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Role of fairness, accountability, and transparency in algorithmic affordance

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ABSTRACT

As algorithm-based services increase, social topics such as fairness, transparency, and accountability (FAT) must be addressed. This study conceptualizes such issues and examines how they influence the use and adoption of algorithm services. In particular, we investigate how trust is related to such issues and how trust influences the user experience of algorithm services. A multi-mixed method was used by integrating interpretive methods and surveys. The overall results show the heuristic role of fairness, accountability, and transparency, regarding their fundamental links to trust. Despite the importance of algorithms, no single testable definition has been observed. We reconstructed the understandings of algorithm and its affordance with user perception, invariant properties, and contextuality. The study concludes by arguing that algorithmic affordance offers a distinctive perspective on the conceptualization of algorithmic process. Individuals' perceptions of FAT and how they actually perceive them are important topics for further study.

1. Introduction

The use of algorithms and analytics in society is drastically increasing. Nowadays, artificial intelligence (AI) increasingly arbitrates decisions in our lives through a wide variety of implementations, such as online machine learning recommender systems, tailored news aggregation services, credit scoring methods, and location-based services. Advancements in algorithms provide unprecedented venues for breakthroughs in important decision-making fields, such as content curation, health and safety, security, and public management (Shin, 2019). Driven by the substantial amounts of big data that have become available, algorithms have emerged as the new power agents in society (Diakopoulos, 2016), as algorithm technology is drastically revolutionizing society and becoming an integral part of everyday life.

The rapid adoption of algorithm technologies has the potential to greatly improve user experiences and human life, but poses problems and challenges that must be addressed when such a system is widely diffused and pervasively used in societies (Ettlinger, 2018). Although algorithms have the potential to offer increasingly sophisticated products and services, thorny topics arise such as fairness, accountability, and transparency (FAT). The question as to whether an algorithm is fair or does not discriminate, who should be held liable for the results of algorithms, and how to ensure the purpose, structure, and underlying actions of algorithms remain unsolved and controversial (Beer, 2017). These topics, including user privacy, data policy, and ethical considerations regarding how we design and develop the algorithms, will be critical to its sustainability and long-term effects (Ananny & Crawford, 2018; Mittelstadt, Allo, Taddel, Wachter, & Floridi, 2016). Despite the importance of such issues, little consensus is observed regarding a single, testable definition of the issues (Lee, 2018), and this creates confusion for the academia and industry involved in algorithms. On the basis of this context, this study aims to conceptualize FAT in relation to the increasing use of algorithms and clarifies the roles of such problems in the user acceptance of algorithm services. The following research questions guide this study:

RQ1. What are the normative and operational definitions of FAT in the algorithm context? How do users perceive FAT and what constitutes FAT?

RQ2. How and what does perceived FAT afford users? How is FAT related to other factors in the course of algorithm experience?

RQ3. How does FAT influence the adoption and diffusion of algorithms? What are the roles of affordance in algorithms?

This study views an algorithm as a socially recreated artifact based on users' cognitions and contexts. FAT in the algorithm context may be a subjective concept and is reconstructed through user cognitive processes (Just & Latzer, 2018). In fact, evaluating how transparent, fair,

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and accurate are under the users' disposition (Kemper & Kolkman, in-press) and these are subjective in nature as they are dependent upon contextual and user disposition, importantly related to users' trust (Bedi & Vashisth, 2014). An argument that we posit in this study is that FAT is largely based on the character of algorithm service, users' intrinsic traits, and user cognition (Shin, 2019). Users with higher levels of trust were observed to be more likely to see algorithms as fair, accurate, and transparent, while trust moderating the relationship between FAT and satisfaction.

The results from this study contribute to the literature in three aspects. First, the results contribute to the insights and practical knowledge regarding the interactions between users and algorithms. Algorithm services are increasingly featured with an ecosystem of complex, socio-technical issues (Moller, Trilling, Helberger, & van Es, 2018). By conceptualizing and contextualizing FAT, this study contributes to the understanding of how to ensure such abstract issues in algorithms, how to design algorithm systems that are human-centered and socially-accountable, and how to govern algorithm systems effectively and legitimately.

Second, the ecological interface approach advances the current user literature (user-based experience model) by identifying contextual variables and the underlying relations among them (Shin & Choi, 2014). Although a user-centered approach is useful, it has focused on the individual user or a specific task in systems. The focus of the ecological interface approach is on context or environment; thus, it is better suited to algorithm contexts. That is, an examination of how users perceive algorithm functionality, how their intentions are carried out, what cognitive perceptions are held, and what consequences from cognitive process are derived is critical. The findings of this study, particularly the ecological interface approach and experience-based quality measurement, will enable future researchers to make important strides in the formation of a User Experience (UX) framework.

Third, this study provides guidance to the design for algorithms and future related algorithm services. The AI industry is striving to ensure that algorithm-driven services are accurate and effective. The industry is being increasingly challenged by the development of improved FAT and satisfaction indicators on which many important decisions are based (Helberger, Karppinen, & D'Acunto, 2018). As more interesting content and innovative services are introduced through algorithms, FAT becomes a critical differentiator among diverse algorithm providers (Diakopoulos, 2016). How users perceive and process FAT is considered more important than the technical properties/qualities, such as accuracy and predictability (Lee, 2018).

The fundamental premise of this study is that algorithms' functional features are embodied by users' cognitive perceptions eliciting perceived affordance, which is moderated by trust factors. Affordance thus influences the cognitive processes of quality, usability, and satisfaction (Shin & Biocca, 2018). From an interface and design perspective, algorithmic affordance can be a key concept for user interface for algorithm services (Ettlinger, 2018). This study's results provide additional details regarding the users' cognitive process of algorithms through the affordance frame. Understanding user affordance facilitates the development of a user-centered interface for algorithms.

2. Literature review

2.1. FAT of algorithm

As the FAT (fairness, accountability, and transparency) of algorithms is of growing importance in the recent algorithm system, the nature/definition of FAT and its operationalization become urgent tasks in academia and industry. The issues have emerged from an abstract ideology to a pressing contemporary matter in societies with drastic market environment changes triggered by recent algorithm advancements. With the rapid advancement of impressive algorithms, AI has created unprecedented opportunities, but also concerns from users, industry, and policymakers. Although governments and practitioners have actively addressed the social and ethical issues arising from the algorithmic society, questions remain (Just & Latzer, in-press) and are controversial: first, how can fair algorithms be designed and developed? and second, how we can develop algorithms that are more transparent and accountable (Lee, 2018)? Companies should be able to prepare for these questions because discriminatory and opaque algorithms may turn into serious risks, which lend urgency to a debate on how to develop AI transparent, fair, and accountable (Diakopoulos, 2016).

Fairness in algorithm contexts means that algorithmic decisions should not create discriminatory or unjust consequences (Yang & Stoyanovich, 2017). Fairness in algorithm is related to algorithmic bias, which occurs when algorithms reflect the implicit values of the humans who are involved in coding, programming to train the algorithm (Beer, 2017). Examples of unfair discrimination can be (1) banks providing loans based on race, or gender and not on financial score, (2) firms hiring people based on race and not qualifications, and (3) realtors renting houses to specific communities and not on capability. The fairness in algorithms is from a matter of accuracy and a perspective of fairness. Uncertainties have been increasing regarding the unfair practices of algorithmic decision-making systems. Yet, algorithmic fairness can be a complicated topic, because the definition of fairness is largely contextual and subjective.

The concept of transparency involves the details of the service reasoning, and of other types of data management, involving sensible data, and/or possible consequences about the knowledge that the system is gaining of the user implicitly (Ananny & Crawford, 2018). The black box nature of algorithms refers to people not knowing the inner operations of the algorithms because this information is proprietary and/or sufficiently complex to not be understood. Algorithmic transparency plays a key role in resolving the question of Facebook's role in the Russian interference of the 2016 American Presidential Election. The concepts of understandability and explainability become hot issues: Can stakeholders interpret and understand the operating of a system and its results? Users may forgo the need for complete and transparent access to the underlying algorithm and the dataset if easily understandable information about the system is provided to them by a qualified, trustworthy expert or entity. When people understand how system works, they are more likely to use the system properly and trust the designers and developers (Lee & Boynton, 2017).

Accountability in algorithms and their application begins with the designers and developers of the system that relies on them (Diakopoulos, 2016). Eventually, designers and managers are responsible for the consequences or impacts an algorithmic system has on stakeholders and society. Understanding the possibility of unintended consequences is a critical condition when addressing algorithmic accountability. Normally, senior management is unaware of the business risks inherent with the design decisions related to the algorithms their business depends on. Conversely, algorithm designers are often not in a position to make critical executive decisions on behalf of their business. The result is an accountability loophole that goes unaddressed and uncommunicated, leaving the business vulnerable to unexpected risks for which they later maybe held responsible. Example of algorithmic accountability is that when news recommendation systems generate news articles that contain misinformation or libel, who are accountable for the wrong content? To what extent algorithm producers or carriers is responsible will be an elusive question.

Here it is important to point that the use of citizen data is closely related to FAT. That is to say, how to collect people data in a transparent way, what to collect in a fair manner, and who are responsible for data management are important considerations to address. Eventually, these issues are dependent upon how citizens perceive FAT because the more they believe their data would be treated fair, transparent and accountable way, the more they allow companies to collect their data. Thus, societal attitudes toward algorithms are eventually shaped through public discourse. However, public understanding is limited by a technical barrier. Although algorithms are technologically complex, the public may want to understand an algorithm's inner workings, the black box of the algorithm. The public is eager to precisely know how their data are collected and how the input data are used to produce outputs. Citizens expect visibility and opacity in the algorithmic process. The right to explanation by the EU General Data Protection Regulation, a right to obtain an explanation of specific algorithmic results are in line with such citizens' motivation as to FAT. Users want to have a just and equitable means to participate in the evolution of algorithms.

2.2. What matters in designing algorithms, users, process, and technology?

We re-conceptualize algorithm as a socio-technical system that handles human interaction with technological systems (Kitchin, 2017; Shin, 2019). Algorithm systems comprise one or more technological algorithms, services, platforms, user knowledge and social experience, and interaction with users. What establishes an algorithm system as a socio-technical system is that it is generated by or related to a system adopted and used by social users in societies (Shin & Choi, 2014). Although FAT has been approached from various disciplines and perspectives, research from the user perspective is limited. An approach to understanding user values not typically reflected in economic analyses or market-based indices.

Accordingly, this study argues that the algorithm debate should focus on user interests, because public users should be the eventual beneficiaries. Analytical tools for assessing social impacts of technologies tend to focus on microeconomic approaches such as cost-benefit analyses. As social values are not easily expressed in economic analyses, specific methods of establishing values, such as public value mapping, are adequate tools. This study approaches FAT from the individuals' perspective, also known as user-centered design or user-centered policy evaluation (Baumer, in-press). Per Baumer's argument (in-press), policy design should be based on user perspective, and its evaluation should be performed by users. The need for this user-centered approach is apparent and because the existing approaches to algorithm analysis (although powerful and effective) do not sufficiently analyze the causal impacts between policy and user perspectives.

Therefore, user-centered value mapping can provide insights and implications on the governance and design of algorithms. Regarding the governance, a user-centered view can improve policy capacity by involving individuals not typically involved in the policy-making process. Regarding the design of algorithms, the user-centered approach provides insights into the design of algorithm-driven services. This way, the user-centered approach plays a formative role by helping to continually refine and update policies and a summative role by helping to ascertain whether goals and objectives are being satisfied. Considering the public nature and magnitude of algorithms, considering user-centeredness is useful, specifically under complex socio-technical situations.

2.3. Algorithmic affordance: from blackbox algorithms to interactive affordances

Despite technical sophistication, algorithms rarely provide useful means for users to interact with them (Fink, 2018). In other words, algorithms themselves do not have the affordance that would allow users to understand them or how best to utilize them to achieve their goals. Affordances require the user to detect an object's invariants (e.g., functional properties) relative to the user's capabilities (Shin, 2017). Algorithmic affordances should provide users opportunities for action that people can perceive with respect to features in their environment such as fair, transparent, and accountable.

From a user's perspective, the algorithm is a “black box,” and it is not possible for the user to know how the computation is completed (Shin, 2019). Algorithms collect data from users, transform the data, and output the data in another form. The ability for users to understand how an algorithm reached its conclusions can be challenging. Some algorithms further restrict user understanding and use by reducing high dimensional data into single dimensional list. If users have no means to perceive an algorithm's affordances, or no knowledge of its invariants, the possibility for users to use it effectively significantly decreases.

Thus, algorithms fundamentally change the nature of the cognitive demands and responsibilities of the firms, and often in ways that were unintended or unanticipated by their developers. Algorithm firms can design affordances into their algorithms to facilitate their use. Algorithms must provide some level of observability to users, that is, an affordance they can perceive. Providing explainable observability to the users is a necessary first step to make algorithms more useable and accessible. The key is to offer the user heuristics into the algorithm's process. A means to accomplish this task would be to provide information about the algorithm's training set and its provenance, size, variability, and any known limitations. This information provides a rationale for the algorithm's output. The algorithm could include explanations for individual outputs. For example, recommendation algorithms could identify which features lead to the selection of music or news. Another local approach would be to provide a confidence rating for algorithm outputs. Similar to humans, algorithms have response criteria, that is, they let users know if an output exceeded the response criteria by a large or small amount, which allows users to know to how more effectively interact with the algorithm. Algorithm developers must provide operators with control points to direct input, transformation, and output processes. The input side could include the new cases into the training data set, or mechanisms for providing feedback to the utility of algorithm outputs. Transformation control options could result in changes to feature weighting or approaches used to build the algorithm. Finally, with respect to outputs, developers could provide means for users to personalize or customize algorithm outputs to better accomplish their tasks, that is, tailoring them to their goals and needs.

Although integrating affordances into algorithms will not be easy, the task is not impossible. If the algorithms used by automation are highly complex and different from human cognition or not understood by humans, the algorithmic results will not be accepted. To take full advantage of algorithm tools, we must make the algorithm's opportunities for action observable and understood by its users (Shin, 2019). Without these improvements, algorithms will not realize their potential across industries for improving forecasting and predictive analytics.

3. Hypotheses development

In this study, FAT is proposed as an antecedent variable affecting satisfaction and trust is hypothesized as a moderator influencing the relation path (Fig. 1). There have been growing concerns that

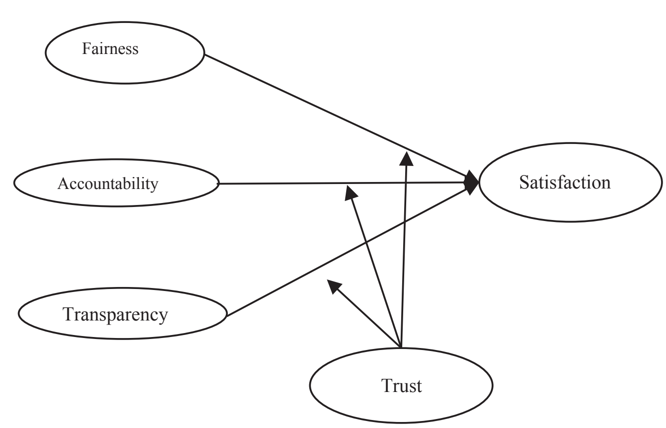

Fig. 1. FAT conceptual model.

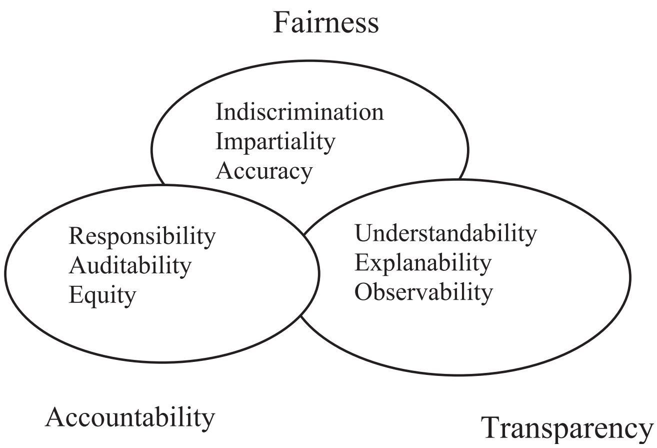

Fig. 2. FAT conceptual model.

algorithms raise new challenges for ensuring transparency, non-discrimination, and due process in decision-making (Lee, 2018). In particular, such factors have been frequently discussed in the design and development of a recommendation system and algorithm-driven services in general (Diakopoulos, 2016). A recommendation system is designed to provide accurate recommendations (Klinger & Svensson, *In-Press*). Whether such recommended results really reflect user preferences or how the processes are conducted remain open questions (Kitchin, 2017). Thus, transparency and fairness emerge as the most critical factors in recommendation systems (Diakopoulos & Koliska, 2016) (see Fig. 2).

Understanding the relationship between the input to the system and output allows us to start a predictable and effective interaction with the system. Users are inclined to trust the system because they know how the data are analyzed and thus how recommendations are generated. With transparent processes, users can revise the input to improve recommendations. Algorithm users can understand the logic and process of recommendation systems.

The algorithm developers should do their utmost to ensure results are accurate and legitimate. Transparency and fairness play significant roles in algorithms by improving user trust in an algorithm (Ananny & Crawford, 2018). When transparent and accurate services are ensured, users are more likely to view the news in more engaged manners. Highly transparent recommendation systems can grant users a sense of assurance; additionally, accurate news affords users a sense of trust. The user understanding of why and how a particular recommendation is generated was found significant. A thought could be that the high visibility and transparency for relevant feedback helped search performance and satisfaction with system. Thus, the following hypotheses are proposed:

H1. Users' assessment of transparency positively affects user satisfaction with algorithms.

H2. Users' assessment of fairness positively affects user satisfaction with algorithms.

Accountability has become as important as transparency and fairness. Perceived accountability of algorithms is the expectation that a user's beliefs, actions, or feelings may need to be justified regarding algorithms. For organizations to be perceived as accountable, users can expect an evaluative process with negative or positive consequences to follow task outcomes. When people perceive accountability, they search more conscientiously for relevant information, find more evidence for decisions, develop stronger rationalizations for choices, and complete tasks themselves more often. This increased accountability can be considered a mechanism to alleviate potential negative consequences from automated algorithmic processes (Aggarwal & Mazumdar, 2008). High levels of accountability may also lead organizations to exert extended effort to justify a decision. Consequently, users will be more likely to use and be satisfied when algorithms are held accountable for outcomes, which could reduce negative results.

H3. Users' assessment of accountability positively influences user satisfaction with algorithms.

3.1. Moderating role of trust

Much of the research examining the role of trust is based on the assumption that trust about a service/product mitigates the uncertainties and risks related to vulnerabilities such as information sharing, legal issues, and privacy (Shin, 2010). Hence, a higher level of trust in a specific algorithm service is posited to increase the likelihood of potential adopters to take risks inherent in adopting algorithm services; thus, greater trust facilitates the greater use and willingness in the experience of algorithms. To test the moderating role of trust, the split sample approach was used: this study divided respondents into two groups based on their prior trust level. Respondents were asked to express their trust, credibility, and beliefs of general algorithm-driven services. The trust measurements of Bedi and Vashisth (2014) were used, and the median value was used to divide the respondents into high and low trust groups.

4. Method

With the rise of algorithms, growing emphasis has been placed on the issues of FAT to find means to provide more stable and socially desirable services. The research questions (RQs) are addressed with different methods and approaches to triangulate the findings. For RQ1 (what constitutes FAT), interpretive methods such as in-depth interviews and critical methods were used. For RQ2 and RQ3 (examine the FAT-based UX model of the algorithm), a survey was conducted to identify the relations of factors and find a user model based on experience.

This study utilized a triangulated mixed method design to understand the FAT issues in algorithms. The quantitative data analysis examines factors in users' perceptions and experiences. The qualitative data analysis identifies users' underlying thinking regarding FAT (Table 1) (see Table 2).

5. Findings

5.1. Exploratory interpretive analysis

A series of components of FAT were identified after the evaluation and analysis of the interview and critical incidence data. Some of the components were comparable to those researched in the literature on algorithms.

Fairness. The concept of fairness was raised during interviews in

Table 1
Demographics of survey respondents.

Age (years)	Percent
Under 20	10
21–35	35
36–45	35
Over 46	20
Prior experience (months)	
1–5	19
6–9	21
10 to 12	22
More than 1 year	38
Gender	
Female	49
Male	51

Table 2
Results of hypothesis tests.

Hypothesis	Standardized coefficient	S.E.	C.R. (*t*-value)
H1: Transparency → Satisfaction	0.394	0.047	7.638[a]
H2: Fairness → Satisfaction	0.518	0.052	9.357[a]
H3: Accountability → Satisfaction	0.215	0.038	4.566[a]

*1.96: 95% (0.05), **2.58: 99% (0.01).
[a] 3.29: 99.9% (0.001).

combination with accuracy. People mentioned fairness is an impartial and just process of algorithms without favoritism or discrimination. Respondents referred to indiscrimination, non-discriminatory treatment, and unbiasedness. Although one group talked about impartiality, other people stated accurate results of the searches and recommendations by algorithms. Commonly, people unanimously agreed that fairness is critical factor in algorithms. Three components of fairness can be drawn: indiscrimination, impartiality, and accuracy.

Accountability. Respondents were concerned that algorithmic systems are vulnerable making mistakes or lead to undesired consequences. The respondents agreed that algorithms can have problems due to human bias or simple oversight. Thus, they viewed that firms producing algorithms should be held responsible in some way and somehow for the results of their algorithms. In case an algorithm delivered discriminatory results because of the bias embedded in data, the system must be liable for the result. Based on the qualitative process, three components of accountability can be drawn: responsibility, auditability, and equity.

Transparency. Transparency has been viewed as a crucial factor in algorithms. As more everyday decisions are automated by algorithms, there is a growing need for transparency as the processes may be opaque and have a risk of biased profiling and discrimination. People viewed that given the impact of algorithms, the decisions made by algorithms should be visible, understandable, and transparent to the people who use, generate, and regulate. Others also raised a balanced view that algorithmic transparency should be balanced with promoting commercial development and industrial profits. Based on the qualitative process, the three components of transparency are derived: understandability, explainability, and observability.

6. Results from the FAT model

The overall fit of the model was acceptable; all relevant goodness-of-fit indices surpassed acceptance levels as recommended by previous research. All other significant fit indices showed that the model provided a suitable fit to the data. Per the root mean squared error approximation, there was no evidence of an unsuitable fit to the data. The standardized root mean residual was also acceptable, and the normed chi-squared value was less than the benchmark of three, which shows satisfactory overall model performance.

The hypothesized causal paths were tested, and all the proposed hypotheses were supported. The results supported the proposed relations and illustrated the significant roles of FAT in the adoption of algorithms. The key relationships between FAT and satisfaction were supported by the data, as indicated by the significant critical ratios (CRs). Fairness had the highest significant effect on satisfaction (H2, CR = 9.357), followed by transparency (H1, CR = 7.638). Overall, the model implies the importance of FAT in algorithmic process and further implies the users’ cognitive process.

6.1. Findings from moderation effect

With the high and low trust group in place, a series of Chow tests (1960) was conducted for each moderator individually (Table 3). Chow tests were used to assess the statistical significance of the difference between the strength of relationship among the variables from the two datasets. The results of the moderation effect show the significantly different structural relationships of all the paths in the model (see Table 4).

6.2. Findings from survey

Effects of trust level and algorithms. A two-way analysis of variance (ANOVA) was used to examine the effects of trust tendency and algorithms on the measured variable. The participants who interacted with algorithm services eliciting high algorithmic features experienced greater satisfaction, $F(1, 95) = 18.38$, $p < .001$, $\eta p^2 = 0.18$, demonstrated higher credibility regarding the results, $F(1, 95) = 21.13$, $p < .001$, $\eta p^2 = 0.14$, and rated higher in transparency, $F(1, 95) = 20.02$, $p < .001$, $\eta p^2 = 0.15$, than those who interacted with non-algorithm services. The results of the ANOVA showed that participants with a high algorithmic tendency experienced greater satisfaction, $F(1, 95) = 4.09$, $p < 0.05$, $\eta p^2 = 0.14$, demonstrated a more positive intention for the algorithm services, $F(1, 96) = 21.31$, $p < .001$, $\eta p^2 = 0.15$, and rated the transparency, accountability, and fairness as higher in quality, $F(1, 95) = 15.03$, $p < .001$, $\eta p^2 = 0.21$; $F(1, 95) = 14.34$, $p < .001$, $\eta p2 = 0.11$; than did those who used non-algorithm services.

Interaction effects. The ANOVA identified an interaction effect between algorithm and trust level regarding attitude and value [$F(1, 32) = 8.09$, $p < 0.01$]. There are combined effects of algorithm and trust level on satisfaction. The results of the interaction effects suggest that the higher trust tendency with the algorithm services (i.e., recommendation system, Chatbot) produced a greater positive value, and thus, a more positive attitudethan the low trust tendency with non-algorithm services (conventional search engine, online news). That is, people with a high trust tendency found algorithm-driven services more satisfactory and useful than non-algorithm services, whereas people with a low trust level found non-algorithm services more satisfactory and comfortable than algorithm-driven services. That is, users' intrinsic trust tendencies and the service's properties have combined effects on satisfaction. The high trust group perceives higher value and feels more satisfied, whereas the low trust group feels more comfortable with non-algorithm features.

7. Discussion

This study is an effort to deepen the current understanding of the issues surrounding algorithms and clarify the definitions and the effects of FAT on the users' cognitive processes. The findings show that user perceptions of algorithm FAT can significantly influence users’ cognition and adoption, with (1) the perceived FAT playing significant roles in user satisfaction of algorithm services and (2) trust playing a moderating role in the effects of FAT on satisfaction. This study also found that the interaction effect between trust and algorithm features influences the satisfaction with the algorithm. The findings together implied the heuristic role of FAT regarding its underlying link to trust, as this study contributes to the understanding of what constitutes the public notions of FAT, how people view them, and what leads users adopt algorithms.

7.1. Contextuality and subjectivity of FAT

The quantitative findings of this study imply that FAT issues are diversely accepted and multi-functionally related, and that user attitudes about FAT are highly dependent on the context in which it takes place, as well as on the basis who is looking at. This is in line with the previous studies (e.g., Lee, 2018), which have shown diverse views regarding FAT. The qualitative findings, on the other hand, have implied that topics regarding FAT are somehow related and overlapping,

Table 3
The Chow tests of trust moderation.

F/p-value	Transparency-Satisfaction	Fairness-Satisfaction	Accountability-Satisfaction
High trust (n = 110)	0.481	0.712	0.641
Low trust (n = 120)	0.181	0.210	0.225
F(4; 1312)	3.45	1.31	2.13
p-value	< 0.05	< 0.05	< 0.05

making them difficult to distinguish or separate (as shown Fig. 1). The issues altogether still raise active user roles in the algorithm development and users' rights regarding data collection and analysis. Although the model shows the general relationship among the factors, the further tests will corroborate the argument that the FAT issues are dependent on the users’ cognition and perception. As FAT issues are high abstract terms, of course, people understand, perceive, and process FAT differently. For example, while personalized results have great benefits to certain users, other users may find it as unfair, depending on what characteristics are perceived in personalized experiences. Transparency can disadvantage some users when it is predicated on negative assumptions. Moreover, it is often hidden from users, limiting their requests of responsibility.

The moderating roles and the interaction effects imply that the issues are mostly subjective matters. A common sentiment is that FAT is inexorably subjective, and maybe this is true in algorithm contexts. FAT may be incapable of being measured by objective standards. User perception of FAT may be formed out of their own intrinsic process of trust and motivation independent from the actual nature of FAT in algorithms. Users with a lower trust level intrinsically consider algorithms less trustworthy and consider FAT issues skeptically. This finding is consonant with the moderating role of trust. Trust is found to play significant role in processing FAT, which then affects satisfaction. Although the positive role of trust on adoption behavior has been widely validated (e.g., Shin, 2010), the interaction and moderating effect imply that an algorithm is dependent on users’ trust.

An inference is that algorithmic applications form everyday lives and actualities just like the construction of realities by the mass media. Just and Latzer (2018) argued that automated algorithms influence people's perception of reality and behavior. From the view, the co-evolutionary perspective of algorithms can be drawn: organizations, ideologies, intermediation, and people influence the construction of reality. Similarly, Mager (2012) argued that personalized searches influence user perspectives because algorithms selectively guess what information a user would like to see based on information about the users past experiences and search history. User perception and belief are created, amplified, or reinforced by algorithms and vice versa.

7.2. FAT is eye of the beholder

On a broader conceptual ground, these lend support to the idea of social construction of algorithms. Extending the frame of the Social Construction of Technology, an assertion can be made regarding the Social Construction of algorithm: an algorithm and its ecosystems can be considered a socially constructed artifact. Algorithm technologies are the results of technological innovations that industry has made, and the algorithm services reflect the people's aspirations. For example, algorithmic selection has become an increasing source of social order, of a shared social reality (see Park, Chung, & Shin, 2018). Algorithm applications shape and form everyday lives and realities, influence the perception of the outside, and affect actions. As users become increasingly involved with the personalization and customization of the algorithm, co-evolutionary perspective become more persuasive than pure social construction of algorithm.

Different from pure social constructionism by technologies, algorithmic reality construction increases personalization, individualization, and customization to increase transparency, accuracy, and predictability. For example, the algorithm search recommendations try to match with users’ previous experiences. Just like selective exposure, users 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, 2014). The more users use algorithms, the narrower their perspectives become. For example, people perceive what they want to in algorithmically recommended contents while try to ignore other viewpoints. Cognitive processes form the way users perceive FAT.

In this sense, a reasonable assertion is that users are the source and creators of algorithms by invoking deep subconscious cognitive processes. What users see through algorithms is a cognitively constructed reality (or its version) that emulates the form of an accumulated experience shaped by a priori mental constructs. As Just and Latzer (in press) argued, algorithmic selection has become a shared social reality and shapes daily lives and realities, affecting the perception of the world; additionally, humans and algorithms co-evolve and create reality together as they influence each other.

Although algorithms reflect users this way, the negative effects of such a reflection have social ramifications at different levels. At a micro level, how to create user-centered algorithms is a matter of how to create algorithms that are more responsible and processes that are more transparent. The notion of accuracy is not a matter of reflecting what users want, but suggesting socially and politically correct results to users. In fact, algorithms are prone to amplify racist and sexist biases from the real word. COMPAS is an algorithm widely used in the U.S. to guide sentencing by predicting the likelihood of a criminal reoffending. Yet it is viewed racially biased as the system predicts that black defendants pose a higher risk of recidivism than they do, and the reverse

Table 4
Two-way analyses of variance indicating the effects of the independent variables.

Measured variables	Mean (Standard error)					
	Algorithm level			Trust level		
	Algorithm	Non-Algorithm	F	High trust	Low trust	F
Transparency	5.24(.14)	4.87(.15)	22.11**	5.98(.10)	5.92(.14)	15.11**
Accountability	5.12(.09)	4.56(.11)	15.22**	5.14(.09)	5.16(.04)	15.99**
Fairness	5.23(.13)	5.23(.15)	19.49**	5.72(.11)	5.97(.19)	4.15*
Satisfaction	5.38(.14)	4.56(.14)	20.17**	5.49(.12)	5.43(.12)	21.23**

*$p < 0.05$, **$p < 0.001$.

for white defendants.

7.3. Are transparency and accuracy objectives?

The overall findings of this study indirectly suggest that perceptions of transparency and accuracy are not purely objective responses to media content. Instead, the model in this study lends strong support to the argument that, to a significant extent, similar to perceptions of information in general, perceived transparency and accuracy in the algorithmic media is subjective. Transparency and accuracy can be more subjective perceptions held by users rather than objective criteria. Given this insight, we can use various dimensions to measure the transparency and accuracy of a recommendation. Transparency and accuracy depend on users' perceptions. Although transparency and accuracy have been popular topics in algorithmic services, such concerns are socially constructed and cognitively reconstructed within users' cognitive dimensions. Rather than such issues being uniformly or collectively given to users, users create their own versions of transparency and accuracy based on their levels of trust and other personal intrinsic factors (Shin & Biocca, 2018). In other words, transparency and accuracy are cognitively constructed realities of their own making (as argued by constructivism) because they depend on users' perceptions. This result is consistent with the literature: Shin's argument that "immersion may be in the eye of the beholder" (2018). The argument can be applied to algorithms, in that transparency, fairness, and accuracy depend on the user's perspective, and all are at the disposition of the user (Lee & Boynton, 2017). This point can help clarify the concept that algorithmic qualities are more about the users' own cognitive perceptions and less about technical features.

Although UX emphasizes user focus and perspectives in relation to technology, the UX of algorithms advises us to focus on users in terms of experiencing the quality provided by technologies. In this regard, the algorithm experience comprises users' perceptions of quality, interactions with services, and the technological features that users see, feel, and interact with. This argument can make sense because algorithms are reflections of user preferences, experiences, and values. Thus, what users expect from algorithms and what users experience may be subjective (Just & Latzer, in press).

7.4. Measuring transparency and accuracy

Transparency and accuracy cannot be measured as features of algorithms or in the context of legal terminology because they involve subjective dimensions that can be experienced and perceived by users. Per Kemper and Kolkman's argument (in press), transparency may be viewed from users' perspectives or user-based approaches. Transparency is a form of awareness in the eye of the beholder, the degree of which reflects the concentration of their emotional, cognitive, and sensual links to the content and modality of technology. Because transparency and accuracy partially constitute the user experience of algorithms, industry may develop a framework that applies a user-centric approach to recommendation systems. An increasing criticism of FAT is that such issues are inevitably subjective and incapable of being determined by objective criteria. There might not be an objective standard of transparency, fairness, and accountability. The subject of FAT lies in the eye of the beholder. Its implementation, however, is in the hands of the policymakers or company's algorithm developers. What is a seemingly transparent and equitable solution to a service provider may not be the same to its users. What each user deems transparent and fair is subjective. In algorithm services, the problem is the gap between the users' views and how the issues were applied. This criticism poses a serious problem in measuring and operationalizing FAT in algorithm services. Related to this problem, Kemper and Kolkman (2018) raised a question: "if transparency is a primary concern, then to whom should algorithms be transparent?" If FAT is a complicated topic, then the best means to conceptualize FAT is through the user perspective. How users see, perceive, and feel should be the first criteria for measuring and operationalizing FAT.

Here the concept of affordance is helpful for a theoretical conceptualization of algorithmic cognitive processes. Affordance denotes the direct perception of the utility of an object through the perception of its features. Users expect algorithms to offer accurate, convenient, and credible results, and such desirable properties are ensured with FAT. Trust and affordance have a circular relationship that once users trust algorithm services or the providers, they perceive that the services are easy to use, adopt, and continue to use. Algorithmic affordance provides a plausible cognitive process for perception in humans and the perceptions of transparency, fairness, and accountability (Butcher, 2017).

With the users' trust, the users continue to cooperate with algorithms by allowing their data to be collected by algorithms, and such increased data provide better predictive analytics to users (Lee, 2018). When users acknowledge a certain process to be transparent, accurate, and fair, their trust levels increase. Transparency and accuracy build trust. When trust is created, it leads to a heightened sense of intention and satisfaction. The literature has widely shown that transparency and accuracy positively influence users' levels of trust (Shin, 2010). The trust feedback loop is a positive feedback loop that diminishes users' concerns regarding transparency and accuracy, and user satisfaction and intention increase significantly. Positive feedback is possibly positively related to trust, satisfaction, transparency, fairness, and intention. Such feedback may demonstrate the importance of examining the complex cognitive mechanisms relating to feedback. Future studies should examine the positive feedback loop of trust.

8. Conclusion and practical implications

For industry, this study provides insights on a new design principle for effective algorithm design and development. The recent advances in algorithm technologies enable establishing socio-technical systems that closely interweave users and their social structures with technologies. With the emerging importance of the algorithm, the question is how to make human-centered algorithms (Baumer, in-press). The first practical suggestion is that the related industry should address the UX of algorithm services. Subjective perceptions and psychological effects are critical in rationalizing how and why people perceive what they do regarding the issues of algorithms, and how they use and engage with algorithm-generated news. The results suggest that the user perceptions of the FAT issues of algorithm systems induce affordance, which affects UX. Understanding how users search, find, and consume algorithms allows firms and algorithm designers to perform more efficiently and naturally. This study suggests FAT framework evaluating UX of algorithm users. Transparency, fairness, and accuracy have been thorny issues in algorithms and recommendation systems. UX is important to make more precise and accurate recommendations. The FAT framework provides the algorithm designers with guidelines on how to combine transparency and fairness issues with the other factors, for example, how to collect user data/implicit feedback effectively while promoting the user trust and assurance.

Second, industry can utilize the algorithmic affordance as a guiding principle of programing algorithm services. As Bucher (2017) argues, users' understanding and perceptions of algorithms, the ways in which users imagine and expect certain algorithmic affordances, affect how they approach technologies. Industry can use algorithmic affordance as a key base to create feedback-loop of machine learning systems like Facebook make user beliefs an important component in shaping the overall system behavior. For example, firms can constantly monitor online product reviews to identify consumer affordance. As user activity is generative of the system itself, industry can establish some forms of affordance repository to better predict user needs and preferences. Future algorithms must go beyond perfunctory transparency or mechanical accuracy and toward actual user needs and perspectives.

Hence, understanding algorithmic affordance will be critical in predicting the future interests of users for better recommendations. This task will be even more difficult as users may have ever-evolving interests and predicting the changes in a dynamic ecology is difficult. The affordance model in this study provides guidelines on how to integrate transparency and fairness with trust factors and behavioral intention. The eventual goal of algorithms and recommendation systems is to develop the services human-centered approach. Applying a user cognitive process to UX design presents users with relevant information they need. Algorithms that are user-centered and trust-based feedback loops will be key in designing such human-centered systems.

Third, based on the findings of FAT, industry is suggested to develop observable or explainable algorithms. Deep learning and AI algorithms are considered opaque and are not allowed for users to look inside or understand. Users want interpretable, understandable explanations about why certain results are presented. Exposing users to their algorithmically-derived attributes led to heightened FAT. Revealing parts of the algorithm process can satisfy user's “right to explanation” (EU General Data Protection Regulation) of algorithmic computation that affects them. Given the importance of FAT and the user perception of such issues, it is worthwhile to develop new methods to make algorithms more explainable and interpretable, and a way revealing parts of the algorithmic process to users. The explainable algorithms involve three levels of explainability: (1) Explain the intention behind how system impacts users, (2) Explain the data sources algorithm use and how it audits outcomes, and (3) Explain how inputs in a model lead to outputs in a model. When companies able to explain these to users, to governments, and even to other competing industry in markets, algorithm become more responsible, observable, and effective socio-technical system.

Algorithmic affordance not only benefits users by providing them opportunities and understanding of how transparent, fair, and accountable of algorithms, but could also help industries to establish user trust and satisfaction with their algorithmic services.

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