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Why am I seeing this? Deconstructing algorithm literacy through the lens of users

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Abstract

Purpose – As algorithms permeate nearly every aspect of digital life, artificial intelligence (AI) systems exert a growing influence on human behavior in the digital milieu. Despite its popularity, little is known about the roles and effects of algorithmic literacy (AL) on user acceptance. The purpose of this study is to contextualize AL in the AI environment by empirically examining the role of AL in developing users' information processing in algorithms. The authors analyze how users engage with over-the-top (OTT) platforms, what awareness the user has of the algorithmic platform and how awareness of AL may impact their interaction with these systems.
Design/methodology/approach – This study employed multiple-group equivalence methods to compare two group invariance and the hypotheses concerning differences in the effects of AL. The method examined how AL helps users to envisage, understand and work with algorithms, depending on their understanding of the control of the information flow embedded within them.
Findings – Our findings clarify what functions AL plays in the adoption of OTT platforms and how users experience algorithms, particularly in contexts where AI is used in OTT algorithms to provide personalized recommendations. The results point to the heuristic functions of AL in connection with its ties in trust and ensuing attitude and behavior. Heuristic processes using AL strongly affect the credibility of recommendations and the way users understand the accuracy and personalization of results. The authors argue that critical assessment of AL must be understood not just about how it is used to evaluate the trust of service, but also regarding how it is performatively related in the modeling of algorithmic personalization.
Research limitations/implications – The relation of AL and trust in an algorithm lends strategic direction in developing user-centered algorithms in OTT contexts. As the AI industry has faced decreasing credibility, the role of user trust will surely give insights on credibility and trust in algorithms. To better understand how to cultivate a sense of literacy regarding algorithm consumption, the AI industry could provide examples of what positive engagement with algorithm platforms looks like.
Originality/value – User cognitive processes of AL provide conceptual frameworks for algorithm services and a practical guideline for the design of OTT services. Framing the cognitive process of AL in reference to trust has made relevant contributions to the ongoing debate surrounding algorithms and literacy. While the topic of AL is widely recognized, empirical evidence on the effects of AL is relatively rare, particularly from the user's behavioral perspective. No formal theoretical model of algorithmic decision-making based on the dual processing model has been researched.

Keywords Algorithmic literacy, Algorithmic platforms, Over-the-top, Dual processing, Transparency, Fairness, Accountability, Explainability

Paper type Research paper

1. Introduction

Algorithmic systems and data-driven practices exercise increasing influence over today's societies, reshaping how cultural, social and political systems function (Cotter, 2019). The information environment has radically changed over the past few years. The transition and transformation of information platforms have enabled algorithms and machine learning to take over information processes such as content recommendation, curation, personalization

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and filtering of information (Burrell, 2016). Algorithms are becoming an important part of information optimization and gatekeeping (Willson, 2017). Social media algorithms sort posts in the users' stories or feeds. Journalism algorithms prioritize what news users read in their feed by the probability that they would actually want to read it (Shin *et al.*, 2020). Over-the-top (OTT) platforms have been using algorithms to drive their business, and OTT systems have been leading the way for digital content (Bishop, 2019).

Algorithms learn from data, can limit the options made available to users online, and influence people's choices (Lee *et al.*, 2019). Amazon has tremendous information about the items people like. Facebook echo chambers lead people prone to fake news. Netflix offers a highly curated experience by understanding what people like. Yet, users are often unaware of the rationale used behind the algorithmic services to inform their actions when dealing with increasingly complex interactions seeming simplified at the forefront. There has been a growing need for people more aware of how algorithms and AI sort them and shape reality (Lloyd, 2019). Against this backdrop, algorithmic literacy (AL) emerges as a practical guideline (Hobbs, 2020) as user perception/understanding constitutes algorithms (Shin, 2021) as well as a normative principle that people deserve to know how algorithms work (Koenig, 2020). The ways users could interact with elements they see on the user interface, transparently test the algorithmic systems they use, and critically understand the algorithm-based processes lead to discussions of fairness, accountability, transparency and explainability (FATE), which become essential design guidelines as well as components of AL (Dörr and Hollnbuchner, 2017; Rader *et al.*, 2018). People are increasingly realizing how algorithms impact humans and how to counter them. An understanding of algorithms and how they affect adoption processes and how they are shaping our lives could determine how users perceive and form their actions towards algorithms (Courtois and Timmermans, 2018). Recent research to redefine information literacy further the goal of identifying algorithmic components and has led to the need for research on AL in the AI context. Rainie and Anderson (2017) have called for education and research on AL across different sectors. Shin (2021), for example, proposes user cognition of fairness, transparency, and responsibility as relevant to the experience of algorithmic personalization. Haider and Sundin (2021) have conceptualized users' understanding and literacy of the impact of algorithm-driven systems. How users cognize algorithmic attributes, how users interact with algorithm systems, and how AL plays a role in such processes will be imperative questions to address in designing and developing future AI. Understanding these processes is critical because user's practices on algorithmic platforms in turn form these algorithms themselves, and hence may subsequently influence the information that they receive (Cotter and Reisdorf, 2020; Shin *et al.*, 2022).

Recent studies on algorithm adoption (Shin and Park, 2019; Shin *et al.*, 2020) reveal the facilitating roles of FATE in the adoption of algorithmic services. When users experience algorithms, they face issues of FATE, which are subsequently related to people's perception of and engagement with algorithms (Lee *et al.*, 2019). Thus, it is essential to examine the users' cognitive process applying AL to algorithms through which users work to make sense of the issues. This area of analysis of the users' cognitive way of doing things with AL is key when designing an interface for user-friendly algorithms. AL can be best understood as a set of user experiences in terms of the ways people experience algorithms in their everyday lives and the actual practices that are mediated by real-world algorithmic services (Koenig, 2020). The processes of creating algorithmic awareness and understanding in situations of high complexity are necessary to foster algorithm behavioral decisions (Kotras, 2021).

The present study responds to the call for research in AL by examining what roles AL plays in the adoption of OTT platforms and how users experience algorithms, particularly in contexts where AI is embedded in OTT algorithms to generate personalized recommendations. Despite its importance, the roles and dimensions of AL have remained largely unexplored, let alone the mechanism or consequence of such AL (Hobbs, 2020). Although some people may be ostensibly aware of the function that algorithmic curations play in deciding the content and structuring our world, few understand the essential roles of algorithmic platforms and the effects these platforms have on their consumptions. Our goal is to analyze the effects of AL on the adoption of OTT platforms by tracing how users experience OTT platforms, what awareness the users have of the algorithmic platform, and how awareness of algorithmic literacy may impact their interaction with these systems. Examining the roles and processes of AL provides relevant implications both for academic and industry. Theoretically, conceptualizing the cognitive process of AL and trust has made relevant contributions to the ongoing debate surrounding algorithms and literacy. Users' information processing begins with heuristic examinations of AL then continues to a performative evaluation of the service of algorithms. This finding contributes to theoretical knowledge by clarifying a dual-processing framework for algorithmic context and by highlighting the role of AL as a heuristic mechanism. While the topic of AL is widely recognized (Shin *et al.*, 2022), empirical evidence on the effects of AL is relatively rare, particularly from the user perspective. From a practical viewpoint, the relation of AL and trust in an algorithm lends strategic direction in developing user-centered algorithms to facilitate algorithm development in platform contexts (Reisdorf and Blank, 2020). It is difficult for people who are not AI professionals to comprehend AI decision-making mechanisms. Due to this literacy gap, most users have a limited understanding of the underlying processes and this makes it even harder for them to apply AL effectively. To help users better understand how to cultivate a sense of literacy regarding algorithm consumption, the AI industry could provide prototypes of what positive engagement with algorithm platforms looks like.

2. Literature review: how platforms use algorithms to shape user experiences

As AI becomes pervasively integrated into human lives, recognizing the dimension that algorithms exert in human lives is becoming critical. There have been increasing concerns over the control that these algorithmic platforms have over human interactions (Shin, 2021), how they reinforce biases (Henderson *et al.*, 2020) and distort realities based on biases and prejudices (Noble, 2018). Despite advances in the area of algorithmic experiences, gaps in the research literature still exist in examining AL and awareness of everyday users. How users understand the operations of algorithmic curation and how they engage with these selections remain unknown.

2.1 Algorithmic literacy: deciphering algorithms

The concept of AL has been recently derived from related concepts like information literacy and data literacy as the importance of algorithms has increased over all sectors of society. While it extends beyond traditional literacy, AL has not yet been well conceptualized nor well measured (Cotter, 2019). While there is no single universally accepted definition of AL, most conceptual approaches incorporate users' knowledge and skills. One of the most recent studies refers to the understanding of what algorithms are, how they are used, how they can benefit people and how they can negatively impact individuals and certain groups (Cotter and Reisdorf, 2020). Koenig (2020) defines AL as the social processes and practices of reading and writing what algorithms produce and mean. AL commonly means being aware of the presence of algorithms in daily life, and the increasing role they play, both for good and bad (Swart, 2021). At a basic level, AL may consist of at least acknowledging when an algorithm is present behind the scenes and making inferences about what it is trying to do (Rieder, 2017). At a higher level, AL helps people to assess and interact with algorithmic systems on the basis that informed judgments make informed decisions (Cotter, 2019). Ideally, AL also helps people to evaluate how media, firms and the government are using these technologies and, in doing so, enable them to advocate for responsible technology design and use that avoids problematic biases and helps to safeguard privacy (Rainie and Anderson, 2017). AL engages meaningful efforts to enable more users to impact data flows and perceive if or when they or others are being marginalized (Klawitter and Hargittai, 2018). The influence of these efforts may be constrained depending on the extent of technical knowledge required. In this study, we define AL as understanding what algorithms do and why, but also about what they mean. We take an expanded perspective of AL and define it as a set of capabilities used to organize and apply algorithmic curation, control and active practices relevant when managing one's AI environment. This definition signifies AL as the precondition for these activists to take action and underscores the importance of AL for governing platforms and their algorithms. Through the definition, we develop the conceptual framework of AL, which examines values as situated (Shin, 2021) and involves the cultivation of a critical consequence through recognizing algorithms as expressions of broader systems of power (Cotter, 2019).

Recently, there has been a discussion of what constitutes AL. Considering that AL includes understanding what algorithms are, knowing where algorithms are deployed, appreciating the intent and goals of those owning or deploying the algorithm, and taking control of user data and privacy, concepts like FATE can be duly considered as factors of AL. Because AL involves critically recognizing the inherent biases and errors in the programming (Cotter, 2019), FATE can be a basis for AL. Per the FATE perspective, AL regards participants' understanding of the way algorithm programs curate and process information, recommend social connections, and reconstruct realities for them. Increasing AL is a needed response to calls for enhanced FATE of algorithms (Courtois and Timmermans, 2018).

2.2 Formulating algorithm norms: AI and human values

The effects of algorithms depend on how and what they are programmed to do, who is responsible for the programming and to what goal, how the algorithms operate, and what is done with the collected personal data they feed on (Shin, 2021). These subjects provide a fundamental requirement for sustainable algorithms and offer important clues in designing AIs (Ferrario, 2021), and they can be legitimate factors of AL. In the ongoing debate on algorithms and AI, subjects of FATE are thought of as important norms in AI (Dörr and Hollnbuchner, 2017).

Fairness in AI contexts refers to algorithmic processes that should not create discriminatory or unjust consequences (Shin, 2021). A fairness question begins with concern that algorithms do not always behave objectively. The fairness in algorithms is rooted in the critical realization that algorithm systems can unfairly and systematically discriminate against certain people in favor of others (Noble, 2018).

Algorithmic accountability is the process of clarifying the culpability of underlying algorithms for harm when algorithmic decision-making results in undesirable consequences (Moller *et al.*, 2018). It is a concept measure aimed at holding the providers of automated decision systems responsible for the results generated by their programmed decision-making (Lewis *et al.*, 2019).

The notion of transparency in the context of personalized OTT mandates that decisions by algorithmic filtering are clear and understandable to users (Shin, 2021). Netflix, for example, utilizes an algorithm to serve up content based on a user's programming and searching history, but still faces criticism that it is difficult to see the transparency of how the recommendations were made. Explainability is the extent to which the inner mechanism (black-box process) of an algorithm system can be explained in human languages (Shin, 2021). It can be a seeing-through to comprehend the internal mechanism by which an algorithm operates (Rai, 2020).

2.3 OTT and algorithms

OTT platforms often refer to internet-streamed video pushed onto television screens via Internet connections. OTT services can bundle several types of content, such as drama, film, and music, social network platforms, and software such as apps and smartphone operating systems. Prevalent OTT platforms like *Netflix, Amazon Prime* and *YouTube TV* commonly build a robust recommendation engine and content discovery mechanism by using AI. AI can play a big role in content recommendation. AI algorithms have become enormously relevant in the OTT space, especially with the enhanced processing power of devices. One of the most important tasks in current OTT platforms lies in delivering a better user experience. Netflix has been making good use of AI to drive content recommendations. Netflix's recommendation system exerts a key influence over how the platform runs and how users engage with the service. It offers personalized content based on recommendation algorithms fed by thousands of users watching and rating the content on the platform. These algorithms are based on metadata and user behavior data and based on the concept that similar viewing patterns represent similar user preferences or tastes. The algorithmic curation of content is the accumulated result of users' interactions with these platforms (Lloyd, 2019). Despite this, OTT platforms, in general, have offered limited transparency on how their systems are designed and operate and have provided only a limited set of controls over how algorithmic decisions shape their platform's experience. This is worrisome considering that the firm's personalization systems have raised concerns related to discriminatory and biased results.

2.4 Dual processing model of algorithmic decision-making

User heuristics concerning algorithmic qualities have become a legitimate subject of research in the design and development of algorithms (Bolin and Schwarz, 2015). Since AI-based systems entail numerous processes and mechanisms, it is important to investigate users' *a priori* expectations and how these expectations are met. Dual-process theories can be a relevant conceptual lens for this inquiry since the theories hypothesize that perception and thought changes occur in different ways as a result of two different processes. The dual processing theory of human cognition argues that reasoning and decision-making can be explained as a role of both a heuristic, experiential, affective system and a deliberative and analytical processing system (Petty and Cacioppo, 1986). To date, no formal analytic model of algorithmic decision-making based on dual processing theory has been developed. Dual-process theories provide an architecture for the interaction between intuitive and deliberate thinking. Using dual-processing theories, we can examine how users process the algorithmic information they receive, beyond merely responding to stimuli. A dual-process helps us to examine how users process different stimuli and the influences of these processes on cognitive processes. A dual-process is used as a theoretical basis to examine user sense-making in algorithms by examining the role that algorithmic features play in influencing user perception of humanness and sense-making of algorithms, as well as how user actions affect their sense-making. The theory is appropriate for this inquiry in the AI context since algorithms consist of dual aspects – frontend and backend processes.

2.5 Research questions

How does critical evaluation of algorithms and algorithmic sources play out as it is folded into algorithmic processing in which different forms of information are filtered and curated by the algorithms and embedded into the interfaces? Given the interactions between algorithms and users from a user-centric perspective, we examine how users make sense of, perceive and engage with algorithmic content curation on OTT and when such everyday experiences contribute to their AL. An increasing body of research has attempted to articulate a set of literacies to describe the analytic tools that people can use to understand, probe, and question the algorithmic systems that shape their lives. How might designers support the development of AL? As per the literature review, the research questions (RQ) are developed to address the influence of AL:

RQ1. How does AL influence users' trust in the context of an OTT personalized recommendation, and how does that perception influence user experience with the algorithms?

RQ2. How is AL related to trust in the adoption and use of OTT platforms? How does AL help users to envisage, understand, and work with algorithms, depending on their understanding of the control of the information flow embedded within them?

Through the RQs, we present the constituents of AL and present design principles that help users to develop literacies that allow them to understand not only how algorithms work, but also to critique and manage them.

3. How does the AL play out in the user acceptance?

Understanding why some users are algorithmically literate and others are not involved in user-centered inquiry that includes cognitive, attitudinal, behavioral and technological considerations. Given these considerations, the model includes the elements of FATE as AL constructs that influence user trust, which then influences performance value (Figure 1).

3.1 Algorithmic literacy and user heuristics

Previous research has shown that AL is closely related to the trust in AI services (Haider and Sundin, 2021). Algorithmic-generated contents involve inherently the exploitation of FATE, which looms as normative requirements in the design and development of algorithm systems (Shin and Park, 2019). Personalized OTT algorithms are designed to generate predictive customized content. How the personalization processes are performed, whether the outputs represent the inputs of user data, and whether the outputs are legally binding relate to matters of AL (Kant, 2020). FATE emerges as the most relevant component of AL.

There is a very limited understanding as to exactly how trust is constructed when users interact with algorithms. Over the last years, there has been extensive research on how users perceive algorithmic news (Swart, 2021). Beyond general credibility and quality assessments, one of the key issues has been the impact of perceived normative values on algorithmic trust. In OTT, trust is deemed one of the key questions concerning transparency (Shin *et al.*, 2020).

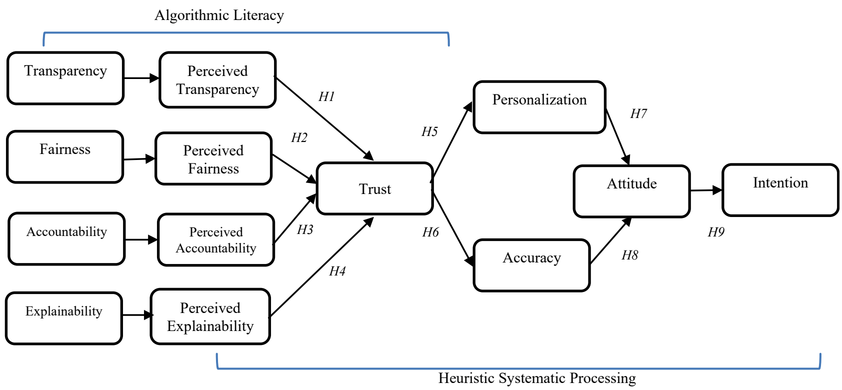


Figure 1. Heuristic and systematic processing in OTT adoption

In the OTT personalization context, trust signifies how much users believe the recommendations and reflects the belief in the accuracy of news filtering and user willingness to accept a recommender system's capacity. Trust was introduced as an intermediary between the normative value of AL and the performance value of the system.

Whether users trust certain systems impacts users' judgments, and in turn, such trust leads to users' willingness to share more data with the AI. The quality of the result is highly dependent on the quality of the data that is fed into it. The quality of the output is contingent on the quality of the data that is fed into it. If users are assured of accountability – including that algorithm is supposed to operate in a manner that contributes to the public good – they feel reassured, and trust is established (Shin *et al.*, 2020). The extent to which users trust certain services or systems apparently impacts user attitude, and in turn, such trust leads to users' intention to share more data with AI. When fair, transparent and accountable services are warranted, users are more likely to believe in higher credibility in personalization (Hobbs, 2020). High levels of transparency in an algorithm can give users a feeling of personalization pertaining to the algorithm experience (Rader *et al.*, 2018). Accountable and fair recommendations allow users to build a sense of faith and confidence in using the algorithms. User understanding of the process of a particular output is produced has been confirmed to be significant. It has been confirmed that AL has a significant influence on platform trust (Cotter and Reisdorf, 2020). When users have higher algorithmic literacy, they will attribute more trust to OTT.

H1. The higher perceived transparency, the more users are likely to trust OTT.

H2. The higher perceived fairness, the more users are likely to trust OTT.

H3. The higher perceived accountability, the more users are likely to trust OTT.

H4. The higher perceived explainability, the more users are likely to trust OTT.

3.2 Algorithmic personalization

Customized search results, targeted advertisements, tailored information feeds and personalized content are highly prevalent and widely accepted online, but at the same time, it is ironic since very few people have that realization that it is so heavily personalized. In the context of algorithms, extensive research has confirmed that perceived utilities are associated with user adoption and the experience with algorithmic journalism services (Shin *et al.*, 2020). Regarding OTT algorithms, users anticipate specific preferred attributes through algorithm services, such as personalization and accuracy (Gursoy *et al.*, 2020). Personalized algorithm systems show users what they think they want to see to help users browse through a tremendous amount of data. By tracking and analyzing users' behavior, a selection of choices of entertainment, information and recommendation can be produced in highly customized ways to users, affecting how they use the online. Personalized content is supposed to be accurate as users expect personalized outputs to match their needs (Kant, 2020). Personalization and accuracy are related and are the key conditions defining a user's perceived value of the system (Lury and Day, 2019). Accuracy in AI represents how precisely and correctly predicts items and outputs that people like or prefer. Accurate AI systems will prioritize relevant and opportune news for their users. When users believe that news items are personalized to their taste or made specifically for them, they evaluate the system as useful and are gratified with the content. People consider the algorithm as accessible and useable as long as they consider the curated news or contents to be relevant and correct (Shin *et al.*, 2020). Prior research has confirmed these relations in diverse AI services, in which trust has been found to be a determinant of accuracy/personalization. Hence, personalization and accuracy can be postulated in light of trust:

H5. The more trust users have, the more likely users perceive OTT personalized.

H6. The more trust users have, the more likely users perceive OTT accurately.

3.3 Feeling about algorithms

Attitudes have garnered increasing interest in many AI-related disciplines, most notably in human-algorithm interaction. Recent algorithm research has focused on the importance of attitude in AI such as emotional AI (Lee, 2018). Prior research has shown that attitudes exert a vital role in user interactions with AI (Kotras, 2021). It has been proposed that the attitudes of AI users play an underlying role in their interaction with an algorithm, particularly concerning the adoption of algorithmic platforms and AI services (Lee, 2018). In AI, how people feel and what they think provide heuristic indicators of their attitudes towards AI. As AI develops to interpret and respond to human attitudes, it is essential to consider attitudes as a facilitating factor for improving user behavior. When users assure the value of a system, their attitudes toward the algorithm become willing and positive. Hypotheses regarding the path of personalization and accuracy to attitudes have been broadly confirmed in many contexts, including algorithms (Shin *et al.*, 2020):

H7. The more users perceive personalization, the more likely users have a positive attitude toward OTT.

H8. The more users perceive accuracy, the more likely users have a positive attitude toward OTT.

H9. The more users have a positive attitude toward OTT, the higher likely users have the positive behavioral intention of OTT.

4. Method

4.1 Data collection and sample groups

We employed multiple-group equivalence methods to examine whether the hypothesized relationships among the model variables are equivalent across groups of different AL. Two groups of different levels of AL were recruited (Table 1). In determining the level of AL, we measured users' objective and self-reported knowledge of algorithms by asking their explicit and implicit understanding of algorithms: explicit algorithmic knowledge of coding, programming, data structure, and architecture, and implicit FATE issues, such as search skills, awareness of the way algorithms curate and weave information, recommend content and construct social realities for them. The pre-selection questionnaire was composed of ten

	High literacy group	Low literacy group	Total
N	385	390	775
Age (Mean/SD/Median)	28.30/13.13/32	29.22/15.10/34	29.10/14.02/34
20–29 (%)	38	34	37
30–39 (%)	37	38	39
40–49 (%)	13	12	12
50–59 (%)	9	10	9
Over 60 (%)	3	6	3
Gender (female rate %)	51.21	50.20	51.30
College educated (%)	32.24	28.98	31.01
Prior experience	1.9 years	1.2 years	1.5 years

Table 1.
Descriptive statistics

questions, which were reviewed by experts in AI and machine learning. Respondents were informed about ethical issues of AI in the particular context of OTT algorithms since these notions are vague and possibly outside of common knowledge for laypersons. Based on the pre-screening process, the respondents were parted into high and low AL groups. We recruited 385 individuals for the high and low AL groups, respectively, through *Amazon Mechanical Turk*, in return for a small incentive about \$20–30. The participants got paid initially \$4 upon entering the experiment and further got paid by the extra hour they participated. Normally, the participants got paid around \$25 to \$40 for their participation. The 25-min survey included a wide range of questions on algorithm consumption, use of OTT platforms, content-seeking behaviors and demographic factors. A total of 390 questionnaires were acquired for the high AL group, 385 of which were valid (98.7%). For the low AL group, 390 questionnaires were finalized, of which 401 (97.2%) were submitted. Finally, 775 questionnaires were considered for further analysis. Among the participants, 51% were female ($N = 354$). The percentage of participants who were 20–29, 30–39, 40–49, 50–59 and over 60 years old was 37, 39, 12, 9 and 3%, respectively (Table 1).

4.2 Procedures

In the two sample groups, respondents were required to recall their experiences with personalized OTT algorithms such as *Watcha* (contents recommendation service), *Amazon* (Amazon Personalize) and *Netflix* (Hybrid recommender systems). The respondents experienced using and subscribing via OTT by submitting their data on socio-demographics, user characteristics, use history and preferences on certain products (personalizing user experience), and evaluating the extent to which the recommendations were personalized to their preferences. They also experienced searching their preferred personalized algorithms about the contents, such as news, music, TV programs, stories and books. The experiment took about 2–3 h. We ensured the possible effect of common method variance by examining a model that included an unmeasured latent methods factor, and the results indicate there is no significant common method variance that threatens the quality of the measurements.

4.3 Scales and measurements

The AL measurements were drawn from Shin (2021) and Lee *et al.* (2019). The explainability scales were derived and revised from Rai (2020) and Renijith *et al.* (2020). The measurements of accuracy and personalization were taken from Gursoy *et al.* (2019) and Lury and Day (2019).

We modified the trust measurements from Lee (2018). The attitude and intention measurements were drawn from Shin *et al.* (2020). Some measurements required changes to reflect new features of machine learning and algorithms. Fifteen people with active experience with algorithmic products completed a pretest about a specific content topic. The Cronbach's alpha shows acceptable values in all scales, ranging between 0.750 and 0.905, indicating that the measurements and each scale are consistently what they claim to measure (Table 2). To assess validity, the correlation coefficient of the score of items and the sum of the scores of items were calculated. The correlation coefficient for reliability was acceptable, and Cronbach's alpha coefficient was 0.91. The correlation coefficient was high for validity as well. To appraise reliability, we calculated the correlation coefficient, compared the total scores of the obtained sample and calculated Cronbach's alpha coefficient. A confirmatory factor analysis was utilized to examine all the factor models. The analysis shows that the items had satisfactory factor loadings. We evaluated the discriminant validity issue by using the square root of the average variance extracted (AVE). There is no discriminant validity issue in our data (Table 3). The AVE from the construct was greater than the inter-construct

Variables	Mean	Standard deviation	Cronbach's alpha	AVE	Composite reliability
Transparency	3.54	1.708	0.782	0.582	0.802
	4.30	1.452			
	4.10	1.310			
Accountability	4.04	1.407	0.750	0.624	0.765
	4.60	1.216			
	3.56	1.359			
Fairness	4.04	1.261	0.797	0.715	0.704
	4.46	1.212			
	4.07	1.068			
Explainability	4.04	1.261	0.760	0.705	0.760
	4.46	1.212			
	4.07	1.068			
	4.36	1.123			
Trust	4.23	1.060	0.905	0.840	0.940
	4.13	1.049			
Accuracy	4.40	1.202	0.797	0.814	0.929
	4.32	1.145			
	4.64	1.219			
Personalization	4.18	1.006	0.805	0.698	0.814
	3.84	1.066			
	4.10	1.051			
Attitude	4.40	1.119	0.768	0.506	0.723
	4.09	1.283			
	4.18	1.231			
Intention	4.38	1.107	0.885	0.722	0.886
	4.53	1.183			
	5.27	1.138			

Table 2.
Validity and reliability

	1	2	3	4	5	6	7	8	9
Transparency	0.72								
Fairness	0.35	0.88							
Accountability	0.37^{**}	0.75	0.81						
Explainability	0.42^{***}	0.25^{***}	0.72	0.79					
Trust	0.02	0.03	0.21^{**}	0.24^{*}	0.84				
Personalization	0.29^{***}	0.26^{**}	0.41^{***}	0.21^{*}	0.36	0.82			
Accuracy	0.14^{*}	0.06	0.28^{***}	0.42^{***}	0.31^{***}	0.39^{***}	0.84		
Attitude	0.08	0.16^{*}	0.23^{***}	0.01	0.59^{***}	0.70	0.10	0.73	
Intention	0.07	0.16	0.27^{***}	0.80	0.10	0.04	0.14	0.22	0.71

Note(s): $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; Off-diagonal values indicate correlations between constructs. Diagonal values represent the square root of AVE of each construct

Table 3.
An inter-construct correlation matrix with the square root of AVE of each construct

correlation. Model fit was evaluated using fit criterion and theoretical considerations. Chosen goodness-of-fit indices were compared with prespecified recommended values. The combination of these different indices indicates a good fit to the model and well-defined parameters (Table 4).

The model was designed in a parsimonious way that excludes other minor variables other than trust, attitude, and intention in the OTT contexts. The factors are drawn from previously validated measures and the paths in the model have been confirmed through previous research. We excluded possible control variables in the model since they are considered minimal or minor at best in affecting main relations in the model.

Table 4.
Model fit statistics and the criteria for goodness-of-fit

Fit indices	Measurement model	Structural model	Suggested value
χ^2/df	1423.3/308 = 4.62	1420/312 = 4.55	<5
p-value	0.000	0.021	<0.05
RMSEA	0.041	0.039	$0.05 < x < 0.10$
GFI	0.923	0.920	$0 < x < 1$
AGFI	0.901	0.921	>0.90
CFI	0.910	0.909	>0.90
NFI	0.921	0.920	>0.90
IFI	0.841	0.843	>0.80
TLI	0.819	0.820	>0.85
RFI	0.865	0.870	>0.80
AIC	810	810	
HOELTER	126	127	

4.4 Measurement equivalence

We used a multigroup structural equation approach to examine if the hypothesized associations among the variables would differ across different conditions of the AL variable. The multigroup analysis provided a direct test of measurement invariance as well as structural invariance across conditions. The approach is a way of testing measurement invariance and in-group comparison. This nature is good for our case where we see the difference between high and low AL groups. A multigroup equivalence test was utilized to analyze cross-group invariance and the hypotheses regarding differences in attitudes between the groups. First, multiple-group comparisons without constraints on the parameters were tested concurrently to determine whether the model form held across groups. The next step was to parallel the unconstrained model with a constrained one, in which equality constraints were imposed across the groups. The factor structure was found to be similar across groups if the fit of the unconstrained model did not differ significantly from the fit of the constrained one, implying invariant factor structures across groups.

5. Results: contextualizing an expanded definition of AL

A comparison of the data from the two groups points to the role of AL in OTT adoption. The findings of the multigroup analysis are notable in terms of both the AL and algorithmic performance.

5.1 Group differences

The results in the independent t-test reported the significant differences between the groups in all dimensions. Summated scales were calculated to test any differences between the groups regarding the variables in the model. The summated scales were calculated by averaging the scores of individual items belonging to each of the constructs. Standard deviations and averages are given, along with the corresponding t-tests for the differences (Table 5). The multiple t-test suggested higher levels of AL among high literacy users, whereas low literacy users were more concerned with performance values. A low literacy group was significantly more concerned with personalization and accuracy than a high literacy group. Because all p-values in the dimensions were <0.05 we can conclude that at a 95% confidence level, the groups were statistically different in the literacy and performance dimensions.

5.2 Multigroup invariance

We used the method of Shin and Hwang (2018) for a multigroup analysis with PLS Path modeling to evaluate the structural paths from the model across the two groups. The results

	Low literacy (n = 390)		High literacy (n = 385)			
	Mean	*SD*	*Mean*	*SD*	t-value (Sig. 2-tailed)	Partial Eta squared (η^2)
Transparency	3.41	1.554	4.56	1.078	−1.29 (0.042)*	0.220
Fairness	4.19	1.178	4.59	1.184	−5.432 (0.004)**	0.293
Accountability	3.80	1.414	4.33	1.135	−1.72 (0.048)*	0.239
Explainability	3.51	1.468	4.10	1.253	11.225 (0.000)***	0.230
Trust	4.01	1.076	4.24	1.080	3.114 (0.01)**	0.410
Personalization	4.04	1.040	4.45	1.191	7.321 (0.001)**	0.439
Accuracy	4.45	1.188	4.56	1.078	6.328 (0.003)**	0.310
Attitude	4.23	1.212	4.22	1.212	0.442 (0.000)***	0.259
Intention	4.03	1.141	4.72	1.145	1.227 (0.040)*	0.193

Note(s): *d.f.* 773; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Table 5.
T-test for group differences

show variation in the users' perceptions and acceptance. Different patterns were detected in path formation and item configuration, providing hints on dissimilar structures of AL versus algorithmic performance (Table 6). Those with higher AL were more accepting of FATE issues and showed a higher tendency of trust. On the contrary, those with lower AL were more skeptical of FATE and showed less trust but showed a higher tendency in personalization and accuracy.

In the high literacy group, all the paths from FATE to trust were supported, and in the low group, all the paths were rejected. The paths from trust to personalization and accuracy were significant with high coefficient values in the high AL group (CR 0.683; 0.662), whereas their counterpart values in the low AL group were low. In general, algorithmic factors were significant antecedents to trust for the high AL group, whereas performance factors were

	Low literacy				High literacy			
	Unstandardized coefficient	SE	Critical ratio	p	Unstandardized coefficient	SE	Critical Ratio	p
H1	0.119	0.108	0.009	No	0.368	0.072	5.098	***
H2	1.052	7.479	0.014	No	0.093	0.030	3.123	**
H3	0.339	29.665	0.011	No	0.358	0.061	5.837	***
H4	3.805	18.011	0.020	No	0.205	0.078	2.648	*
H5	0.599	0.053	2.367	*	0.683	0.054	12.630	***
H6	0.621	0.060	2.419	*	0.662	0.062	10.590	***
H7	0.310	0.053	5.828	***	0.180	0.054	3.333	***
H8	0.274	0.070	3.896	***	0.152	0.070	2.164	*
H9	0.967	0.039	24.800	***	0.964	0.039	24.660	***

Note(s): $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

R^2 Comparison

	Low literacy	High literacy
Intention	0.523	0.609
Trust	0.461	0.691
Accuracy	0.428	0.284
Personalization	0.502	0.394
Attitude	0.602	0.351

Note(s): The result of the multicollinearity test shows no signs of a multicollinearity problem

Table 6.
Summary of hypothesis testing

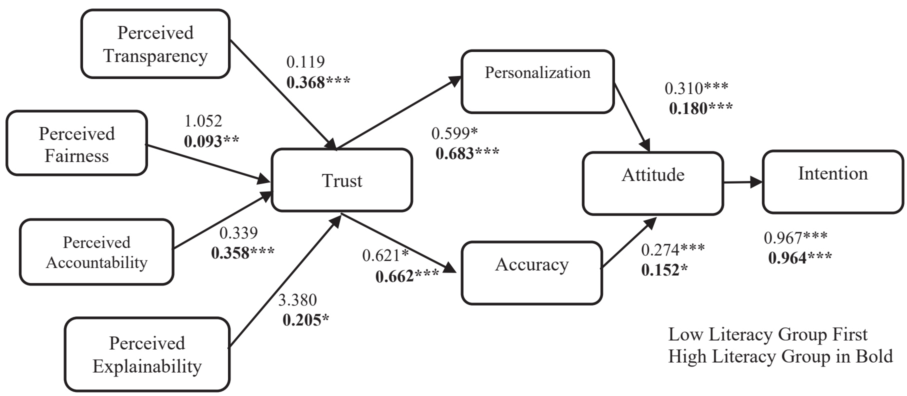
more critical determinants to attitude for the low AL users (CR 0.310; 0.274 vs 0.180; 0.152). The results of squared multiple correlations also supported the idea of the different value structures in the two groups. The R^2 of trust in the high literacy group was 0.691, and the counterpart value in the low literacy group was 0.461. The R^2 of attitude in the low AL group was 0.602, and the counterpart value in the high AL group was 0.351. Additionally, the R^2 values of accuracy and personalization were higher in the low AL group than in the high AL group (0.428 and 0.502 vs 0.284 and 0.394, respectively).

Figure 2 shows the validated model with the coefficients and their estimates for both groups. A few contrasting patterns emerge from the two-group comparison in the heuristic and systematic process. The results imply that the low literacy users generally face algorithms as black-box technologies whose operations are too technical, highly complicated, and vague to understand. On the other hand, AL processing is evident in the high literacy users in that AL affects trust and subsequent assessment. The models also show that users' trust in algorithmic recommendations is significantly determined by the FATE issue or their level of comprehension of the algorithm.

6. The role of AL in the AI adoption process

Our findings provide a conceptual framework for AL that captures a broad range of the important cognitive development by highlighting proof-of-concepts insights for the AL processing model in an OTT context. The model clarifies that interacting with algorithms engages AL processes wherein algorithm attributes are utilized to forge a heuristic of the user discovery process and to trigger actions in OTT services. The model offers relevant theoretical support in so far as it provides insights on the connections of literacy, performance and trust in OTT platforms. The discussions can be summarized in three parts.

First, this study identified what types of AL practices users engaged in algorithms (Cotter and Reisdorf, 2020) and beyond that, it confirmed that FATE plays a role of AL by developing a heuristic for AL in the use of OTT platforms (Shin, 2021). The findings show that AL determines users' trust and attitude through dual routes of cognitive processing: heuristic and systematic. Users' heuristic process of AL affects their trust, and enhanced trust influences systematic processing of performance expectancy, which is significantly related to attitude and intention. Not only do qualities of AL exert a key role in stewarding trust, but they also exert a certain influence in guiding user evaluations of performance in terms of the



Note(s): * 90% confidence level, ** 95% confidence level, *** 99% confidence level

Figure 2.
Results of the effects of AL on adoption

usefulness of the predictions of OTT algorithms. These findings imply that if users understand the mediating role of algorithms on these platforms, they are likely to evaluate the performance of the information favorably. User responses to perceived performance are dependent upon or closely related to how users perceive, appraise, and respond to the algorithms regarding FATE as AL (Swart, 2021). Such a relation can be explained as a heuristic insofar as users rely on their perception of FATE to formulate their attitude towards personalization and accuracy around OTT services. Users determine performance value in the context of an algorithm according to their perceived FATE of content.

Second, the findings empirically validate that FATE can be a basis for AL in OTT systems (Shin *et al.*, 2020). The high literacy group showed the heuristic role of FATE, whereas the low literacy group focused on the performance aspects of OTT systems. Low literacy users have a basic knowledge of the manner that algorithmic platforms function, yet they do not have significant awareness of the critical implications of these algorithmic platforms, nor do they completely recognize FATE issues. High literacy users have a clear understanding of what OTT can do for users and, at the same time, what drawbacks come with the services. Thus, heuristics play a role in understanding algorithmic attributes and judging trust. The identified significant role of trust in an OTT platform implies that people trust the recommendations of an OTT algorithm when their literacy test is completed with FATE. How trust is shaped and evolves in the process of adoption may present key hints in designing OTT platforms, as people realize that algorithms are not neutral and that they may reflect human biases.

Third, from the heuristic systematic processes of AL, it can be inferred that AL and performance values are positively connected to trust (Reisdorf and Blank, 2020). Processed AL is significantly related to performance assessment through trust mediation. Users consider the personalization and accuracy of OTT algorithms through a dual process. First, through FATE heuristics, and second, a systematic process through trust. Heuristic processing (peripheral route) engages the use of simplifying the assessment of FATE to quickly evaluate the service norms. Systematic processing (central route) involves performative evaluation of personalization and accuracy. Trust connects the two processes linking the heuristic and systematic mechanism (Shin, 2021). This trust link can be a key clue among algorithmic attributes, user experiences and their interactions with AI (Haider and Sundin, 2021). Processed algorithmic features provide users with clues for trust, and trust affords users to adopt algorithms with feelings of usefulness and efficiency. Trust formed through heuristic processing is more likely to have cognitive attributes that reflect the AL appraisal, whereas that shaped through systematic processing is more likely to exert effects on performance evaluation due to a lack of understanding of FATE.

7. What do users know about the algorithms that shape their experiences?

Algorithm adoption and consumption can be a mental process – a dynamic active process of thinking and acting. It is a mental process of analyzing and evaluating algorithmic information, particularly procedural values or performance that algorithms have offered. Heuristic understanding and systematic comprehension are the major routes of such processing, in which AL plays a key role. These implications can be both theoretical and managerial. The heuristic-systematic process together with the accompanying role of trust in OTT platforms can be meaningful theoretical contributions as highlighting the active role of users in the algorithmic experience. Practically, our results have design implications for AI practitioners to support effective AL (Cotter and Reisdorf, 2020), particularly, how to echo normative values in AI interface design.

7.1 Contributions to research: conceptualizing and contextualizing AL

The findings of this study are in line with earlier work on AL (Lloyd, 2019), algorithm experiences (Shin *et al.*, 2020) and trust (Haider and Sundin, 2021) in the context of OTT algorithms. Our work expands literacy literature by conceptualizing AL along with FATE and highlighting the heuristic role of AL. This result contributes to theoretical knowledge by clarifying what constitutes AL, formulating an AL processing model, how AL works and what effects of AL there are in OTT use, and from there, how trust can be theorized, conceptualized and measured. Understanding the effects of AI as well as utilizing it in a responsible way requires a level of awareness and skill that is not provided by current digital literacy or information literacy literature. Previous concepts of technology literacy or information literacy may not be applicable to justify the uniqueness of users' interaction with OTT platforms since AI is considerably dissimilar from present services (Shin, 2021). Current conceptualizations of literacy have mainly remained on the surface of knowledge (know-what), leaving users' active learning process delving into the roots of an application (know-how/know-why). While algorithms have been proposed as experience technologies that users learn about by doing (DeVito, 2017), consuming algorithmic systems does not necessarily create literate for users. This study argues this process hinges on users' dual-information processing; how users process algorithmic services heuristically and systematically. This finding suggests that AL is context-dependent that meaning is relational, and formation depends on users' subjective sense-making. This point implies that AL goes beyond the technical nitty-gritty as people should possess a contextual understanding of the way algorithms convey meaning, persuade us and influence us. AL is more than using and is how users make sense of AIs and how they make meaning through conscientious cognitive activity. This includes the heuristic understanding of the social practical and technological processes by which algorithms are generated, processed, and used, as well as the knowledge that offers users control over these processes.

AL should include users' understanding of the way algorithms convey context, structuring our interactions with others, and the processes affecting what we see, how we see, and what we think. With heuristic AL, users can question why and how certain search results are favored by both algorithms and users. A critical heuristic is a key to heuristic algorithm experience. Just like algorithms sort users and shape societal realities, users can maneuver algorithmic functions and shape algorithmic decisions by proactively controlling their data, configuring their privacy and critically evaluating algorithm performance.

We clarify the antecedents of and associations among algorithmic attributes, highlighting the algorithmic information processing of these antecedents and trust, clarifying how AL is applied and how it exploits different social cues and showing how the effects of AL are maneuvered and enhanced. We confirm that AL constitutes a precondition for users to trust the information algorithm presents in algorithmic personalization contexts. These findings are significant because algorithms have increasingly become a virtual human agent; thus, how users appreciate algorithmic personalization and thus react to recommendations becomes *a priori* issue to address (Lee *et al.*, 2019; Shin, 2020). These findings contribute to theoretical development through conceptual refinement of how algorithmic trust is formed, how it is enhanced heuristically and systematically (Petty and Cacioppo, 1986), and what interplay effects of dual-process are present in OTT users (Shin, 2021). While numerous studies have attempted to explain AI models, approaches to assess the AL from a user cognitive perspective are currently missing from the literature. If literacy is supposed to truly safeguard users' interactions with algorithms, it should be approached in such a way that users understand, feel about, and engage with the algorithms.

By theorizing and developing scales to measure FATE as AL, our research contributes to the development of how to warrant literacy topics in OTT, how we can best apply machine learning to support users and offer meaningful insights while avoiding biased and unfair decisions, and how we can balance the need for algorithmic advancements with the societal interest of fairness and transparency to users. Since AI becomes increasingly embedded in everyday life, AL will be even more vital. The relationship of AL to trust is valuable as it clarifies where the user trust originates. While FATE has been deemed as a critical factor in AI, how users appraise FATE information and how it induces trust remain under-researched. The confirmed roles of literacy and trust will be a stepping step towards framing literacy in this ever-changing AI era.

Our results also show more integrated views of how users understand AI characteristics, how their trust is established and maintained, what cognitive affordances are involved, and what behavioral results are derived from the processes. Although prior research consistently has revealed the role of trust in AI (e.g. Haider and Sundin, 2021), this study proves the role of trust in OTT algorithms, their antecedents, their mediating function, and the heuristic-systematic process. In OTT algorithms, users get a strong trust when they are assured of AL. When people trust algorithm systems, they are more likely to accept that the services are valuable as they are individualized and personalized to their needs, and thus are accurate (Lee, 2018). The mediating role of trust supports the accompanying function of trust in algorithmic processes by integrating heuristic and systematic algorithms (Shin, 2021). Users process OTT services in two ways, peripherally and centrally. While heuristic processing entails the use of AL as a value-based decision route, systematic processing involves itemized function-based and analytic evaluation of a service. Our findings further foreground the interplay between processing modes that users' heuristic processing by AL affects systematic processing as well as vice versa. Systematic processing influences users' heuristic processing that when users have AL, they tend to see algorithms as more useful and workable. When users have beliefs in the functional qualities of algorithms, they tend to view algorithms as more FATE-oriented. Users use systematic processes to derive information about procedural aspects from algorithmic qualities and subsequently, make use of the expertise heuristic to arrive at an attitude. Our results show that the effect of performative quality on users' attitudes is partially mediated by perceived FATE. Trust significantly mediates the effects of literacy on users' attitudes and intentions. Strong user trust may warrant users that their personal data will be handled in fair and accountable manners, thereby triggering trust in OTT recommendations and platforms, and finally leading to heightened levels of intention to use.

7.2 Contributions to practice: users-in-the-loop

As many important human decisions are arbitrated by algorithmic processes, the need for an awareness of these processes increases. Our implications can be constructive in designing AI interfaces and integration frameworks for OTT platforms. As AI continues to impact the mode we interact with technologies, how to warrant fair interaction and transparent algorithms and how to embed explainability in the algorithms will be pressing issues to address. The results highlight the need for educating AL, and those who develop algorithms should be guided in ethics and required to design code that reflects social values and their interactions with context (Shin, 2021). It is not simply the calls to know the tactics of identifying fake news or addressing data breaches of personal information, it is the AI systems that are intended to predict and project what is perceived to be what users of algorithmic systems want.

A better understanding of AL, particularly as it intersects with algorithmic control, can help us in effectively managing the societal impacts of algorithms. As we provide a framework to assess AL with users in their social practices, the framework can be used as guidelines for informed AL practices that could be implemented in OTT platforms. Issues of FATE have been important agendas in AI, and users seek assurances on such issues in adopting AI. Trust is interlinked with literacy issues as it plays a facilitating role in developing user heuristics and systematic evaluations. When users confidently appraise the FATE issues, users' trust increases, and they are willing to provide more of their data to be gathered and analyzed. The stronger trust between users and algorithms, the more fair and transparent processes will be. Greater quality of data enables AIs to generate more precise and accurate results tailored and individualized to user preferences and individual histories.

This study underpinned the need for integrating FATE by a design approach when developing OTT systems and applications. Reaching consensus and realizing collaboration across stakeholders is a precondition for the effective diffusion of AI in practice. The industry can design innovative "users-in-the-loop" algorithmic systems to leverage people's literacy to cope with algorithmic experiences. AL is best approached and practiced as a set of social practices in terms of the ways people consume algorithms in their everyday lives and the events that are mediated by actual algorithms. Algorithms can be seen as experience technologies in which their use enables users to learn how a specific algorithm works (Cotter and Reisdorf, 2020). User's psychological state of mind and perceptions are critical in rationalizing why and how users sense and feel what they do about issues about AI, as well as how they experience and accept AI services.

8. Where do we go from here?

Awareness and understanding of how to deal with algorithms have become key for judiciously consuming today's increasingly personalized platform environment. The results suggest that AL goes beyond technical knowledge of coding and instead involves critically and contextually evaluating and weighing the FATE issues behind algorithms. The findings in this study offer guidelines on how to incorporate FATE with literacy and functional features and behavioral intentions. As AI is rapidly evolving and changing our lives so deeply, the industry must devise feasible plans of developing algorithms to be human-enabled and user-centric. The development of explainable and understandable AI is critical in forming trust and credibility by engaging human agency in the AI ecosystem. Promoting the adoption of algorithms and enabling trust to oblige a user perspective of explainable AI, which affords users to develop AL accordingly.

Our results provide important implications for the algorithmic divide. Just as the digital divide has separated those with access to the internet from those without, an emerging and prevalent algorithmic divide now threatens to take away the numerous social, political, economic and cultural opportunities provided by AIs. An algorithm-guided future will deepen the gap between the algorithmically savvy and disadvantage those who are not nearly as connected or able to participate. Additionally, social and political polarizations will be reinforced by algorithms, as algorithm-driven insights guide people to live in echo chambers of repeated and reinforced media and political content. Algorithmic processes are complex socio-technical systems and AL would help us effectively manage many problems arising from AI.

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Appendix

Variables	Measures
Transparency	(1) The evaluation and the criteria of algorithms used should be publicly released and understandable to people (Understandability)
	(2) Any outputs produced by an algorithmic system should be explainable to the people affected by those outputs (Explainability)
	(3) Algorithms should let people know how well internal states of algorithms can be understood from knowledge of their external outputs (Observability)
Fairness	(1) The AI system has no favoritism and does not discriminate against people (Nondiscrimination)
	(2) The source of data throughout an algorithm and its data sources should be accurate and correct (Accuracy)
	(3) I believe the AI system follows the due process of impartiality with no prejudice (Due process)
Accountability	(1) An AI system requires a person in charge who should be accountable for its adverse individual or societal effects in a timely fashion (Responsibility)
	(2) Algorithms should be designed to enable third parties to examine and review the behavior of an algorithm (Auditability)
	(3) Algorithms should have the ability to modify a system in its entire configuration using only certain manipulations (Controllability)
Explainability	(1) I found AI algorithms are easily comprehensible
	(2) I think the AI services are interpretable and understandable
	(3) I can figure out the internal mechanics of machine learning
Trust	(1) I trust the recommendations by algorithm-driven services
	(2) Recommended items through algorithmic processes are credible
	(3) The algorithm service results are trustworthy
Personalization	(1) I think that the recommended items reflect my personalized preferences
	(2) I found the recommended items are a great match for my needs
	(3) It seems that the algorithm-based service is customized to me
Accuracy	(1) The contents produced by algorithms are accurate
	(2) Recommended items by algorithm systems are in general precise
	(3) Algorithm-enabled recommendations are exact and correct
Attitude	(1) I am fairly pleased with algorithm services
	(2) Overall, the algorithm services fulfill my initial expectations
	(3) Generally, I am satisfied with the contents of algorithm services
Intention	(1) I would like to intend to use algorithm services
	(2) I will continue to use algorithm services
	(3) I intend to use and will further adopt algorithm services

Table A1. Measurements

About the authors

Donghee Shin has been Professor and Chair at the College of Communication and Media Sciences at Zayed University, Abu Dhabi Campus since 2019. Over the last 19 years, he taught at various universities in the US and Korea, including Penn State University and Sungkyunkwan University. Prior to Zayed University, he was a Professor at Sungkyunkwan University, Seoul, Korea. He also was founding Chair of the Department of Interaction Science, an interdisciplinary research initiative sponsored by the Ministry of Education and Samsung Foundation. Don received his bachelor's degree from Sungkyunkwan University (1997), his master's degree from Southern Illinois University (1998), and his master's degree and PhD degrees from Syracuse University (2004). Donghee Shin is the corresponding author and can be contacted at: dshin1030@gmail.com

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Anestis Fotiadis is Professor at Zayed University, College of Business, Department of Management, Abu Dhabi, UAE. He also holds a PhD (2009) in International Business Administration from the University of Pecs in Hungary. He has delivered lectures both at the undergraduate and the postgraduate level as a tenured faculty in universities in Greece and Taiwan before he joined Zayed University. More of that he worked several years as head of IT and research development for the public sector in Greece. For four year he was member of CCMS college where he was delivering lectures on "Event Management" and "Principles of Tourism."