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Suspiciousness and Fast and Slow Thinking Impact on Trust in Recommender Systems

Dana RAD[*]
Aurel Vlaicu University of Arad, Arad, Romania
[*]*Corresponding author, dana@xhouse.ro*

Lavinia Denisia CUC[*]
Aurel Vlaicu University of Arad, Arad, Romania
[*]*Corresponding author, laviniacuc@yahoo.com*

Ramona LILE[*]
Aurel Vlaicu University of Arad, Arad, Romania
[*]*Corresponding author, ramonalile@yahoo.com*

Paul Nichita CUC[*]
Bucharest University of Economic Studies, Bucharest, Romania
[*]*Corresponding author, paulnichtacuc@gmail.com*

Mioara Florina PANTEA[*]
Aurel Vlaicu University of Arad, Arad, Romania
[*]*Corresponding author, mioarapantea@gmail.com*

Darius ANTA[*]
Adlai E. Stevenson High School in Lincolnshire, Illinois, USA
*Corresponding author, *danta24@students.d125.org*

Abstract. *By offering consumers more proactive and individualized information services, recommender systems have proven to be a significant answer to the problem of information overload. And collaborative filtering approaches have proven to be an important component of many such recommender systems, allowing for the development of high-quality recommendations by harnessing the preferences of communities of similar users. In this study, we argue that individual personality traits may play an essential role in ensuring general end-user confidence in recommender systems. Individual elements to be examined include social suspiciousness as a personality feature and Daniel Kahneman's fast and slow thinking styles, which distinguish between two modes of thought: System 1 is rapid, instinctual, and emotive, while System 2 is slower, more deliberate, and more rational. Due to a lack of explanation or inaccurate recommendation results, users may not trust current recommender systems, which poses a significant challenge for those systems. As such, having a trustworthy recommender system is essential. Three different trust-aware recommender system types are analyzed systematically in this study: robust systems that filter misleading information such as spam and fake news; social aware conscious systems that benefit from users' social connections; and explainable systems that offer justifications for recommended products. On a sample size of 487 Romanian respondents, in an online survey, we have analyzed the impact of individual factors on the trustworthiness of the three types of recommender systems. Results show that fast thinking fully mediates the relationship between social suspiciousness and trust in all three types of recommender systems.*

Keywords: recommender systems, social suspiciousness, fast and slow thinking, trust, mediation analysis.

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Introduction

By offering consumers more proactive and individualized information services, recommender systems have proven to be a significant solution to the information overload issue.

In response to the so-called information overload problem, where users are finding it more and harder to access the correct information at the right moment, recommender systems have become an important tool (O'Donovan & Smyth, 2005).

In a number of e-commerce areas, recommender systems have been effectively implemented under a variety of guises, frequently in the shape of intelligent virtual assistants (Melville & Sindhwani, 2010; Schafer, Konstan & Riedl, 1999). Recommender systems have shown to be effective at providing the user with a more intelligent and responsive services provider by making specific product or service recommendations that are sensitive to their learned preferences and requirements. This is achieved through integrating ideas from user profiling, information filtering, and machine learning (Lu, at al., 2012; Jannach, et al., 2010; Bobadilla, et al., 2013; Ricci, Rokach & Shapira, 2010; Drachsler, et al., 2015; Konstan, 2004; Radu et al., 2018; Bucerzan & Bejan, 2021; Raţiu, Bucerzan & Crăciun, 2013).

The use of computational applications has expanded beyond personal computers to support social interaction and collaboration. The convergence of social and human sciences is the focus of the information technology field known as social computing (Tavakolifard & Almeroth, 2012). The research of social-based recommender systems has just recently begun, despite the fact that recommender systems have been thoroughly examined over the previous ten years (Ma, et al., 2011). There are innumerable methods for creating tailored suggestions in the literature, and they all make advantage of various user- and/or item-features. As a result, creating correct profiles is crucial in this situation, and the effectiveness of the system depends heavily on how well the learnt profiles capture the preferences and requirements of the user (Martinez-Cruz, et al., 2015).

The following three techniques are the most often employed in recommender systems: social-aware recommender systems (Asabere, et al., 2017; Ojagh, Malek & Saeedi, 2020; Xiao, et al., 2017) that take advantage of users' social connections, robust recommender systems (Burke, O'Mahony & Hurley, 2015; Tang, et al., 2019) that filter false information such as spam and fake news, and explainable recommender systems (Zhang & Chen, 2020; Caro-Martínez, Jiménez-Díaz & Recio-García, 2021; Tsai & Brusilovsky, 2021) that offer justifications for recommended products.

Individual's behavior and interests are significantly influenced by their personalities. There is a strong likelihood that adding user attributes to recommender systems would improve both the quality of recommendations and the user experience (Hu & Pu, 2010; Chen, Wu & He, 2013).

When facing problematics of individual trust in any technological interface (Dinu et al., 2022; Dinu, 2021; Radu, Sendroiu & Demeter, 2018), like the recommender system algorithms and functionality, behavioral psychology research has identified as the most influential trait the individual level of social suspiciousness (Johnson, et al., 2009) and more recently the behavioral economics (Schwartz & Hursh, 2022) perspective added the fast and slow thinking paradigm to choice and decision making processes people take on a daily basis. At all levels of social organization, from the interpersonal to the communal, mistrust and suspicion are frequent and recurring issues (Pytlik, Soll & Mehl, 2020).

For many years, psychologists have been quite interested in the two types of thinking: whereas System 2 directs attention to the mentally demanding activities that necessitate it, such as difficult calculations, System 1 runs automatically and rapidly with little to no effort and no

sensation of intentional control. System 2 functions are frequently linked to the individual's sense of agency, control, and attention (Kahneman, 2011).

This research looks at the individuals' trust into three different kind of recommender system: social-aware, robust, and explainable recommender systems from the behavioral economics perspective. The main objective of the research thus is to analyze the mediation effect of fast and slow thinking over the relationship between social suspiciousness as a personality trait and overall trust in the three different types of recommender systems.

Literature review

Recommender systems

A recommender system is a type of information filtering system that suggests items based on what the user will find most useful (Burke, Felfernig & Göker, 2011; Lu, et al., 2015; Burke, 2000). When a person must select an item from a service's possible overwhelming selection of things, recommender systems are very helpful (Del Olmo & Gaudioso, 2008; Guy & Carmel, 2011).

In recommender systems, collaborative filtering, sometimes referred to as the personality-based approach, content-based filtering, and other methods like knowledge-based systems are widely utilized (Vozalis & Margaritis, 2003; Lops, De Gemmis & Semeraro, 2011). The models created by collaborative filtering techniques are based on the prior actions of a user, things previously chosen or purchased, and/or numerical ratings provided to those goods, as well as comparable choices made by other users. Then, this model is used to forecast the ratings for things or items themselves that the user could be interested in. The purpose of content-based filtering techniques is to suggest other objects that share comparable qualities by using a set of distinct, pre-tagged features of an item.

A recommender system's goal is to make user-friendly recommendations for items. Collaborative filtering approaches and content-based methods are the two main kinds of techniques available to accomplish this goal (Kunaver & Požrl, 2017; Ma, et al., 2011; Park, et., 2012).

The two sub-categories of collaborative filtering algorithms are commonly referred to as memory-based and model-based techniques. Memory-based techniques are mostly based on nearest neighbor searches and operate directly with values of recorded encounters, assuming there is no model. Model-based techniques adopt the assumption that a generative model underlies the user-item interactions and seek to identify it in order to develop new hypotheses (Herlocker, et al., 2004; Elahi, Ricci & Rubens, 2016). The fundamental benefit of collaborative techniques is that they may be applied in a variety of circumstances since they don't need to know anything about the users or the products. Also, given a fixed set of users and goods, fresh interactions recorded over time add new information and increase the system's effectiveness. The more people engage with items, the more accurate new suggestions become.

Content-based techniques employ extra information about users and or things, in contrast to collaborative methods that exclusively depend on user-item interactions. The goal of content-based techniques is to attempt to create a model that can account for the observed user-item interactions based on the features that are already accessible (Lops, De Gemmis & Semeraro, 2011; Javed, et al., 2021; Bagher, Hassanpour & Mashayekhi, 2017). Compared to collaborative techniques, content-based solutions are far less susceptible to the cold start issue since new individuals or things may be characterized by their qualities (content), which allows for the creation of pertinent ideas for these new entities. This disadvantage will presumably only affect new users or products with previously undiscovered features, but once the system is old enough, this has little to no probability of occurring.

Users' potential lack of trust in recommender systems due to either erroneous recommendations or a lack of explanation is a serious issue that still faces existing recommender systems. It is therefore crucial to have a reliable recommender system (Wang, et al, 2021).

One major continuing issue with the current recommender systems is that users may not trust them if there is either a lack of explanation or erroneous recommended results. It is therefore crucial to have a reliable recommender system. This study offers a comprehensive overview of three types of trust-aware recommender systems (Moradi & Ahmadian, 2015):

- robust recommender systems that filter false inputs (such as spammers and false information) or improve attack resistance (Burke, O'Mahony & Hurley, 2015);
- social-aware recommender systems that take use of users' social interactions (Ojagh, Malek & Saeedi, 2020);
- explainable recommender systems that offer explanations of recommended things (Zhang & Chen, 2020).

The robustness or the resilience of the recommender systems is put to the test by a variety of designed and unexpected noised inputs. While the majority of consumers rely on online product reviews to guide their purchasing decisions (Fei, et al., 2013), some reviews are unreliable as a result of spambot and spammer assaults. Moreover, recommender systems encounter sounds brought on by manual or system faults. There are two research focuses for enhancing recommender system resilience. Prior to running the recommendation algorithm, the initial step is to remove harmful or obtrusive feedback from the data. Finding trends in user ratings to spot harmful material is the goal of this line of research (Si & Li, 2020). The second strategy seeks to create algorithms that are immune to noise attacks to enhance the denoising capabilities of the recommender system.

Recommender systems that are socially aware refer to those that provide product recommendations based on user social ties. Current research suggests that user ratings for both trust-alike and trust connections have a favorable link with the mean of the social neighbors (Wang, et al., 2019). Based on the phenomenon that users' tastes are frequently influenced by their friends, leveraging the trust connection has a huge potential to provide the user with a trustworthy recommender system and raise the quality of the suggestions (Dong, et al., 2022). Yet, using social data helps classic recommender systems overcome their cold start issue.

When given the necessary information to comprehend the recommendation process and results, users are more likely to believe a recommendation. Explainable recommender systems (Zhang & Chen, 2020) not only give consumers individualized suggestions, but they also produce justifications for the recommendations. As a result, explainability raises the openness and dependability of recommendation findings. In general, the information source and approach of explainable recommender systems may be used to categorize them. Currently used material includes user and product features (Zhao, et al., 2016), text reviews (Zhang, et al., 2014), product photos (Lin, et al., 2014), and social connections (Wang, et al., 2014).

Personality aspects in Recommender Systems

Because personality traits and user preferences have such a significant link, recommender systems have been changed to include personality traits in its structure. This not only provides consumers with a greater range of products to choose from (McNee et al., 2006), but it also enhances group suggestions and boosts the precision of recommender systems (Kompan et al., 2014; Recio-Garcia et al., 2009). Eysenck (2012) defines personality as a person's internalized interpersonal processes and persistent behavioral patterns, and it may be discovered either openly by answering questions on a questionnaire or implicitly by seeing how users behave. From a psychological perspective,

personality is a crucial element that explains cognition, emotion, and behavior patterns (Bandura, 1999). The fact that people frequently have a constant behavioral pattern, regardless of their circumstances, is another crucial aspect of personality. There are also a number other personality characteristic models that may be used to describe human behavior, although both computer science and psychology studies have shown a greater interest in the Five Factor Model (Becker, 1999).

In terms of personality traits, two characteristics emerged as prominent in influencing consumer behavior. Personality qualities that explain consistency in behavior, such as social suspiciousness and fast and slow thinking are crucial factors influencing decision making approaches in the consumer behavior research (Samson & Voyer, 2012; Earl, 2012).

As the danger of unintentional disclosure of personal information is increased by the information that recommenders collect, malevolent individuals have the ability to skew or undermine the suggestions made to other users, thus suspiciousness becomes crucial when investigating individuals' trust in recommender systems. The second key aspect in making decisions is related to consumer behavior (Pelau, Dabija & Ene, 2021; Pelau, Dabija & Serban, 2023; Pelau et al., 2023; Pelau, Barbul & Bojescu, 2022).

The individual level of social suspicion has been found to be the most influential trait when it comes to issues of individual trust in any technological interface, such as the algorithms and functionality of recommender systems (Johnson et al., 2009), and more recently, the behavioral economics (Schwartz & Hursh, 2022) perspective added the fast and slow thinking paradigm to the choice and decision-making processes people undertake on a daily basis. Mistrust and suspicion are regular and recurring problems at all levels of social structure, from the interpersonal to the communal (Pytlik, Soll & Mehl, 2020).

For many years, psychologists have been quite interested in the two types of thinking: whereas System 2 directs attention to the mentally demanding activities that necessitate it, such as difficult calculations, System 1 runs automatically and rapidly with little to no effort and no sensation of intentional control. System 2 functions are frequently linked to the individual's sense of agency, control, and attention (Kahneman, 2011).

Decisions must be made often while making purchases online (Ogrean &Herciu, 2020; Ogrean &Herciu, 2020; Pop, Hlédik & Dabija, 2023; Grădinaru et al., 2022), and the decision maker's expertise and personality attributes have a significant impact. We thus examine how such characteristics affect the level of confidence users have in recommender systems.

From a behavioral economics standpoint, this study examines people's confidence in three different types of recommender systems: robust, social aware, and explainable. The primary goal of the study is to examine how fast and slow thinking can mediate between social suspiciousness as a personality feature and general trust in the three distinct types of recommender systems.

Methodology

This study investigates people's trust in three different recommender systems: robust, social aware, and explainable, from a behavioral economics perspective. Examining how fast and slow thinking can mediate between social suspiciousness as a personality trait and overall confidence in the three different types of recommender systems is the study's main objective.

This research represents a quantitative cross-sectional methodological approach, using an opportunistic sampling method. An online questionnaire was shared online and a total of 487 valid and consented responses were returned. In terms of demographics, 35% of the respondents represent males and 65% represent females, with a mean age of 27 years old. Regarding the

respondent's educational level, 50% have a high school diploma, and 50% have higher educational degrees.

This research used three measurements for the three main variables: social suspiciousness, fast and slow thinking and trust in three types of recommender systems. Social suspiciousness was measured with The Social Suspiciousness Scale (SSS) (Linett et al., 2019) representing a 22-item self-report questionnaire, using a Likert scale from 1 to 5 to rate each statement. Fast and slow thinking was measured with 10 items Fast and Slow Thinking Questionnaire (Hardy et al., 2020), the thinking styles being conceptualized with dual processing models of reasoning, using an identical rating scale with the other two measurements. For trust in recommender systems, we have designed a novel scale with 10 items, inspired from previous research (O'Donovan, & Smyth, 2005; Guo et al., 2014), using the same 1 to 5 rating system.

The 10 items are rated on a 1 to 5 Likert scale and refer to trust in robust (R), social aware (S) and explainable (E) recommender systems. The following items were used: *1. Recommender systems I have interacted with are trustworthy (E). 2. Recommender systems I have interacted with are effective in helping me decide on the purchase decision (R). 3. Recommender systems I've interacted with effectively filter out information I don't need (R). 4. I appreciate recommender systems that give me explanations for recommended products or services (E). 5. When I intend to purchase something online, I always trust the recommendations provided by these systems (R). 6. Recommender systems I have interacted with always present me with relevant alternatives (E). 7. It is relevant for me to know that other people bought a certain product and were satisfied (S). 8. Before I buy something online, I always look at the reviews of that product or service(S). 9. If a product or service has received negative reviews from other people, I no longer consider buying it (S). 10. I don't feel coerced in my decision to buy online by recommendation systems that give me suggestions (R).*

Data was processed with SPSS V.26 and Process Macro model 4 for mediation analysis.

In terms of overall means, standard deviation, and Cronbach's alpha reliability coefficients, the results are presented in Table 1, showing reliable results.

Table 1. Instruments descriptors

Scale	Grand mean	Standard deviation	Cronbach's alpha
Trust in recommender systems scale	34.79	6.17	0.81
Social suspiciousness scale	60.97	14.80	0.90
Fast and slow thinking questionnaire	34.72	5.25	0.64

Source: authors own conception

In terms of correlations, among all subscales we have received significant positive correlation coefficients, ranging from 0.161 to 0.739, correlation being significant at the 0.01 level (2-tailed) and 0.05 level (2-tailed).

Results and discussions

The results revealed a significant indirect effect of suspiciousness as a personality trait on all three types of recommender systems: social aware, robust and explainable recommender systems through the mediator fast thinking, supporting our hypothesis.

Mediation summary for the three mediation analyses is presented in Table 2.

Table 2. Mediation summary

Total effect (suspiciousness → recommender system)	Direct effect (suspiciousness → recommender system)	Relationship	Indirect effect	Confidence intervals		*t* = *Indirect Effect /SE*	Conclusion
				Lower Bound	Upper Bound		
0.0906 *p> 0.05*	0.0593 *p> 0.05*	H1: **suspiciousness → fast thinking → social aware recommender system**	0.0313	0.0069	0.0638	2.1148	**Full complementary mediation**
0.0134 *p> 0.05*	-0.0339 *p> 0.05*	H1: **suspiciousness → fast thinking → robust recommender system**	0.0473	0.0171	0.0846	2.7341	**Full complementary mediation**
0.0109 *p> 0.05*	-0.0399 *p> 0.05*	H1: **suspiciousness → fast thinking → explainable recommender system**	0.0508	0.0176	0.0920	2.6596	**Full complementary mediation**

Source: authors own conception

In the first mediation analyses, results revealed a significant indirect effect of suspiciousness as a personality trait on trust in socially aware recommender systems, through the mediator's fast thinking (b=0.0313, t=2.1148), supporting our hypothesis. Furthermore, the direct effect of suspiciousness on trust in social aware recommender systems in the presence of the mediator fast thinking was not found significant (b= 0.0593, t=1.1172, p>0.05). Hence, there is full complementary mediation of fast thinking on the relationship between suspiciousness as a personality trait and trust in socially aware recommender systems. Recent methodological studies (Kenny & Judd, 2014; O'Rourke & MacKinnon, 2015) have demonstrated that mediation effects can exist even in the absence of a total or overall effect, i.e., researchers may still find real, significant mediation effects even if the intervention effect on an outcome is not statistically significant.

The mediation model explained an overall 2% of trust in socially aware recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and complementary mediated the relationship between suspiciousness as a personality trait and trust in social aware recommender systems (IE = 0.0313, 95% CI: LL = 0.0069 to UL = 0.0638), indicating that individuals with a high level of both suspiciousness and fast thinking decisional system, were more likely to have higher trust in social aware recommender systems.

In the second mediation analyses, results revealed a significant indirect effect of suspiciousness as a personality trait on trust in robust recommender systems, through the mediator's fast thinking (b=0.0473, t=2.7341), supporting our hypothesis. Furthermore, the direct effect of suspiciousness on trust in robust recommender systems in the presence of the mediator fast thinking was not found significant (b= -0.0339, t= -0.7623, p>0.05). Hence, there is full complementary mediation of fast thinking on the relationship between suspiciousness as a personality trait and trust in robust recommender systems.

The mediation model explained an overall 6% of trust in robust recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and

complementary mediated the relationship between suspiciousness as a personality trait and trust in robust recommender systems (IE = 0.0473, 95% CI: LL = 0.0171 to UL = 0.0846), indicating that individuals with a high level of both suspiciousness and fast thinking decisional system, were more likely to have higher trust in robust recommender systems.

In the third mediation analyses, results revealed a significant indirect effect of suspiciousness as a personality trait on trust in explainable recommender systems, through the mediator's fast thinking (b=0.0508, t=2.6596), supporting our hypothesis. Furthermore, the direct effect of suspiciousness on trust in explainable recommender systems in the presence of the mediator fast thinking was not found significant (b= -0.0399, t= -0.7799, p>0.05). Hence, there is full complementary mediation of fast thinking on the relationship between suspiciousness as a personality trait and trust in explainable recommender systems.

The mediation model explained an overall 6% of trust in explainable recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and complementary mediated the relationship between suspiciousness as a personality trait and trust in explainable recommender systems (IE = 0.0508, 95% CI: LL = 0.0176 to UL = 0.0920), indicating that individuals with a high level of both suspiciousness and fast thinking decisional system, were more likely to have higher trust in robust recommender systems.

A study with related results demonstrated the key effects of user-related components (personal qualities) and their interactions with system-related elements (initiative approach) and context-related elements (task complexity) on user trust in conversational recommender systems (CRSs) (Cai, Jin & Chen, 2022). Findings show that subject expertise and trust propensity have a direct impact on user trust. Moreover, individual traits like conscientiousness and topic expertise may have an impact on users' trust in CRSs using various initiative tactics.

Personality-aware recommendation systems perform better than conventional recommendation algorithms, especially when dealing with cold start and data sparsity challenges. Nevertheless, the need to safeguard the user's personal information's privacy and the challenge of upholding a high degree of personality detection accuracy coincide with the user's personality advantage (Dhelim et al., 2022). Personality effectively solved the cross-domain preferences issue, the cold-start issue, group ideas, and the creation of varied recommendations (Tkalcic & Chen, 2015).

In terms of slow and fast thinking, recommender systems must assist users in making decisions and provide them with individualized ideas in order to be considered intelligent. In the real world, individuals are inclined to share interests with others who have similar personalities, (Yakhchi, Ghafari & Orgun, 2021).

Research on human trust in recommender systems has uncovered that: The effectiveness of recommender systems depends on how much faith people have in them. When recommendations are personalized, people lose faith in inaccurate recommendations more quickly than when recommendations are not customized. Participants also disclose less trust and lowered ratings for personalized but misleading recommendations particularly in comparison to recommendations that are not tailored to individuals (Harman et al., 2014; Berkovsky et al., 2018). Furthermore, perceived suggestion quality and trust in the source of the recommendation were both highly impacted by explanation quality (Kunkel et al., 2019). In another study it has been shown that although preference elicitation features considerably boost user trust in the recommender system, there is no influence of embodiment on it. Another recent study found that users with strong conscientiousness tended to trust the mixed-initiative system, and that users' trust propensity and domain expertise positively affected their confidence in recommender systems (Cai, Jin & Chen, 2022).

However, despite their immense potential and capabilities, recommender systems may also have unintended side effects on users, products, producers, platforms, or even society at large. For instance, lack of transparency may erode user trust, different consumers or producers may be treated unfairly, and extensive use of user privacy data for personalization may raise privacy concerns (Ge et al., 2022).

The majority of prior research, however, has been on algorithms and recommendation approaches, and less attention has been paid to the decision-making processes utilized by users and potentially aided by the system. The priority that the community places on evaluating recommendation algorithms still falls short of the variety of ongoing research projects that are currently being conducted on human decision making. Various decision-psychological phenomena can affect how users of recommender systems make decisions, and research in this area is becoming more significant (Chen et al., 2013).

Recent research (Shin, 2020) focused on users' cognitive processes to understand how characteristics and attributes are absorbed and translated into experiences and interaction in order to examine the user experience and usability of algorithms. The study looks at how users interact and feel about problems with news suggestions, as well as how they perceive and feel about those problems. It suggests a news recommendation algorithm experience model that incorporates the heuristics of cognitive, emotional, and behavioral variables. The underlying algorithm can have a variety of effects on how the user sees the system and how confident they are in it. The heuristic effect happens when users' subjective perceptions of correctness and transparency serve as a mental shortcut: people found accurate and transparent systems to be convenient and helpful. According to the mediating function of trust, building algorithmic trust between users and NRS may improve algorithm performance. The model depicts the users' cognitive mechanisms for making perceptual judgments as well as the driving forces behind their actions. The results (Shin, 2020) provide a clearer perspective of user-centered development and the assessment of algorithm-based services by highlighting a connection between news recommendation systems and user involvement.

Yet, if we consider that one of recommender systems' key purposes is to aid users in making better decisions, then follows that those who study and create recommender systems should have a solid grasp of how users make decisions and how they might be helped (Jameson et al, 2015).

Thus, in the light of key findings from past research, our research looked in an original way at hoe humans decision-making system of fast and slow thinking might mediate between suspiciousness instead of trust as a personality trait and trust in three different kind of recommender systems: social aware, explainable and robust recommender systems.

Conclusion

Being digitally linked has a significant impact on how businesses compete and flourish. With the development of information technology, e-commerce has become a significant part of daily life and offers customers a lot of ease. Yet, the ever-increasing volume of product-related content that customers get tends to overwhelm them and cause information overload, which can result in poor decision-making. Recommender systems are gradually becoming a crucial tool in e-commerce as a means of coping with this information overload. The capacity of recommender systems to analyze user activity, particularly to identify which items a certain user would be interested in, and then to further give users with item suggestions based on their preferences and behaviors is its key characteristic.

In this study, we focus on individual confidence in recommender systems while examining three characteristics of trust-aware recommender systems: robust, social aware and explainable.

We discuss the impact of individual personality traits on trust in the three various types of recommender systems, such as suspiciousness and fast thinking.

This research looked at the individuals' trust into three different kinds of recommender systems: social-aware, robust, and explainable recommender systems from the behavioral economics perspective. The objective of the present research was to analyze the mediation effect of fast and slow thinking over the relationship between social suspiciousness as a personality trait and overall trust in the three different types of recommender systems.

The results revealed a significant indirect effect of suspiciousness as a personality trait on all three types of recommender systems: social aware, robust and explainable recommender systems through the mediator fast thinking, supporting our hypothesis.

Regarding trust in social aware recommender systems, the mediation model explained an overall 2% of trust in social aware recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and complementary mediated the relationship between suspiciousness as a personality trait and trust in social aware recommender systems, indicating that individuals with a high level of both suspiciousness and fast thinking decisional system, were more likely to have higher trust in social aware recommender systems.

Regarding trust in robust recommender systems, the mediation model explained an overall 6% of trust in robust recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and complementary mediated the relationship between suspiciousness as a personality trait and trust in robust recommender systems, indicating that individuals with a high level of both suspiciousness and fast thinking decisional systems, were more likely to have higher trust in robust recommender systems.

Regarding trust in explainable recommender systems, the mediation model explained an overall 6% of trust in explainable recommender systems variance, a result that represents a low percentage. Overall, the fast thinking mediator fully and complementary mediated the relationship between suspiciousness as a personality trait and trust in explainable recommender systems, indicating that individuals with a high level of both suspiciousness and fast thinking decisional system, were more likely to have higher trust in robust recommender systems.

The convenience sampling method might be limitative in the generalization of the results of the present research, and also the original research approach integrating suspiciousness and fast thinking as mediators into the assessment of trust in the recommender system. The mediation analyses that explained 2% and 6% of the variation in recommender system trust might have been taking into consideration also other relevant personality characteristics as mediators, to obtain a higher variance explainability percentage.

Overall, the results show that trust in recommender systems and their expectations of those systems' performance are significantly influenced by their social suspiciousness level and fast thinking decision-making mechanism.

Theoretical implications of our research point to the fact that researchers and practitioners have been working on creating accurate recommender systems for a considerable amount of time. In recent years, there have been more and more dangers to recommender systems, including assaults, user- and system-generated noise, and bias in the system. As a result, it is obvious that a strict focus on recommender systems correctness has its limitations and that the research must take other crucial characteristics, including trustworthiness, into account. For the benefit of end users, a trustworthy recommender system should be reliable in the face of noise and assaults, as well as transparent, unbiased, and fair. Also, social context is a considerably larger notion that encompasses not just social (network) linkages but also different kinds of ancillary data, such as

tags or folksonomies. In addition, the social context may be viewed as a specific instance of context-sensitive recommender systems, independent of the network. Trust is only one of many human-centric characteristics that are brought about by the social environment. The trust element is significant when users are aware of the identities of the players taking part in the feedback process.

In terms of managerial contributions, our work demonstrates that recommendation systems may strengthen the already present information cascades effect, thereby increasing the popularity of popular items. It is important for designers and managers of online shopping platforms to be mindful that while recommendation algorithms improve informative cascades, users' welfare may actually decline rather than rise. So, it is ideal for the owners of online shopping platforms to redesign their suggestion algorithms in order to choose more pertinent items to suggest.

The study on recommender systems underwent a paradigm shift as a consequence of these results, moving from accuracy-oriented recommender systems to trustworthy recommender systems. Unfortunately, there is a paucity of systematic literature reviews and discussions among academics in this fresh and rapidly expanding field, thus more research is needed on the topic of human decision-making process influence over the consumer behavior under the new paradigm of recommender systems.

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