusted. Based on the above analysis, consumers are more likely to accept algorithms for objective and data-driven applications; however, they may be hesitant about algorithms used in cases of subjective judgment or high-stakes decisions, especially after learning of algorithmic errors. In addition, the above analysis also shows that emotional trust may be a mediator in the intention to delegate decision-making to AI agents. In short, this paper offers a theoretical discussion on algorithmic reliance and proposes strategies to build more transparent and trustworthy AI recommendation systems that can improve the user experience.

Keywords

Artificial Intelligence; Consumer Trust; Recommendation Systems; Algorithm Aversion; Explainable AI; Decision Making.

1. Introduction

With the development of the digital economy today, people's habits have changed; now, AI is used to support "AI-assisted consumption decisions" rather than independent information gathering. Advanced Recommender Systems are based on machine learning and a large volume of data to act as digital intermediaries that proactively filter choices and recommend good options for users. These intelligent agents are available on many platforms and influence people's choices at all levels, such as low-involvement media consumption and high-stakes financial and medical decisions. Although these systems are computationally far more powerful than the human brain in terms of data processing, they have not been consistently demonstrated to have achieved real-world success solely based on technical accuracy.

The main reason for the limited application of AI recommendations is a lack of trust in people. The older technology tools were generally passive devices, but now AI systems can be viewed as quasi-autonomous agents that significantly affect the outcomes of people's lives. Therefore, in addition to the function, consumers will also be concerned about other factors such as the stability, kindness and openness of a system. If the people do not trust or are unaware of algorithms, they will not use the efficiency improvements provided by these systems and continue to use the old decision-making mode.

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Convenience is usually added through AI-assisted decision-making, but at the same time, the distribution of agency among consumers and platforms may change. When the algorithm needs to handle some of the cognitive tasks, people lose some of their freedom to choose. Delegation can introduce a defect because the recommendation system may prioritise choices based on hidden commercial interests, such as sponsored placement or platform profits. If the consumer believes that the recommendation agent has altered the choice set based on its own interests, then trust will be lost. Therefore, a trustworthy AI recommendation system should be transparent, fair and honest.

To learn why people are more or less trusting of artificial intelligence, we should not use the previous model of technology acceptance. Trust in artificial intelligence refers to all the cognitive judgments people make about a machine's capability and their emotional reactions to personalised interactions with that machine. In addition, this trust is also relatively unstable; it varies according to the specific circumstances of the decision, how familiar the user is with the interface, and whether the system can explain the reasons for its operation.

Although this human-algorithm interaction system is required, the current studies have produced contradictory results. Some research shows that people are generally suspicious of algorithms, and other studies have presented cases where consumers have voluntarily chosen machine guidance. There is an urgent demand for a new system that can address the above problems and specify the conditions under which consumers are willing to give up their own choice and have intelligent machines make decisions for them.

Systematically investigate the concept of consumer trust in intelligent recommendations under the condition of AI-assisted decision-making in this paper. Based on the above introduction, Section 2 will present the basic theories of trust in automation and the dichotomy of algorithm aversion and appreciation. Section 3 investigates the specific roles of personalisation and emotional trust in recommender systems. Section 4 presents the problem of algorithmic opacity and the corresponding role of Explainable AI (XAI). Finally, Section 5 draws together all the above to offer a concluding thought on the future development of trustworthy consumer AI. As a conceptual literature review, this paper will not be carried out experimentally or via surveys. Based on the above, it combines the existing research on trust in automation, algorithm aversion and appreciation, personalisation, and explainable AI to build a theoretical system for consumer trust in AI-assisted recommendations.

2. Trust in Automation and the Dichotomy of Algorithmic Reliance

The foundation of the knowledge supporting research on consumers' trust in smart recommendation systems is the study of human trust in automation. In the past, trust in automated systems has been considered a type of cognitive judgment about reliability; that is to say, whether a machine will perform its intended function accurately under conditions of uncertainty and vulnerability is judged [1]. Given the current state of artificial intelligence, many algorithms are now deployed in various consumer environments and are not under full control. When a user of an AI recommender makes a choice, they are weighing the risk of an imperfect result against the cognitive cost of making a decision independently.

Thus, the evaluation process has resulted in a problem of algorithm aversion. Pioneering experimental research has shown that people are very unwilling to accept algorithmic forecasts after learning of an error made by the algorithm, even when the overall error rate of the algorithm is significantly lower than that of a human forecaster [2]. This is because people have formed a double standard in their minds: human errors are generally overlooked and blamed on circumstances, but algorithmic errors are considered serious and irreparable defects in the system. Therefore, in high-stakes consumer cases such as medical decisions, a clear algorithm error will reduce consumer trust and willingness to be led by AI [3].

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The two standards are based on the evolution psychology of people. Over time, people have used social cues, empathy and the history of relationships to determine whether others are trustworthy. When the human advisor makes a mistake, we may feel that they are fallible and therefore unreliable; thus, we will be unable to trust them in the future. Algorithms do not have this social capital. They are regarded as cold and unemotional mathematical systems. When they fail, there is no common emotional reference point for rectifying the damage to trust. Therefore, the threshold of algorithmic failure is relatively low compared to that for human error. Therefore, even if the machine-learning model has been statistically outperformed by a human expert, some consumers may be reluctant to use the algorithmic recommendations after observing a small forecasting error.

It is possible that, for this reason, the consumers are not very worried about forecasting errors. Research shows that consumers are less sensitive to forecasting errors and place an unreasonable demand on the prospect of perfect prediction [4]. Because algorithms prioritise the overall accuracy and consistency of the majority, they are often unable to address rare but serious anomalies effectively; thus, consumers facing high-stakes uncertainty may not be able to trust the algorithm and will choose human judgment instead.

At the same time, under certain circumstances, consumers exhibit the opposite behaviour: algorithm appreciation. Based on the above research, when the decision-making task is highly objective and rich in data without emotional bias, such as logistical routing or quantitative financial forecasting, people are more likely to choose algorithmic recommendations than those provided by humans [5]. In this case, consumers believe that people have limited thinking ability and will thus choose computers because they are more capable. Therefore, consumers' trust in AI recommendations may differ based on the circumstances of decision-making and the kind of products involved; transparency, credibility and appropriateness in the choice situation all influence this [6].

3. The Role of Personalization and Emotional Trust

The extent of personalisation in an AI recommendation system may also influence users' confidence in using it. The current generation of recommendation systems does not provide general-purpose recommendations but, based on cooperation and behaviour analysis, offers highly personalised suggestions. Personalization can be interpreted as a response to people's demands for personalisation. When the system can correctly address the special circumstances of users, they will come to believe that the algorithm is honest and good-willed [7].

Personalized interaction changes the basis of trust in people and computers. Technology-acceptance-oriented studies generally focus on explaining the perceived usefulness and perceived trust in AI-enabled customer experience [8], and research on recommendation agents has also shown that emotional trust may affect users' willingness to adopt [7]. Emotional trust is a person's feeling of safety, comfort and dependence in their relationship with an agent. Based on the above research, cognitive trust is sufficient for consumers who use AI only to provide information support for decision-making; however, if full delegation of decision-making authority to an AI agent is required, emotional trust will also need to be built [7].

The AI's presentation and interaction style will also affect people's emotions. Systematic reviews of human trust in artificial intelligence have shown that anthropomorphic design elements, such as conversational interfaces and human-like avatars, can quickly establish initial emotional trust [9]. However, this way also has deficiencies. If an anthropomorphised AI gives an incorrect recommendation, the damage to users' trust will be more severe; they will feel it is a betrayal by a person rather than a software error. Therefore, although personalisation and a sense of humanity can inspire emotions, they should be realised in line with the actual capabilities of algorithms.

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The effectiveness of personalised construction of emotional trust through technology also differs significantly based on a person's previous experience with such technology. Familiarity is cognitively convenient. After a user repeatedly interacts with the same recommendation agent for a long time, the initial anxiety of algorithmic novelty will gradually decrease. The user learns the specific parameters of the system, is aware of its deficiencies, and has formed a habit. Repeatedly and successfully engaged, the user's demand for active, high-level cognitive processing gradually decreased in favour of passive emotional habit. As consumers become more familiar with the brand, they are more willing to trust recommendations for high-involvement, expensive or socially prominent products based on their existing emotional connection to the brand and are no longer required to collect data on all such products meticulously.

4. Explainable AI and the Mitigation of Algorithmic Opacity

One reason why there is a reduced trust in the new-generation recommendation system is the so-called black-box problem. Many modern artificial intelligence systems, especially those based on deep neural networks, are often referred to as 'black boxes'. Although they can provide very accurate recommendations, the internal process and weight distribution that lead to such a result are generally unknown. For high-involvement or high-risk purchases by consumers, algorithmic opacity will increase the sense of uncertainty and reduce the willingness to be recommended. The system will not be trusted by the public if it is out of sight and out of mind.

Due to the aforementioned reasons, there has been a relatively recent development of Explainable Artificial Intelligence (XAI) in the field of consumer-facing algorithms. Explainability is the degree to which a system's internal decision-making process can be shown in an understandable way to human users [10]. Add transparent explanation styles to the interface of a recommender system to boost user trust in the AI recommendations [11]. When a consumer is presented with a recommendation and its reason is explicit and understandable (e.g., "This item was recommended because you bought X and liked Y"), they are less puzzled by the algorithm and find the collaborative filter more transparent.

The strategic application of explainable AI can also address the public's concerns about data privacy in recent years. In order to give users more personalised and accurate recommendations, the AI system needs to collect and analyse a large amount of their personal data, such as search records and location information, biometrics, etc. Therefore, some people are concerned about the loss of privacy. When the AI system is an unexplained "black box", people are uneasy about how their personal data will be used and, as a result, do not wish to use the system. In line with the principles of XAI, the company will be able to provide an explicit explanation of which data points were used and how these particular inputs affected the final recommendation. When consumers believe that the data they have provided will directly and reasonably lead to a personalised benefit for them, they will be more willing to share their data willingly and view it as a fair and trustworthy transaction rather than feeling that they are being monitored. To make the data-intensive services more attractive to users, they should be more open and transparent.

XAI can reduce the uncertainty of the psychological source of consumer scepticism and thus address it. If the user knows why the algorithm recommended it, they will be more willing to believe in and use the system. An open explanation can also help to address the problem of a serious loss of public trust in the event of an algorithm error. If the AI system provides an explanation for an incorrect recommendation, the consumer will be more likely to believe that it is a reasonable error in calculation based on the available data, rather than a result of systemic incompetence.

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The design of these explanations should also avoid an excessive cognitive load. The presented numbers may cause some damage to people's trust in and acceptance of AI recommendations, so explanations need to provide relevant information in an accessible manner [12]. Optimal XAI design should be both sufficiently transparent and cognitively accessible; that is, the explanation needs to help people make decisions but should not require too much cognitive effort.

5. Conclusion

Research on consumers' trust in intelligent recommendation systems based on AI-assisted decision-making has found that this trust is relatively complex and unstable. As Artificial Intelligence systems have developed, they have gradually changed from passive tools into active, near-autonomous agents, and thus, trust in these systems is now required for their application in society. Based on the synthesis of the above studies, it can be concluded that people's reliance on algorithms is due to an unstable balance between their cognitive evaluation of machine accuracy and their emotional response to personalised interaction.

Algorithm aversion and algorithm appreciation are also context-dependent phenomena of human-AI interaction. Consumers are willing to have machines handle objective, data-intensive work; however, they are very anxious about losing their personal freedom in subjective matters and often require the algorithms to be perfect. Therefore, in order to reduce the impact of psychological biases, explainable artificial intelligence (XAI) will be introduced by the system. XAI can show people how a model reaches a particular decision in a more understandable way, thereby alleviating their fear of an opaque "black box" and boosting trust in and cooperation with the model.

Finally, the future of AI-assisted commerce will be determined by how smartly and stably we can build these systems. Due to the complexity of people's cognition and emotions about trust in others, intelligent recommendation systems have recently begun to be applied to consumers. Such a system will be able to process the data and, based on this, offer people a safe, personalised and convenient decision-making reference for daily life.

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