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How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance

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ABSTRACT

Although algorithms have been widely used to deliver useful applications and services, it is unclear how users actually experience and interact with algorithm-driven services. This ambiguity is even more troubling in news recommendation algorithms, where thorny issues are complicated. This study investigates the user experience and usability of algorithms by focusing on users' cognitive process to understand how qualities/features are received and transformed into experiences and interaction. This work examines how users perceive and feel about issues in news recommendations and how they interact and engage with algorithm-recommended news. It proposes an algorithm experience model of news recommendation integrating the heuristic process of cognitive, affective, and behavioral factors. The underlying algorithm can affect in different ways the user's perception and trust of the system. The heuristic affect occurs when users' subjective feelings about transparency and accuracy act as a mental shortcut: users considered transparent and accurate systems convenient and useful. The mediating role of trust suggests that establishing algorithmic trust between users and NRS could enhance algorithm performance. The model illustrates the users' cognitive processes of perceptual judgment as well as the motivation behind user behaviors. The results highlight a link between news recommendation systems and user interaction, providing a clearer conceptualization of user-centered development and the evaluation of algorithm-based services.

Algorithms play increasingly central roles in our lives. The usage of analytics and artificial intelligence in society is drastically increasing (Karimi, Jannach, & Jugovac, 2018). Recently, algorithms have been increasingly used in the media, particularly in news services (Diakopoulos & Koliska, 2016; Jung, Song, Kim, & Oh, 2017). News recommendation systems (NRS) produce the most relevant news article recommendations to users based on their personal interests and preferences (Beam & Kosicki, 2014). These services can be very useful as information overload is problematic because too much information especially of little relevance causes confusion.

Despite rising popularity and growing mainstream adoption, it remains to be seen if the services recommend news that users like or prefer and in what way the user experience (UX) is improved by automated processes (Helberger, Karppinen, & D'Acunto, 2018; Beam & Kosicki, 2014). The algorithm systems are supposed to improve UX and increase revenues of online news services, algorithm providers, and many others, but how they improve UX remains an open question. It is unclear how users experience the services, how the interaction between users and the algorithms occurs, and how it plays out in the experience and post-adoption (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012; Shin & Park, 2019). This gap becomes even more obvious along with other issues whether the system correctly reflects users' preferences and how the algorithms of such services work. The black-box nature of algorithms becomes problematic in news recommendation and raises fundamental questions: (1) Are the algorithm-driven results accurate? (2) What are the results of transparent processes?

These questions are related to the issues of transparency and accuracy of recommendation services, which have been problematic and a source of debates amongst scholars, practitioners, and policymakers (Ananny & Crawford, 2018; Shin & Park, 2019). Thus far, research regarding these issues, particularly the UX of NRS, remains largely unexplored (Shin & Park, 2019). Thus, it is unclear whether recommended results are user-based and how users cognitively accept and experience such recommended news (Jung et al., 2017). To conceptualize user-based NRS, it is important to examine how users recognize recommendation systems' function and value, how users' attitudes/motivations are created, how the perceptual process works, and how people perceive trust in algorithms during the interaction with NRS. How individual users encounter recommendation services and interact with these systems are not only legitimate matters to address, but also practical concerns in designing NRS and user-centered recommendation systems in lieu of system-oriented methods. To assess this issue, this study suggests a news recommendation experience model

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incorporating algorithm quality (transparency and accuracy) and perceived value (utility and convenience) as antecedent factors of confirmation and satisfaction. With this model in place, the purpose of this study is to explore what it is like to experience news via algorithm systems, focusing on the following inquires:

RQ1: How do people perceive recommending functional quality and how do system features factor into the UX of news recommendation systems?

RQ2: What are the roles and relationships of trust with other factors in experiencing recommended news?

RQ3: How do interactions between users and systems occur? What are the consequences of such interactions in terms of qualities and user satisfaction?

The user model and the factors provide heuristic guidelines for user-based systems and an analytical methodology for the design and evaluation of UX for NRS. The findings indicate that users' perceptual algorithm quality plays a triggering role in the activation and acceptance of algorithm news as well as the continuing usage of the system overall. The algorithmic heuristic occurs when users' subjective perceptions about transparency and accuracy act as a mental shortcut of usability, satisfaction, and trust (Shin & Park, 2019). Users' perceptual cognizance of recommendation quality and trust are key mediators (heuristics) in determining the effects of objective systems on the three aspects of UX: algorithm characteristics, trust as a contextual factor, and perceived value. The results imply a possible underlying link between algorithm systems and user interaction, providing a clearer conceptualization of user-centered development and the evaluation of algorithm-based services.

Also, the results further imply that users find the capability to actively shape or control news recommendation mechanisms a useful and needed feature. It can be inferred that users actively engage and contribute to news recommendations and algorithms respond to the users' desires and actions. NRS recommends the content users want to see and thus the content is based on the users' cognitively reconstructed reality. From the findings, it can be reasonably inferred that users are the driver of algorithms and the creators of NRS by invoking cognitive processes. What users see through algorithms, as far as their cognition is related, is a cognitively constructed reality that emulates the form of an accumulated experience that has been shaped by a priori mental constructs. As Shin and Park (2019) argue, algorithmic selection has become a shared social reality and shapes daily lives and realities, affecting the perception of the world. Further to their arguments, users and algorithms are co-evolving and create reality together as they influence each other (Alvarado & Waern, 2018). Based on the findings, it is worthwhile for future studies to explore how algorithm systems change the way how we perceive social reality and the way how people influence the way algorithm work and operate.

1. Algorithms and heuristics

A NRS is considered as a heuristic system that advice useful information and can be applied in other domains. While an algorithm is a set of processes to follow, heuristics can be rough approximations. While algorithm-driven NRS produce news systematically, users have their own heuristic processes that help them make judgments quickly and efficiently (HYPERShin, Zhong, & Biocca, in-press).

Algorithms and Recommendation Systems. Recommendation systems have been made possible by algorithms (Moller, Trilling, Helberger, & van Es, 2018). Recommender systems are recent tools used by online services to help users access the ever-growing set of services and data available on the Internet (Karimi et al., in press). The user chooses news to read or products to purchase and the system then proposes items that may potentially interest the user based on his/her previous history. Thus, users are given recommendations as a result of products that they have already rated or purchased (Alvarado & Waern, 2018).

Recently recommendation algorithms have been widely used in news recommendations (Shin & Park, 2019). Reading news online has become quite common as the web offers unlimited access to news articles from many sources. As the sheer volume of news articles can be overwhelming to users, building a news recommendation system to help users curate articles that are most appealing to them is a crucial task for online news services (Beam & Kosicki, 2014). With the advancement of algorithm technologies, NRS have been widely adopted and will be further diffused in societies. NRS shape profiles of users' news preferences based on their behavior on the Internet. NRS aim to identify news that best fits user preferences. NRS are often considered a primary source of news articles for readers (Karimi et al., 2018).

Although few would dispute the vast benefits offered by algorithms and NRS, especially in terms of efficiency through improved automation and quality through complex filtering, there are questions regarding the extent to which user decision-making will be supported by algorithm (Shin & Park, 2019). It has been also noted that once a story is promoted by NRS, there is a sudden rise in its popularity and viewership. It has been shown that these systems have a self-reinforcing nature and are easily susceptible to manipulation. This has recently been noted in popular press articles and the problem of manipulation in particular is garnering greater attention among industry and policy makers. There is also a rising concern over the transparency of algorithm services, which requires companies be honest regarding the strategy, structure, and underlying procedures of analytics used to search for, process, and deliver information (Diakopoulos & Koliska, 2016). The issues of transparency and fairness can significantly undermine algorithm-based services by generating a set of undesired and even harmful problems in algorithm systems (Shin et al., in-press).

User Heuristics of Algorithmic Feature Evaluation. As algorithm-based news content provides various innovative features, it is critical to examine what users' expectations are and how they are met and how users' recognized confirmation affects satisfaction, which then influences intentions. Users evaluate algorithm in terms of their existing knowledge and the information (cue) given in the interface of algorithm news (Fig. 1). This typically involves users' informal evaluation relying on their gut feeling of how transparent and how accurate the news content might be. Some NRS provides information (and links) on how personalized and customized news are made and recommended. Some NRS shows links to artificial intelleigence recommendation news where users can access information on why and how specific contents are recommended (Fig. 1). This gives an idea of explainability and interpretability of algorithm. With these processes, users have some ideas of transparency and accuracy of the news items recommended. Such information (transparency and accuracy) are associated with users' perceiving the nature/characteristics of technological freatures of NRS. These afforance can trigger or stimulate users' emotional reactions to NRS.

Expectation confirmation theory (ECT) can be a solid frame for this investigation as the theory posits that both pre-behaviors and post-behaviors influence confirmation, which in turn influence satisfaction and continuance intention (Bhattacherjee, 2001; Shin & Biocca, 2018). Per ECT, higher perceived performance leads to positive confirmation and the level of confirmation then provides the basis for following actions. Users feel satisfied or unsatisfied based on their confirmation levels. While satisfied users form an intention to reuse the product in the future, dissatisfied customers discontinue the subsequent behavior. ECT is emplyed in this study as a lens to examine the UX of algorithm news content. ECT is right for this analysis since it is structured to describe user behaviors as a function of expectations, performance, and confirmation of beliefs based on cognitive processes. As algorithms and recommendation systems afford users unique experiences, ECT can be extended by including algorithm-specific factors (e.g, transparency and accuracy) as antecedents of confirmation and trust and utility/convenience as a performance value.

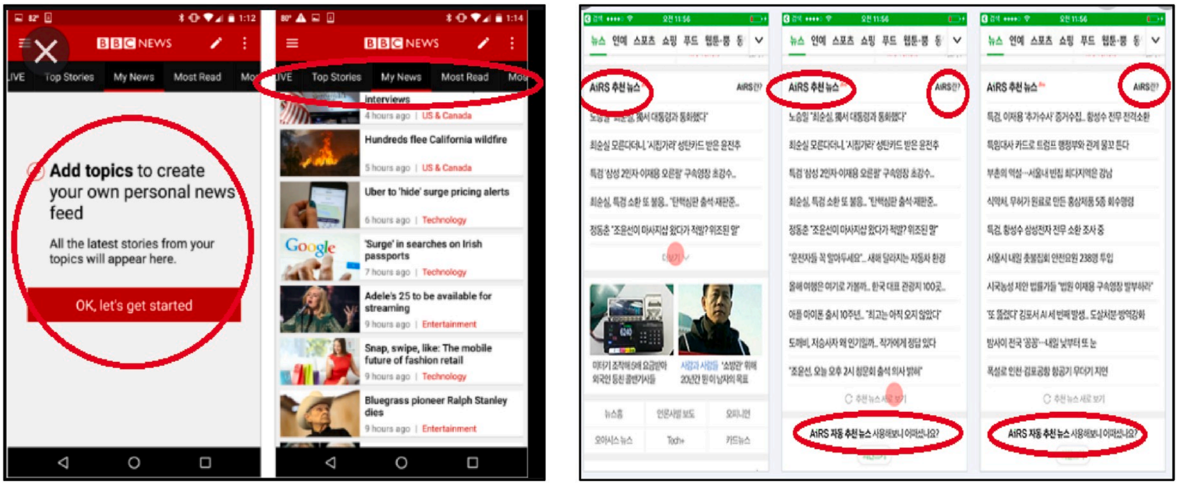


Fig. 1. User heuristics of transparency/accuracy in NRS.

1.1. *Algorithms in news recommendation system*

NRS makes reading suggestions to users in a personalized and individualized manner (Shin & Park, 2019). Currently, there are three approaches in NRS: collaborative filtering at the level of news items, content based recommendation and a hybrid approach. Collaborative filtering mimics user-to-user recommnendation by predicting user preferences as a linear, weighted combination of other user preferences (Robin, 2007, pp. 377–408). It uses user behavior for recommending items by analyzing behavior of other users and items in terms of ratings, shopping and purchase information, and transaction data. Two parameters (past and future) are used. For the past parameter, the number of news articles to be considered for recommendation and the number of steps needed to reach a given state is considered for the future parameter. Content-based filtering makes recommendations based on user preferences for product features. It considers both user and product. It constructs and then compare user-profile and item-profile using the content of shared attribute space. In the hybrid approach, collaborative and content filtering are combined where collaborative filtering is applied at the level of topics. This study used the NRS using hybrid approach as most NRS use a combinational approach. Fig. 2 illustrates the architecture used in testing in this study.

2. User interaction model of NRS

The NRS cognitive model in this study includes cognate constructs that influence satisfaction, which then affects continuance intention (Fig. 3). Based on the previous studies, transparency and accuracy are posited as antecedents of NRS usability evaluation, and the model includes the additional key factor of trust as a mediator.

Transparency and Accuracy. Transparency and accuracy are two important concepts in media and journalism and have also been considered critical to NRS. These two concepts frequently arise in the design and development of NRS and algorithm journalism (Diakopoulos

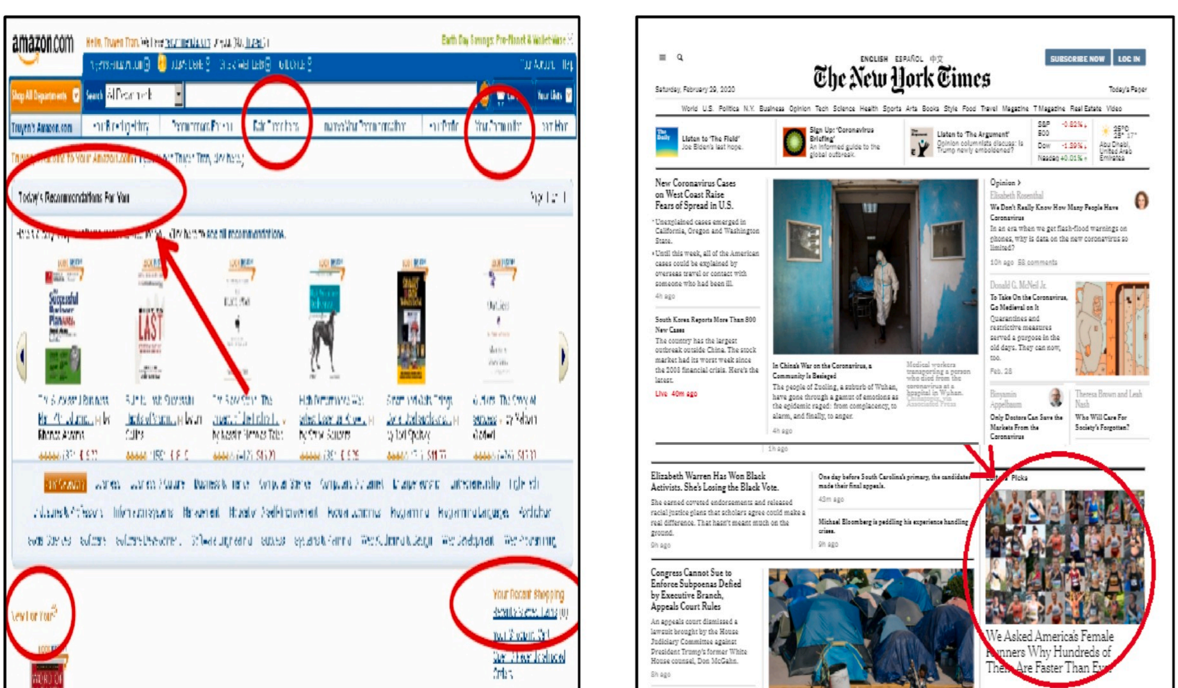
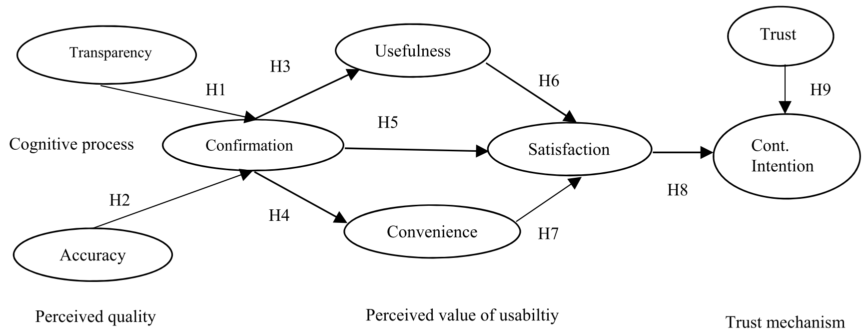


Fig. 2. Content recommneder system & news recommender system.



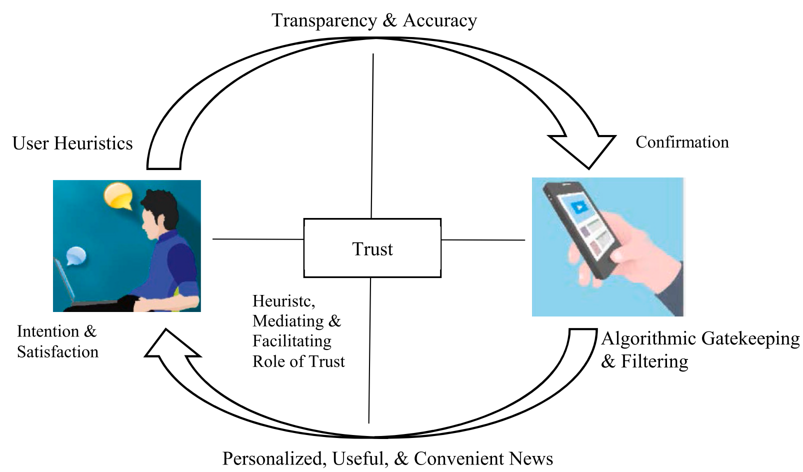


Fig. 3. Human interaction model of NRS

& Koliska, 2016). NRS are essentially designed to provide accurate recommendation systems. Whether such recommended results are actually reflecting user preferences or how the processes are accomplished remain open questions (Kitchin, 2017). Hence, accuracy and transparency emerge as the key factors in NRS (Diakopoulos & Koliska, 2016).

Understanding the assocation between the input to the system and output allows us to start a predictable and effective interaction with the system (Parizi, Kazemifard, & Asghari, 2016). Users are inclined to trustworthy systems as they know how the data are analyzed and thus how the recommendations are generated. With a transparent process, users can revise the input in order to improve recommendations. Users of NRS are able to understand the logic and process of NRS. The providers of NRS should ensure that the results are accurate and legitimate. Transparency and accuracy together play significant roles in NRS by improving user trust in algorithms. When transparent and accurate services are ensured, users are more likely to view the news. Highly transparent NRS can grant users a sense of assurance, and concomitantly, accurate news affords users a sense of trust. The user understanding of why and how a certain item is recommended was found to be significant in previous studies (Cramer et al., 2008; Sinha & Swearingen, 2002, pp. 830–831). Transparency and visibility for relevant feedback increase search performance and satisfaction with the system. Thus, the following relationships are hypothesized:

H1. Users' heuristics of transparency positively affect user confirmation of NRS.

H2. Users' heuristics of accuracy positively affect user confirmation of NRS.

User-Perceived Value. In technology acceptance literature, usefulness and ease of use have been widely employed as the basis for analyzing end-user acceptance of technology. There has been an intense focus on these beliefs in previous studies of consumer acceptance and the adoption of recommendation systems (Jung et al., 2017; Pu, Chen, & Hu, 2012; Zheng, Yang, & Li, 2014). The idea of algorithm is related to techniques for modifying the behavior of algorithmic agents over time in order to improve its usefulness to users (Shin et al., in-press). How useful to users depends on how users perceive the usefulness. In perceived usefulness, this study highlights the aspect capable of being used advantageously compared to traditional news services. This study attempts to conceptualize usefulness in relation to relative advantage, how consumers perceive NRS are useful and convenient compared to traditional news services. Convenience has been drawn from perceived ease of use: the degree to which a person believes that using a certain system will be effortless (Knijnenburg et al., 2012). Users would consider NRS acceptance in terms of how useful and convenient they are to use. Hence, the following can be hypothesized:

H3. User confirmation positively influences the perceived usefulness of NRS.

H4. User confirmation positively influences the perceived convenience of NRS.

When users confirm usefulness, they tend to be satisfied. In the same manner, when users understand the convenience of NRS, their satisfaction levels increase. These relations have been widely confirmed in various services (Shin & Park, 2019 for algorithm, Shin, 2010, for SNS; Kim, Shin, & Park, 2015, for smartwatch). Particularly, Zheng et al. (2014) argue that transparency and accuracy are the determinants of satisfaction. Thus, the following relationships can be hypothesized:

H6. Perceived usefulness has a positive effect on satisfaction of NRS.

H7. Perceived convenience has a positive effect on satisfaction of NRS.

Confirmation and Satisfaction. User satisfaction measures the user's perception of the recommendation performance and quality. The user's overall satisfaction with a system is related to the perceived recommendation or service quality of an NRS. Sinha and Swearingen (2002, pp. 830–831) showed that using explanation can improve the users' overall satisfaction with a recommender system. HShin and Biocca (2018) argue that a user's confirmation level directly influences satisfaction in technology adoption. Other studies such as Kim et al. (2015) have consistently confirmed a positive correlation between confirmation and satisfaction. Similarly, in other research, it has been empirically tested that confirmation has a causative relationship with satisfaction (HShin, 2010). Zhang, Wang, and Jin (2014) confirmed the causal relationship of confirmation and satisfaction in the algorithm context. Based on the previous studies, the following is hypothesized:

H5. Confirmation positively influences satisfaction with NRS.

Satisfaction and Intention. Drawing on ECT, Bhattacherjee (2001) showed that users' intention, particularly continuing intention, is determined by their satisfaction with a technology experience. Satisfaction is a psychological effect related to and resulting from a cognitive assessment of the expectation-performance agreement (Shin, 2010). Satisfaction with NRS can refer to an affect that is conceived as a positive, indifferent, or negative feeling about NRS. Affect has been conceptualized and validated in technology acceptance literature as a significant factor of user experience (Shin, 2010). In NRS, the causal relationship of satisfaction and continuance intention can be reasonably conceived.

H8. Satisfaction positively influences continuance intention of NRS.

Trust. Recommendation algorithms and trust metrics comprise the two stalwarts of recommender systems. Trust plays a steward role in technology adoption, particularly complicated systems (e.g., Shin, 2010). Numerous studies have consistently shown the key role played by trust in the process of evaluation, intention, and diffusion (Zhang et al., 2014). Whether users trust certain systems or services obviously affects the users' assessment and such assurance influences the users' willingness to provide more data to the systems and services (Bedi & Vashisth, 2014). In the context of NRS, trust is defined as the reliability to believe in the accuracy of the news recommendations and using the recommender system's capabilities (Alexander, Blinder, & Zak, 2018; Cramer et al., 2008). Thus, trust signifies how credible and reliable the system is. Many trust factors affect the decision to use a technology, but few studies to date have focused on algorithm services, particularly NRS.

H9. Trust positively influences the continuance intention of NRS.

3. Study design

This study is exploring the recommendation system in news consumption to examine the cognitive and psychological mechanisms of UX and trust in NRS. This study was approved by an ethics board and compliant with related human subject research. It utilized a triangulated mixed method design to clarify the factors affecting the experience of NRS. The quantitative data analysis examines factors in users' perceptions and experiences, then identifies users' underlying thinking regarding NRS.

Qualitative Method. Qualitative inquiry is used to focus on the respondents' interpretations and experiences of algorithmic accuracy and transparency, as well as their ascriptions of credability. This study conducted qualitative methods with 30 participants from several populations. Interviews, brainstorming, and the critical incidence method were used to gather information on algorithms, algorithm services, and NRS, respectively. First, in-depth interviews were conducted with selected algorithm users. Twenty subjects were randomly chosen from comprehensive universities located in metropolitan areas. The interviewees expressed their opinions and views on algorithmic trust and NRS. The interviewees were given the information about the NRS, process, architecture, and viewership.

Second, three focus group sessions were conducted. In the group interviews, groups of four to ten participants discussed their current use of algorithm services and the motivations that would influence their future adoption of the services. The focus groups comprised participants aged in their 20s (32%), 30s (32%), and 40s (21%) who were students (28%), office workers (29%), and factory employees (19%). The results of the focus group sessions produced a list of potential factors regarding the adoption and consumption of algorithms in their everyday lives. These sessions were designed to collect feedback on the preliminary analyses, gather input from users, conduct a needs assessment, uncover items missing from the model, and obtain a preliminary understanding of the factors that affect interaction and experiences.

Finally, the critical incidence technique was employed to uncover the underlying experience with NRS. The technique enabled this study to collect both direct observations of the users' perceptions of NRS and explicit but important information and facts regarding behavior in algorithms. The participants discussed the specific aspects of NRS they had experienced with algorithms. The emphasis was on the incidents of NRS, the reasoning, the conceptualization, and the meaning given. Ten participants identified a series of components of NRS.

Quantitative Method. From August to December of 2018, a pool of participants was collected who had prior experience with NRS or similar algorithm services. In order to determine the sample size for the study, a power analysis was conducted using the method of Cohen (1988). The results of the power analysis showed that a minimum of 300 participants would be needed to achieve an appropriate power level for this study. To examine the effect of algorithm on user behavior, a short-term longitudinal method was utilized. The participants were recruited from online survey firm, who has a large panel data. The participants were given financial remuneration for their time. First recruited participants were asked to read the NRS for three weeks. During the time, the participants were asked to view/read/surf algorithm-produced NRS regular bases. The participants were required to follow specific procedures (agreeing and providing information on personal and behavioral usage to algorithms) to enable algorithmic selection and filtering (Fig. 4). Specific instructions were given to them such as login methods, platform use, usage time, and frequency of NRS exposure. After three weeks, they were reinvited to fill out survey questionnaire via online.

A marketing firm assisted the overall experimentation process, such as recruiting, collecting, and monitoring participants. The firm has a pool of panel data and we recruited a panel data of users using NRS regularary in their everyday lives. With the initially collected responses, a data screen was performed in terms of the consistency of the responses, reliability of the responses, and valid answers. Using the process of data reduction, 40 responses were abandoned due to incomplete or inconsistent responses. A total of 328 data points were finalized and used for analysis (Table 1).

4. Results

4.1. Fit indices

The AMOS procedure and a maximum likelihood-based SEM software was used for structural modeling. The overall fit of the model is adequate, with all of the relevant goodness of fit indices greater than 0.90. The Goodness of Fit Index (GFI) is 0.959, the AGFI 0.92, and the Tucker-Lewis index (TLI) 0.838. There is no evidence of misfit, with the Root Mean Square Error Approximation (RMSEA) showing an acceptable level of 0.09, which favorably compares to the benchmarks by Joreskog and Sorbom (1996), who recommended that values of 0.06 or more reflect a close fit. The standardized Root Mean Square Residual (RMR) was also very good, at 0.113, well below the threshold for a good overall fit. Another positive test statistic was the normed chi-square value (a chi-square divided by degrees of freedom) of 4.94, a value that is appropriately below the benchmark of five, to indicate good

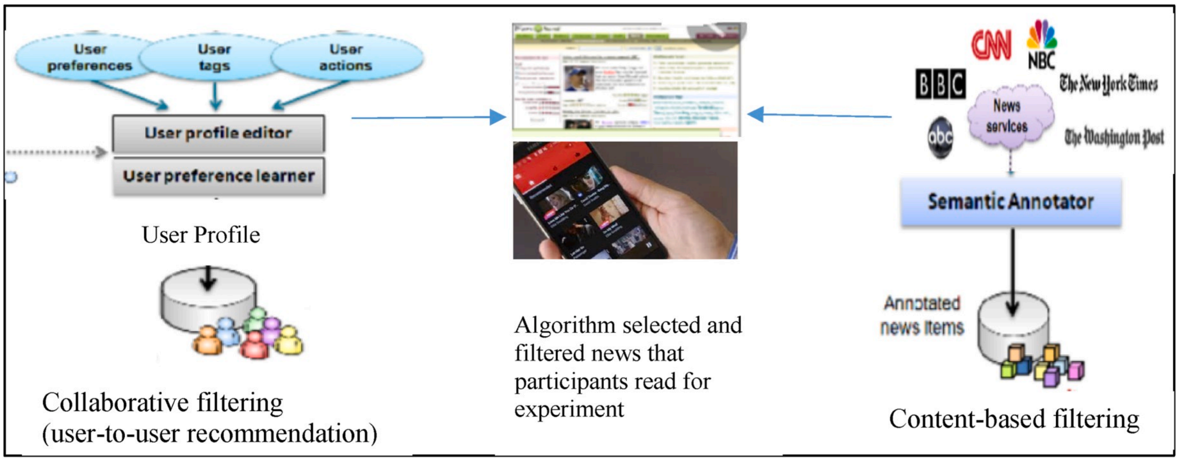


Fig. 4. Architecture of news recommender system.

Table 1
Sample Demographics (N = 328).

Characteristics	N	Mean	S.D.
Age		33.13	3.18
19-40	120		
41-50	110		
Over 50	98		
Gender			
Female	178		
Male	150		
Prior experience (month)		5.1 months	4.10
1-3	120		
4-6	93		
7-9	87		
Over 9	28		

overall model performance.

Findings from Path Analysis. The path analysis showed that relationships outlined by hypotheses were largely confirmed by the data (Table 2). The path coefficients between the variables were highly or moderately significant. Satisfaction was significantly influenced by confirmation (H5 β: 0.643, C.R. = 8.69***), usefulness (H6), and convenience (H7). Satisfaction accounted for approximately 60% by variance of confirmation, usefulness, and convenience. Satisfaction greatly influenced continuance intention (H8; C.R. = 13.713***). The effects of confirmation on usefulness and convenience were significant (H3, C.R. = 11.311***; H4, C.R. = 11.678***). In particular, the effect of trust on continuance intention was notable (H9), denoting an underlying connection between the trust factor and perceived value through a perceived value-confirmation-satisfaction-intention process.

Table 2
Results of hypothesis tests.

Hypothesis	β	S.E.	C.R. (t-value)
H1: Transparency → Confirmation	0.518	0.067	8.458[c]
H2: Accuracy → Confirmation	0.453	0.070	7.557[c]
H3: Confirmation → Usefulness	0.679	0.058	11.312[c]
H4: Confirmation → Convenience	0.737	0.067	11.678[c]
H5: Confirmation → Satisfaction	0.643	0.081	8.690[c]
H6: Usefulness → Satisfaction	0.200	0.058	3.884[b]
H7: Convenience → Satisfaction	0.142	0.059	2.474[a]
H8: Satisfaction → Con. Intention	0.819	0.056	13.713[c]
H9: Trust → Con. Intention	0.183	0.034	4.088[c]

β: Standardized coefficient.
[a] 1.96: 95% (0.05).
[b] 2.58: 99% (0.01).
[c] 3.29: 99.9% (0.001).

Considering the underlying linkage, convenience and usefulness confirm user expectations, which then trigger user assurance of transparency and accuracy. Users determine future intentions with their own verified satisfaction. Continuing intentions are either enhanced or moderated by trust (H9) that users have in NRS. Given the highly significant effect of trust and the previous findings (e.g., Shin, 2013), it is conceivable to ponder possible linkages among such factors. For example, trust affords users to allow more data to be collected and with more data and better accurate and predictive analytics with more data. Then, users are satisfied with highly transparent and accurate results. A first step is to examine other roles played by trust such as mediating effects.

Mediating Role of Trust. Given the significant results from the initial model, it is worthwhile to extend the model by examining the underlying effects of trust. This task would be meaningful given that trust in research literature has consistently shown significant roles such as in the areas of recommendation systems and news services (Cramer et al., 2008). The relationship between intention and satisfaction is an indirect effect that exists due to the influence of the trust mediator. The findings of previous studies (Wang, Townsend, Luse, & Mennecke, 2012) warrant the key role of trust in the context of NRS.

Mediating regression was used to analyze the effect of trust on other variables (Fig. 5). This study tested the mediating effect using the four-step method of Baron and Kenny (1986) as suggested by Shin (2013) who has examined the mediating effects of trust in online shopping. Per their proposed steps, the significant links were confirmed between the independent variable and the mediating variable and between the dependent variable (intention) and the mediating variable. Subsequently, mediation is confirmed if the effect of the independent variable on the dependent variable is decreased by the mediating variable. The mediating effect test is done when the direct effect becomes insignificant.

First, a model was fitted in which satisfaction was regressed on trust. The effect of the independent variable (satisfaction) significantly accounted for the variance in the hypothesized mediator trust. This regression showed that the mediator trust was associated with the independent variable satisfaction whose effects were supposedly mediated. Another regression model was performed with intention as the dependent variable and the mediator trust as the independent variable. Trust significantly accounted for the variance in the dependent variable intention. A third regression model was tested with intention as the dependent variable and satisfaction as the independent variable. A significant result was produced. A fourth model was run with intention as the dependent variable and satisfaction and trust as the independent variables. The effects of intention were insignificant ($t = 1.23$, $p = 0.27$) when the significant effect of the hypothesized mediator trust ($t = 3.68$, $p < 0.001$) was partitioned out. Hence, trust was determined as a full

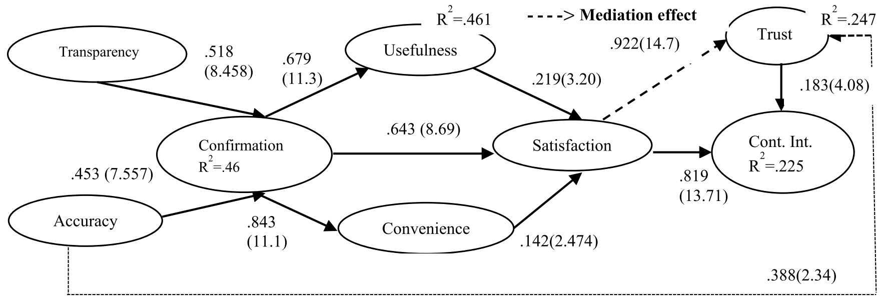


Fig. 5. The results of the mediation analysis.

mediator between satisfaction and intention. Lastly, after analyzing the mediating effect, Sobel's test was conducted for significance testing. The result of the Sobel test was significant ($Sobel = 0.106, p = 0.001$). Sobel the test statistic stands for the amount of variance in the dependent variable for which the independent variable through the mediating variable is responsible.

Providing more user trust and visibility may assure users that their individual data will be used by legitimate and transparent processes, thereby generating trust toward the service and the service providers, eventually leading to a heightened level of satisfaction. Previous research findings provided confirmation of the mediating role of trust in diverse contexts including recommendation systems (Zhang et al., 2014). From the mediating role, it can be inferred that trust between users and algorithms is the basic mechanism in the acceptance and experience of NRS. Trust mediates the relationship between cognitive factors and intention. These trust issues can moderate the success of the adoption of algorithm services. Future studies should explore the moderating effects of trust on individuals, organizations, and contextual-related success factors in the adoption of algorithm services.

5. Discussion

This study proposed and tested the UX model of algorithms to explore individual cognitive processes in interacting with NRS. The model implies that interacting with algorithms involves a number of interrelated cognitive processes. In order to understand user attitudes and behaviors of NRS, research needs to take into account algorithmic quality, user heuristics, and recognized value. The findings can be discussed in terms of user experience, algorithmic quality, and trust.

User Experience of NRS. As the volumes of news can be overwhelming to users, designing an NRS to assist them in sorting news that is relevant and useful to read is a crucial task for every online news service. Users prefer the confirmation of utility and convenience (H3 and H4). Such confirmation can positively influence user satisfaction (H5). While the relationship has been previously validated in ECT and TAM studies, the model in this study clarifies that confirmation is also positively reinforced by transparency and accuracy (H1 & H2). Given the rising issues of transparency and accuracy in NRS, it is understandable to see two factors of determining roles influencing satisfaction. The two factors are unique features of NRS that when users perceive services are transparent and accurate, they become assured of utility and convenience, which then together affect satisfaction (H3, H4, H6, & H7). The R^2 of confirmation and satisfaction are above 40%, which are high values. With the mediating role of trust, satisfaction plays a key role in determining continuance intention (H8).

Overall, the verified significant paths imply that algorithms are not only perceived as news providers, but as platforms to interact with NRS. This means that having news through NRS is more than merely viewing or reading; users want to engage and interact with a system and they expect the system know their preferences. Users expect the process to be transparent and the recommended results to accurately reflect what they are seeking or what they are preferring. Algorithms recommend what users want to see and users allow their data to be processed by the algorithms. Algorithms and users together interactively form a kind of feedback loop binding them together and eventually the two become one entity. The more users are exposed to algorithms, the more likely algorithms will become the users' avatars. As Shin et al. (in-press) argue, algorithm-based services are likely to evolve into interaction platforms to enable users to interact with algorithms through positive feedback loops. Algorithm-based services would redefine how people engage and interact with a system.

Transparency and Accuracy. What qualities or features are critical in NRS and how do users perceive them and with what effects? For these questions, transparency and accuracy were proposed as antecedents of user confirmation. The effects of perceived transparency and accuracy on confirmation were significant (H1 & H2). Just as transparency and accuracy have been considered critical journalistic values in traditional media (Diakopoulos & Koliska, 2016), so to in algorithm-based NRS. Not only do transparency and accuracy play significant roles, but also they play antecedent roles in the development of users' perceptions of usefulness and convenience (Graefe, Haim, Haarmann, & Brosius, 2018). Usefulness and convenience are greatly influenced by the transparent process and accurate results of NRS. That is, users' perceived usefulness and convenience are not automatically formed; rather they are determined by how users recognize transparency and accuracy. This finding has heuristic implications in NRS design and user experience. Subjects of transparency and accuracy have been popular topics in NRS and users are concerned with such issues in using NRS. Such issues have not been clearly conceptualized but it can be inferred based on previous research that trust is closely related to these issues as it plays a significant role in determining satisfaction and confirmation (H9 and the mediating effect). When users are assured with of such troubling issues, their trust levels can increase and they are willing to allow more of their data to be collected and processed. With the increased trust between users and algorithms, more transparent processes are warranted, and more data enables algorithms to produce accurate results tailored and individualized to users' preferences and personal history. Thus, while the relationship of trust and perceived algorithm features are not examined in this study, it is worthwhile to empirically test this relationship. Per the argument by Shin and Park (2019), trust will be a central factor in positive feedback loops in users and algorithm systems.

Mediating Role of Trust in Algorithmic Processes. This study proposed a model in which trust mediates the relationship between satisfaction and future intention. Satisfaction promotes trust and in turn influences intention. Higher satisfaction implies that greater trust and users are more likely to continue to use and adopt. The significant mediating roles exerted by trust imply that NRS users wish to confirm through the trust mechanism in the course of their cognitive decision to adopt. This finding resonates with the findings of previous studies (e.g., Shin, 2013) which point out to the mediating roles of trust in various contexts. The mediating role of trust in algorithms reveals that trust is more than a matter of reliability, reliance, or credibility.

The mediating effects are concordant with the role of the trust mechanism in NRS and recommendation services overall. The heuristic role of trust is key to the concept of actual determinants in NRS. In previous literature, trust has been considered one of the factors affecting another factor. In the NRS context, trust represents more than one of the factors for user decisions; it may be understood by users as a facilitator or a catalytic cue that plays a key role in triggering and forming the UX of NRS. In this light, the domain of trust in NRS can be broadened to embrace diverse roles at different dimensions. The model illustrates that trust plays a key role in the development and stimulation of user motivation, attitudes, and behaviors. This finding has valuable and heuristic implications for both academia and industry. While the findings support previous research on trust, they further clarify the applicability of trust in emerging algorithm areas. Previous research findings on trust have shown that user trust plays a role in determining a person's behavioral intention and actual behavior. Trust plays a steward role in the NRS where transparency and accuracy have been considered key criteria, carrying out users' wishes while interacting with NRS. Trust can be a heuristic providing users mental shortcuts to form judgments and make decisions: How algorithms are formed, how data are collected and analyzed, and how transparent and accurate results are provided are all dependent upon trust. This study found that trust, which is affected by algorithm quality, has significant effects on both intention and satisfaction. This finding implies the heuristic roles of trust in algorithmic processes as well as a positive feedback loop of trust. Users use trust as an information shortcut to evaluate quality and to predict the satifiaction and intention.

Based on the heuristic role, it can be further inferred that user intention regarding algorithms can be formed through a two-tiered process (e.g., heuristic systematic process by Shin et al., 2020): While users may have high satisfaction, they may feel some other supplement to make them further adopt or purchase. Users may want the trusted mechanism to confirm their decision. Objective utilitarian performance cannot provide the necessary emotional cues in quite the way that personal trust can. Users prefer to be motivated, intrigued, and entertained when they use algorithms. Trust in the service built through transparency and accuracy may provide that emotional assurance and affirmation.

Positive Feedback Loop of Trust. As the trust factor plays significant roles in the model, it is worthwhile to test the relationship between trust and transparency/accuracy. The current literature remains inconclusive whether the NRS quality factors measurably contribute to trust and satisfaction. Previous studies have widely shown that transparency and accuracy positively influence users' levels of trust (Cramer et al., 2008; HShin, 2010). When users acknolwedge a certain process to be transparent, accurate, and fair, their trust levels increased. When trust is created, it leads to a stronger intention and satisfaction. Pearson's correlation shows that the trust and transparency/accuracy in the model are significantly correlated (coefficient, $r = 0.606$ to 0.845, $p < 0.01$). Also, when the paths from transparency/accuracy to trust were added, the model greatly improved. The R^2 of intention and satisfaction improved, respectively, which implied the underlying role of trust in the positive feedback loop of transparency, accuracy, and trust in the algorithmic process (Fig. 6). Per Shin et al. (in-press), the trust feedback loop is a positive feedback loop that decreases users' concerns over transparency and accuracy and user satisfaction and intention increase significantly. Positive feedback is significantly related to trust, satisfaction, transparency, and intention. Such feedback implies the need of examining the complex cognitive mechanisms relating to feedback. Future studies should examine the positive feedback loop of trust.

6. Implications

The contributions of this study are both theoretical and practical. Theoretically, it conceptualizes algorithm quality and measures the effects in reference to algorithmic trust.

Practically, the findings provide design implications for NRS industry. Developing effective user-centered algorithm services requires understanding users' cognitive processes and reflecting them in design work.

Theoretical Implications. The results confirmed that algorithm use and interactions were positively related to perceived values, which were positively associated with the users' experiences of transparency and accuracy and with future intention. The findings of this study implied the connections between a dynamic experience, algorithm technology, and users' interactions with the automated environment.

This research contributes to existing literature on trust, UX, and algorithms in the context of NRS. Advancing the work of Shin and Park (2019) and Graefe et al. (2018), the results confirm that algorithmic use and interactions are positively related to perceived values, which are positively associated with users' experiences of transparency and accuracy and with their future intentions to use. The findings of this study stand to contribute to theoretical development by clarifying how trust is formed, and from there, how trust can be conceptualized as affordances.

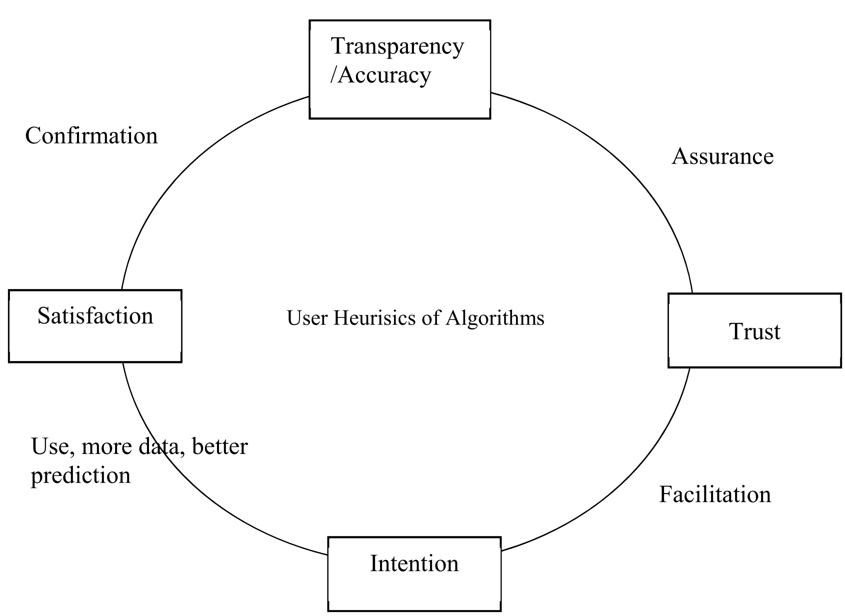


Fig. 6. Positive feedback loop of trust in algorithm.

The results of this study contribute to existing literature in several aspects. First, the results contribute to insights and developments regarding the interactions between human and algorithms at both theoretical and empirical levels. With conceptualizing and measuring algorithm features, this study contributes to the understanding of how to ensure such elusive issues in NRS and how to design algorithm systems that are human-centered and socially responsible in a journalism context. Such discussion contributes to the human-algorithm interaction by coverging a set of interactions: starting form when a users is introduced to NRS system and extending to continuous interactions, AI model and its components, as well as proposing the idea of explainability with trust. One of contributions is that the study highligths the importance of transparency and accuracy. For example, exlaining the performance of an algorithm may impossible if the algorithm itself is not transparent. Personalized news to the user's preferences may not be possible if the system cannot track the correct user input or if the information is inaccurate.

Second, the ECT approach advances the current user literature, specifically the technology acceptance literature, by identifying contextual variables and the underlying relationships among them (Alvarado & Waern, 2018). In preceding ECT literature, perceived values were considered to influence expectations, which then leads to confirmation. The heuristic model in this study shows how such values are formed and how they together influence confirmation in the context of algorithms. The model shows how perceived values are related to confirmation, which then influence transparency and accuracy. As algorithm-specific factors, users' perceived usefulness and convenience are related to transparency and accuracy through confirmation. That implies the users' heuristics or mental shortcuts to confirm algorithmic processes through cognitively constructed mechanisms of transparency and accuracy. Users may feel more confident about news recommendations that they believe are transparent and accurate. By identifying antecedents of perceived value and by clarifying cognitive processes, this result provides a modest but meaningful theoretical progress as to ECT. As innovative algorithm services rapidly develop, traditional technology-based frames or conventional user frameworks must be modified to reflect the ever-changing computing paradigms. As argued by Graefe et al. (2018), an investigation of how people understand algorithm functionality, what cognitive perceptions are held, and what consequences are derived from cognitive processes is important. The findings of this study, particularly the ECT approach and heuristic-based quality measurements, will enable future studies to make meaningful strides in the discussion of a user-based algorithm framework. As the findings imply, algorithmic quality evaluations are closely based on users' cognition, subjectivity and trust. The functional features of algorithms are embodied in users' cognitive perceptions regarding perceived affordances, which are moderated by trust factors. Affordances thus influence the cognitive processes of quality, value, and satisfaction on the part of users (Shin & Biocca, 2018). The results provide additional details regarding users' cognitive and perceptual processes of algorithms through the affordance frame.

Thirdly, this study highlights new dimensions of the various effects of trust on algorithm users' attitudes and behaviors. While prior studies have consistently implied the significance of trust in technology adoption (Pu et al., 2012; Shin, 2010), this study further clarifies the trust matrix by analyzing how trust is formed and what constitutes usability in the algorithm context. Empirically, trust may stand to elucidate users' attitudinal relationships with algorithms. Beyond the matter of choice, trust represents a continuous relationship between users and an algorithm. In this type of relationship, users seek to secure trust before committing to long-term use. Algorithmic trust can be established when users recognize responsibility on the part of algorithms for the content they produce, thereby making algorithms vulnerable to the perceptions of users. In other words, algorithms must accept responsibility with transparency. This is why trust is closely related to transparency and accuracy and why users wish to have personalization and customization in determining their levels of satisfaction. This finding may contribute to theoretical advancement as it clarifies how trust is formed and why mediation occurs via specific mechanisms.

Lastly, an interesting looped relationship can be inferred: first, people invent technologies; then, these products influence human perceptions; later, users receive feedback during use and continually improve an existing technology or develop a new one. User factors or social factors have been considered significant determinants on the design or development of technological products. In the era of algorithms and AI, recommender systems can be a typical example to explain how user factors interact with computational products and solve information problems by algorithmic programming. Per the argument by Shin et al. (in-press), it can be inferred from the cognitive processes the existence of active roles for users in forming algorithms in NRS. Most of the previous studies have assumed users to be passive consumers of recommended services who provide their data to algorithms (Knijnenburg et al., 2012). With the rise of algorithm technologies, the user's role has changed from being a passive receiver of automated processes through algorithms or media to an active and participatory creator of algorithms that generate, adjust, and modify such algorithms depending on the framing and contexts of their everyday lives (Konstan & Riedl, 2012). It can be reasonably inferred that users are the source of algorithms and the creators of NRS by invoking deep subconscious cognitive processes. What users see through algorithms, as far as their cognition is related, is a cognitively constructed reality that emulates the form of an accumulated experience that has been shaped by a priori mental constructs. As Shin and Park (2019) imply, algorithmic selection has become a shared social reality and shapes daily lives and realities, affecting the perception of the world. Further to their arguments, humans and algorithms are co-evolving and create reality together as they influence each other. People want to see what they would prefer to see, they want to view what they would prefer to view, and they want to be reinforced by the algorithmic process (Beam & Kosicki, 2014). Future studies may delve into this pont by empirically validing the relation of user preferences and algorithmic selection. It is worthwhile to advance the theory of algorithmic gatekeeping. Additionally, future studies may examine the positive feedback loop of trust proposed in this study.

Practical Implications. The pragmatic implications of algorithms and NRS include the potential for new service developments and design guidelines. For the developers of NRS or other similar online services, the implications of this study can help advance the systems' performance and UX toward their products.

The first suggestion is that the industries should address the UX of algorithms and NRS. Heuristic process and psychological effects are essential in rationalizing how and why people perceive and feel about the issues of NRS and how they use and engage with algorithm-generated news. The main goal of NRS is to help people sort news that is interesting and intriguing to read. Understanding how users search, find, and read news online allows NRS providers and algorithm designers to perform more efficiently and effectively. There have been numerous challenges to offering recommended results in the NRS context. Recommending news is one of the most challenging recommendation tasks. The findings of this study give an idea of how to reflect these issues in the interface design. The results of this study provide NRS designers with guidelines on how to combine transparency and fairness issues with other factors, for example, how to collect user data/implicit feedback effectively while promoting users' trust and assurance. Algorithm interface issues are not simply cosmetic or stylistic, but constitute an integral part of what it means for algorithm to perform and interact. In this regard, it is further suggested to include human-centered evaluation metrics when assessing the performance of an algorithm. NRS should be evaluated in terms of how they influence user interaction rather than by technical measures of performance.

The findings suggest that future NRS needs to transcend perfunctory transparency or mechanical accuracy and fulfill actual user needs and perspectives. Thus, understanding UX will be paramount to the usability and success of NRS (Shin & Park, 2019). This task will be even more difficult as users may have ever-evolving interests and it is hard to predict changes in journalism. The model in this study will provide insights on how to integrate transparency and fairness with usability factors and behavioral intention. The ultimate goal of NRS and recommendation systems is to develop human-centered services. Applying a user cognitive process to UX design presents users with relevant information that they need. Algorithms that are user-centered and trust-based feedback loops will be key to designing such human-centered systems.

7. Limitations and future studies

Whereas the findings of this study are legitimate, the results must be interpreted with caution for the following reasons. First and foremost, the samples were collected only in Korean populations, and thus the generalizability of the findings may be limited. The sample and the generalizability issue may be inherent problems in general academic studies. Nonetheless, the samples could have been collected in a broader context. Future studies should examine a larger and more diverse cross-section of the population using sophisticated sampling to guarantee a reasonable distribution of the socio-demographic variables.

Second, the findings exhibit limited or partial pictures of UX with NRS. Since algorithms and NRS are not yet mainstream trends, this study is limited in its application to other countries that its findings cannot be fully generalized to the wider population of algorithm users. It remains to be confirmed whether NRS represents a kind of recommendation system. Moreover, the concepts of transparency and accuracy should be further clearly defined and measurably operationalized. This study attempted to address such concepts and incorporated them into the user model as antecedent factors of satisfaction and trust. Such issues are presently popular, but the factors have not yet been validated and this study approached them in on an exploratory basis. While such concepts should be incorporated into algorithm design, how to accomplish this task is as yet uncertain. Also, conceptually such factors have been defined as legal concepts. It is future studies' role to define them further and develop them in reference to UX.

Lastly, this study excluded the various effects of demographic traits such as moderating and interaction effects. Particularly, users' personality may greatly influence the consumption and adoption of NRS. Trust in algorithms may depend on a user's dispositional trust. Since dispositional trust varies with personality traits, these factors may influence users' algorithm experience. Altogether the limitations imply the need for a more meticulous approach and theoretical refinement, specifically on how to best capture the interaction between users and algorithms, how to define the roles of trust in the course of interactions, and how to infuse emerging social issues, such as transparency, fairness, accountability and explainability, into the interface design and application development of algorithms. In a long-term perspective, future studies should examine a wider range of user experiences, including how users' traits influence the perceived accuracy and transparency of recommendations. It is likely to add more and more user elements to algorithm system, which still generates large amounts of inaccurate and irrelevant recommendations.

CRediT authorship contribution statement

Donghee Shin: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

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