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Algorithmic Resistance and Online Privacy: Extending the Meta-UTAUT Model with Particular Privacy Concerns

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Abstract

This study delved into the perceived benefits and privacy concerns individuals face when interacting with algorithms, and explored their relation to algorithmic resistance. Based on technology acceptance research and online privacy studies, an extended Meta-UTAUT model was proposed. A total of 434 valid samples were obtained in China. The results show that perceived benefits (including performance expectancy, effort expectancy, social influence, and facilitating conditions) are negatively related to algorithmic resistance attitude. Moreover, concerns for technology and financial privacy are positively related to algorithmic resistance intention.This result identifies the aspects of privacy highly esteemed in the interaction between individuals and algorithms. Finally, the contributions, practical and theoretical significance, and limitations of this study were discussed.

Keywords: algorithmic resistance intention, privacy concerns, Meta-UTAUT, perceived benefits

1. Introduction

In the contemporary digital era, algorithms, as a crucial form of information screening technology, have been extensively integrated into numerous aspects of social production and life. Different from other information technologies, the operational principle and process of the algorithmic recommendation system are often regarded as a black box (Christin, 2020). Even though the algorithm can only be analyzed based on its inputs and outputs (Burrell, 2016; Introna, 2016), through various endeavors, a growing consensus is emerging to overcome this technical opacity. The Cyberspace Administration of China (2022) classifies algorithmic recommendation into content merging, personalized recommendation, sorting after selection, search content filtering, and decision-making algorithms according to their functions. This classification comprehensively encompasses the algorithmic recommendation functions applied in manufacturing, business, and service industries. In terms of resource requirements, the operation of algorithmic recommendation depends on users' personal data, historical data, similar user preferences, and current popular topics (Möller et al., 2018).

Regarding the working principle, a unified understanding is taking shape: initially, a vast amount of user behavior historical data is collected from mobile terminals, web pages, social networks, and other sources. Then, effective user log data is generated through cleaning and screening. Subsequently, the algorithm extracts user characteristics from the log data and models the user's interest bias to predict their preferences for candidate products, services, or content. Finally, the predicted preferences are ranked, and those with high rankings are recommended to users (Dwivedi et al., 2021; Shin, 2021). Moreover, the user's browsing, clicking, or purchasing of the recommended items generates new interaction records, initiating the next round of interaction between the user and the algorithm.

Although this algorithmic operation mode offers convenience to users in information acquisition and decision-making, it also entails potential risks. Examples include filtered bubbles (Bruns, 2019), algorithmic black boxes (Christin, 2020), algorithmic discrimination (Kleinberg et al, 2018), algorithm bias (Akter et al, 2021), and user privacy security issues (Lau et al, 2018). Consequently, when interacting with an algorithm, users will assess the benefits and risks based on their own perception (Shin & Park, 2019). Depending on the outcome of this assessment, they may adopt strategies such as resignation, resistance, or aversion (Cotter, 2024; Mahmud et al., 2023). Among these, the resistance strategy is commonly employed by users, aiming to intervene in and correct the algorithm's operation results by understanding its mechanism (DeVito et al., 2017; Ettlinger, 2018; Karizat et al., 2021; Velkova & Kaun, 2021). This strategy is regarded as proactive, enabling individuals to enjoy the benefits of the algorithm while minimizing various risks (Chen, 2024; Velkova & Kuan, 2021).

Among the multiple risks posed by algorithms, privacy is a significant concern that has been extensively discussed in previous research (DeVito et al., 2017; Querci et al., 2022; Shin et al., 2022a). Algorithms are integrated into nearly all digital platforms of daily use, and only a few users choose to disable algorithmic recommendations (Chen, 2024), making their influence ubiquitous. In brief, the vast majority of users face privacy risks from algorithms and need to formulate strategies considering the perceived benefits and risks. Privacy calculus provides a theoretical framework for understanding this strategy-development process. It views individual information disclosure and protection as a rational decision-making process (Becker & Murphy, 1988), where the costs and benefits of information disclosure are weighed. Currently, this concept is widely adopted in Human-Computer Interaction (HCI) research to investigate how individuals balance perceived benefits and privacy risks (Lee & Kwon, 2015; Li et al., 2010; Jozani et al., 2020). However, the assumption of complete rationality in individuals has limited the explanatory power of privacy calculus theory in practical situations. For example, the privacy paradox phenomenon indicates that individuals may not always act rationally in information disclosure (Kokolakis, 2017). Individual decision-making is also influenced by subjective factors like prejudice and emotion (Knijnenburg et al., 2013). In the context of algorithms, the privacy paradox persists in HCI research (Vimalkumar et al., 2021), highlighting the need to incorporate subjective factors into privacy calculus.

Considering the above, the Meta-UTAUT model proposed by Dwivedi et al. (2019) is the preferred theoretical model for this study. Firstly, it takes into account the influence of perceived benefits on behavioral intention, allowing for the measurement of perceived benefits as independent constructs. Secondly, extended UTAUT models have demonstrated good compatibility with privacy concerns as external factors (Vimalkumar et al., 2021), enabling the integration of measures of individual privacy concerns into the model. Finally, unlike other UTAUT models, the Meta-UTAUT model emphasizes the mediating role of subjective factors (attitude) between external factors and behavioral intention. The inclusion of attitude facilitates a more detailed examination of how individuals weigh perceived benefits against privacy concerns. Through this extended Meta-UTAUT model, this study endeavors to develop a comprehensive theory of algorithmic resistance in privacy and evaluate its effectiveness from the perspective of a collectivist society.

2. Liturature

2.1 Meta-UTAUT Model

In the field of individual IS/IT acceptance research, the Meta-UTAUT model proposed by Dwivedi et al. (2019) is a well-recognized theoretical framework with demonstrated explanatory power (Alkhowaiter, 2022; Chatterjee et al., 2023; Patil et al., 2020). It stems from the UTAUT model proposed by Venkatesh et al. (2003). With information systems and technology deeply integrated into human society and becoming indispensable for social operation, IS/IT acceptance research has become a vital area. Many theoretical models, like the Technology Acceptance Model (Davis, 1989), Theory on Diffusion of Innovation (Moore & Benbasat, 1991; Rogers, 1983), Theory of Reasoned Action (Fishbein & Ajzen, 1975), and Theory of Planned Behavior (Ajzen, 1991), have been utilized to explore IS/IT acceptance. These models consider various external factors that influence individuals' attitudes, intentions, and behaviors toward IS/IT acceptance. However, the plethora of models requires researchers to make selections, potentially causing them to overlook alternative perspectives. In response, the UTAUT model was developed by synthesizing different technology acceptance models (Venkatesh et al., 2003). Because of its generality and measurability, the UTAUT model has been extensively applied and verified in organizational IS/IT acceptance research (e.g., Chatterjee et al., 2023; Donmez-Turan, 2019; Yang et al., 2024).

Despite its wide adoption, validation, and refinement, theories based on the UTAUT model have inherent limitations (Tamilmani, 2021). For instance, Dwivedi et al. (2020) found that researchers rarely applied the UTAUT model in its entirety and seldom considered moderating relationships. More significantly, the UTAUT model lacks elements related to individuals' interactions with technology, which are vital for explaining users' underlying tendency to use technology at the individual level. Through testing the measurement model, Dwivedi et al. (2019) showed that a clearly defined attitude can notably enhance the UTAUT model's explanatory power, although it only serves as a partial mediator between constructs. In the revised model incorporating attitude, the explanatory power of behavioral intention rose to 45%, compared to 38% in the model without attitude (Dwivedi et al., 2019).

2.2 Algorithmic Resistance Attitude and Algorithmic Resistance Intention

Notably, algorithmic resistance, the core concept in algorithmic resistance research, is defined as the behavior of attempting to understand the algorithm's working principle and process to intervene in and correct its operation results. This behavior is significantly and positively influenced by the attitude and intention of algorithmic resistance (DeVito et al., 2017; Ettlinger, 2018; Karizat et al., 2021; Velkova & Kaun, 2021). In prior research, the attitude and behavioral intention of algorithmic resistance generally pertain to the corresponding concepts in technology acceptance and use models. Here, behavioral intention is defined as an individual's tendency to act when assessing the perceived environment, while attitude represents an individual's positive or negative feelings towards a specific behavior (Ajzen, 1991; Davis et al., 1992; Rivis et al., 2006; Taylor & Todd, 1995; Venkatesh et al, 2003). In IS/IT acceptance theories like the Theory of Reasoned Action (Fishbein & Ajzen, 1975), Technology Acceptance Model (Davis, 1989), and Theory of Planned Behavior (Taylor & Todd, 1995), attitude is a variable related to behavioral intention. The UTAUT model excludes the attitude variable, yet the Meta-UTAUT model (Dwivedi et al., 2019) considers this a significant omission. By integrating a structured attitude, Dwivedi et al. (2019) showed that reintroducing attitude can remarkably enhance the model's explanatory power for behavioral intention. Moreover, multiple Meta - UTAUT - based studies (Chatterjee et al., 2023; Hassaan & Yaseen, 2024; Patil et al., 2020) have proposed and verified a positive attitude-behavior intention correlation. Based on this, the following hypothesis is proposed:

H1: ARA is positively related to ARI.

2.3 Privacy Concerns and Algorithmic Resistance Intention

In IS/IT adoption research, a persistent question is whether and how privacy concerns influence individuals' technology adoption behavior (Kokolakis, 2017). With algorithms as the basis for digital platform-user interaction, they have taken on new significance. Given algorithms' inevitable collection of users' personal information (Jain et al., 2022), privacy concerns are widespread among users (Mahmud et al., 2023). In IS/IT adoption research, a relatively consistent finding is that privacy concerns generally have a negative influence on individuals' attitudes or intentions toward technology adoption (DeVito et al., 2017; Dhagarra et al., 2020; Dienlin, 2023; Velkova & Kaun, 2021; Zhang & Zhang, 2024). Influenced by such attitudes or intentions, individuals are more prone to reject new technologies (Li et al., 2024; Migliore, 2022; Mahmud et al., 2023; Wang, 2024). However, this view cannot be directly applied to algorithm research. Exploratory studies suggest that when users sense privacy risks from algorithmic recommendations, privacy concerns do not always result in privacy-protecting behaviors (Chen, 2024; Ytre-Arne & Moe, 2021). This aligns with research on the privacy paradox in individual technology adoption. In other words, privacy concerns do not necessarily predict an individual's behavior in technology interaction (Boyd & Ellison, 2007; Gerber et al., 2018). Moreover, some studies have even verified a negative correlation between privacy concerns and behavior (Duan & Deng, 2022; Ooi et al., 2018).

To clarify the theoretical relationship between privacy concerns and algorithmic resistance, this study incorporates explicitly defined privacy concerns into the Meta-UTAUT model. In previous studies, privacy concerns have been used as an independent variable and predictor of behavior to extend the UTAUT-related model (Vimalkumar, 2021). However, privacy concerns were often treated as a whole, ignoring the differences between specific privacy concerns (Durnell et al., 2020). Empirical studies on information disclosure have firmly established that users adopt different disclosure strategies for various types of information (e.g., Fogel, 2009; Lee, 2020; Schlosser, 2020; Taddicken, 2014; Tufekci, 2008). In the field of technology acceptance, some exploratory studies have found that not all personal information is considered private, and different types of private information hold varying degrees of importance for users (Durnell et al., 2020; Zhang et al., 2024b). Nevertheless, few studies have verified whether different privacy concerns lead to significantly different behaviors. In this study, four specific privacy concerns, which have been identified and validated in previous research as common concerns among online users (Aw et al., 2022; Durnell et al., 2020; Menon & Shilpa, 2023), are incorporated into the theoretical model as independent variables.

Concerns for Technology Privacy (CTP) refers to an individual's concerns about information leakage from the IS/IT they use, such as communication devices, social networking sites, and Internet platforms (Durnell et al., 2020). Research has shown that privacy-security vulnerabilities in technological products are negatively correlated with individuals' acceptance intention of such technologies (Zhang & Zhang, 2024). Additionally, studies on algorithmic folk theory have revealed that many users believe that companies, governments, or the technology itself access their information through the data they leave on technology products. In response to privacy leaks, users may exhibit behaviors like compliance, modification attempts, or aversion (Wu et al., 2023; Zhang et al., 2024a).

Concerns for Financial Privacy (CFP) refers to an individual's concern about the leakage of economic information, including assets like income, savings, and pensions (Durnell et al., 2020). Research in technology acceptance has confirmed that concerns over financial information disclosure impede the adoption of technologies such as online banking and mobile payment (Hanif & Lallie, 2021; Merhi et al., 2019; Widyanto et al., 2022). Additionally, users suspect that algorithms generate personalized recommendations based on their consumption behavior and expenditure (Banker & Khetani, 2019).

Social Psychological Privacy Concerns (SPPC) involves an individual's concern about the disclosure of psychological and social information, such as personal views and cultural or religious beliefs (Durnell et al., 2020). Studies on algorithmic folk theory suggest that users are aware that algorithms recommend similar users or content based on browsing and posting history. Consequently, users may deliberately regulate their preferences for certain views and content on platforms to influence algorithmic outcomes (Chen, 2024; Cotter, 2024).

Concerns for Legal Privacy (CLP) denotes an individual's concern regarding the leakage of legally protected information, like private and confidential information (Durnell et al., 2020). Evidence shows that when users perceive a lack of legal protection for their information, their technology acceptance intention is negatively impacted (Zhang & Zhang, 2024). Moreover, research on algorithmic folk theory indicates that users generally believe algorithms collect their private and confidential information (Zhang et al., 2024a). Based on the above, the following hypotheses are proposed:

H2: CTP (H2a), CFP (H2b), SPPC (H2c) and CLP (H2d) are positively related to ARI.

2.4 Perceived Benefits, Algorithmic Resistance Attitude, and Algorithmic Resistance Intention

As previously discussed, there are discrepancies in the relationship between privacy concerns and privacy protection behavior in online privacy and technology acceptance research. To account for these differences, the privacy calculus theory, a relatively mature framework, has been widely employed (Chen, 2018; Jozani et al., 2020; Song et al., 2024). Rooted in the assumptions of the utility maximization theory (Awad & Krishnan, 2006) and the social exchange theory (Cook et al., 2013), the privacy calculus theory posits that individuals' attitudes and intentions regarding information disclosure stem from a trade-off between perceived benefits and privacy concerns (Dinev & Hart, 2006; Jabbar et al., 2023; Kucukusta et al., 2015). Prior studies have applied this theory to explore the interaction between individuals and algorithms (Li et al., 2024; Zhu et al., 2017). In this study, the privacy calculus theory offers a potential framework for conceptualizing the process of weighing the perceived benefits of an algorithm against privacy concerns.

The Meta-UTAUT model incorporates four perceived benefits that positively influence individuals' attitudes and intentions toward technology adoption (Dwivedi et al., 2019). These benefits stem from integrating influencing factors in prior technology acceptance models (Venkatesh et al., 2003).

Performance Expectancy (PE) refers to an individual's belief that using technology can enhance problem-solving ability (Venkatesh et al., 2003). It is grounded in concepts such as perceived usefulness (Davis, 1989), relative advantage (Rogers, 1983), business compliance (Thompson, 1991), and external motivation (Davis et al., 1992). In the interaction between individuals and algorithms, PE represents the perceived benefit of algorithm-recommended information for individuals' lives and work. If users believe algorithmic recommendations can offer effective information when solving life and work problems, their resistance to algorithms weakens. Prior studies indicate that performance expectancy significantly affects individuals' behavioral intentions toward algorithms (Aloudat et al., 2014; Lv et al., 2022).

Effort Expectancy (EE) is an individual's expectation of the effort needed to use a new technology (Venkatesh et al., 2003). It is based on perceived ease of use (Davis, 1989) and complexity (Rogers, 1983). Since algorithmic recommendation services are easily accessible, as algorithms are integrated into most applications, users can obtain these services by simply downloading the apps. Thus, in the individual-algorithm interaction, EE is considered the individual's effort expectation when using apps with algorithmic recommendation features. Moreover, research has proven that users' understanding of algorithm mechanisms positively impacts adoption intentions (Fast & Jago, 2020).

Social Influence (SI), as defined by Venkatesh et al (2003), refers to the degree to which important individuals in a person's life think the person should use new technology. It incorporates concepts such as subjective norms (Fishbein & Ajzen, 1975), social factors (Thompson et al., 1991), and image (Moore & Benbasat, 1991). In this study, SI represents the influence of significant individuals on a person's adoption of algorithmic recommendations. Research has indicated that users are more prone to overlook privacy concerns and adopt technology when they observe the benefits others obtain from it or when recommended by friends and relatives (Ayuning Budi et al., 2021; Lv et al., 2022).

Facilitating Conditions (FC), as defined by Venkatesh et al (2003, 2012), represent users' beliefs regarding the degree to which resources and support from specific organizations and technical infrastructure can ease their behaviors. In this study, the resources and support refer to the essential conditions for operating algorithmic recommendation functions, like the GPS and networking capabilities in smartphones. Previous research

(Chatterjee et al., 2023; Li et al., 2023; Ooi et al., 2018; Yang et al., 2024) has confirmed that FC is negatively correlated with privacy protection intentions but positively correlated with technology adoption intentions.

Based on the results of previous studies, the following hypotheses are proposed:

H3: PE (H3a), EE (H3b), SI (H3c), and FC (H3d) is negatively related to ARI.

Furthermore, attitude is considered a crucial mediating factor in the IS/IT acceptance theoretical model (Ajzen, 1991; Davis et al., 1992; Dwivedi et al., 2019). It has been widely verified that attitude fully mediates the relationship between certain external factors and intention. Examples of such external factors include social influence (Balakrishnan et al., 2022), compatibility (Chatterjee et al., 2023), and other factors added to different research topics (Patil et al., 2020). The Meta-UTAUT model also emphasizes the mediating effect of attitude between perceived benefits and behavioral intention. This is because adding attitude can significantly enhance the explanatory power of each factor regarding behavioral intention (Dwivedi et al., 2019). Based on these findings, the following hypotheses are proposed:

H4: ARA (H4a) is negatively related to PE (H4a), EE (H4b), SI (H4c), and FC (H4d).

Combined with the above hypotheses, an extended Meta-UTAUT model (Fig. 1) is proposed. This model incorporates privacy concerns as external factors to explore the process of weighing perceived benefits against privacy concerns in algorithmic resistance. Notably, behavioral intention is a key determinant of behavioral change in many research areas (e.g., Ajzen, 1991; Sommestad et al., 2019). Thus, in the specific applications of UTAUT and its extended models, behavior is often represented and explained by behavioral intention (e.g., Chopdar, 2022; Hanif & Lallie, 2021; Vimalkumar, 2021; Widyanto et al., 2022). Following previous studies, the structure of behavioral intention in this research is also regarded as a measurement factor for individual behaviors.

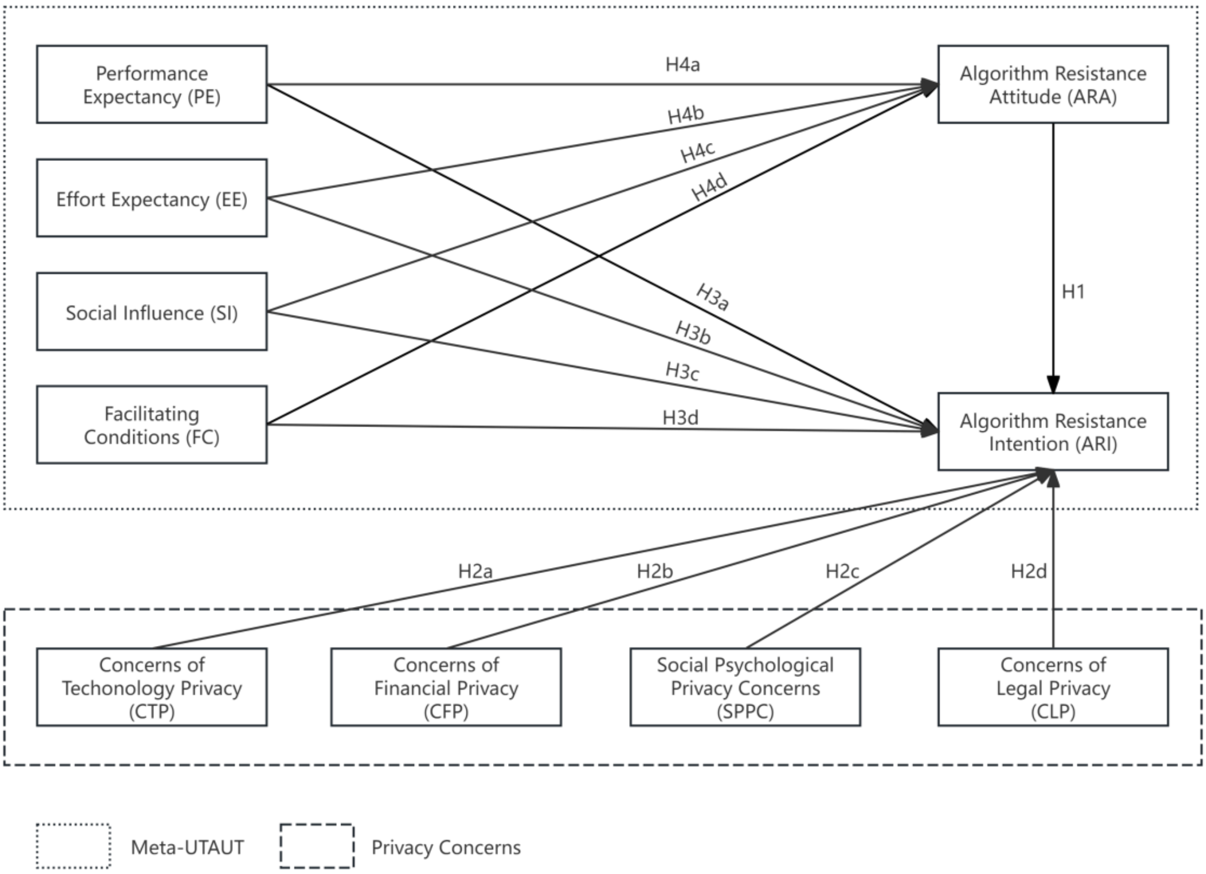

Figure 1. Theoretical research model

3. Method

3.1 Data Collection

Considering that the users recommended by the algorithm are all online platform users, online surveys can cover the target population well. An online survey was distributed on the professional Chinese data collection platform, www.wjx.cn, between December 11 and 18, 2024. Each participant who completed the survey was rewarded with RMB2 as a reward. To avoid selection bias, neither the survey topic nor the purpose was revealed to the respondents during data collection. The number of samples initially recovered was 631. After data screening, 197 questionnaires were excluded due to short response time, attention screening questions, and refusal to sign informed consent. Finally, the effective response rate of the survey is 69.78%, and 434 valid questionnaires are obtained as samples for further analysis.

Among these respondents, Most of the participants were female （66.82%）. Over half were aged 18 - 34, aligning with those showing the most obvious privacy concerns (Baruh et al., 2017) and most affected by algorithmic recommendations (Shin et al., 2022b). In terms of net age, the majority of participants have used it for 6-10 years (35.94%), 29.26% reported being used for 11–15 years (N = 117), and only 14.9% for less than one year (N = 75). Additionally, most respondents obtained a bachelor's degree (see Appendix A for details).

3.2 Measurement

An online questionnaire with three main sections was designed for the data collection. After obtaining the informed consent of the participants, the initial section briefly describes the platform, working principle, and privacy risk of the algorithmic recommendation mechanism. A screening question was set up. Only the participants who understood the description were advanced to the next section of the questionnaire. Thus, the relevance of the participants to the research topic was ensured.

Each construct within these questions was assessed using multiple items drawn from existing literature. Firstly, as the constructs of the Meta-UTAUT model, PE, EE, SI, and FC were measured separately using items adapted from Chopdar (2022) and Vimalkumar et al. (2021). Secondly, CTP, CFP, CPPC, and CLP, as the main aspects of privacy concerns, were assessed via the scale based on the Concerns with the Protection of Informational Privacy (CPIP) scale developed and validated by Durnell et al. (2020). Third, ARA and ARI were assessed by the scale adapted from Kim (2017), Kim and Kankanhalli (2009), and Patil et al. (2020). Each variable was measured using a five-point Likert scale with a scale of 1 (strongly disagree) to 5 (strongly agree).

The third part collected the demographic information of the participants, including gender, age, education level, and net age. In order to ensure the comprehensiveness of the research results, these data will be used as control variables for data analysis.

3.3 Data Analysis

This study aims to investigate the detailed psychological processes involved in algorithmic resistance, which utilizes complex research models that involve prediction, moderating variables, and mediating variables. Thus, the Partial Least Squares Structural Equation Modeling (PLS-SEM) is appropriate to conduct the analysis. According to Hair et al. (2012), the PLS-SEM analysis was divided into two steps: the measurement model and the structural model. SPSS 27.0 and SmartPLS 4.0 were employed for data analysis.

3.4 Common Method Variance

As this study used a single questionnaire for data collection, checking for common method variance effects was necessary. Multicollinearity and Harman's one-factor variance tests were carried out (Podsakoff et al., 2003; Kock, 2015). The VIF values from the collinearity assessment ranged from 1.153 to 3.544, below the 5 - threshold (Diamantopoulos & Siguaw, 2006). SPSS 27 analysis showed the first factor's cumulative variance explanation was 16.60% (<40%). Collectively, these findings suggest that the model is likely free from common method bias (Podsakoff et al., 2003), thereby enhancing the rigor and validity of the research results.

4. Results

4.1 Measurement Model

The measurement model was tested in structural reliability, convergent validity, and discriminant validity. As presented in Table 1, both Cronbach's α (CA) and composite reliability (CR) were employed to access the internal consistency of the constructs. As shown in Table 1, the CR scores of all constructs were higher than 0.8, and the CA values of the vast majority of constructs were higher than 0.65, indicating that all measures demonstrated robust internal reliability (Hair, 2019; Jöreskog, 1971). The outer loadings and average variance extracted (AVE) in Table 1 was used to assess the convergent validity of each construct. Ten items were deleted because of its low outerloeading, such as ARA1, ARA5, ARI1, etc. The final items are presented in Appendix B. All AVE values exceeded 0.5, indicating that the convergent validity was met (Hair et al., 2017b).

Table 1. Assessment of measurement model on reliability and validity.

Indicators	**Abb.**	**Items**	**Outer Loading**	**Average variance extracted (AVE)**	**Composite reliability(rho_c)**	**Cronbach's α (CA)**
Algorithm Resistance Attitude	ARA	ARA2	0.802	0.645	0.879	0.817
		ARA3	0.834			
		ARA4	0.773			
		ARA6	0.801			
Algorithm Resistance Intention	ARI	ARI2	0.820	0.662	0.854	0.744
		ARI4	0.830			
		ARI5	0.790			
Concerns of Finacial Privacy	CFP	CFP1	0.828	0.723	0.887	0.808
		CFP3	0.880			
		CFP4	0.842			
Concerns of Legal Privacy	CLP	CLP1	0.919	0.847	0.917	0.819
		CLP2	0.921			
Concerns of Technology Privacy	CTP	CTP2	0.733	0.655	0.850	0.737
		CTP3	0.827			
		CTP4	0.863			
Social Psychological Privacy Concerns	SPPC	SPPC1	0.693	0.710	0.827	0.664
		SPPC2	0.970			
Effort Expectancy	EE	EE1	0.747	0.574	0.844	0.753
		EE2	0.751			
		EE3	0.738			
		EE4	0.795			
Facilitating Conditions	FC	FC2	0.794	0.603	0.820	0.670
		FC3	0.809			
		FC4	0.725			
Performance Expectancy	PE	PE1	0.890	0.771	0.931	0.901
		PE2	0.880			
		PE3	0.846			
		PE4	0.895			
Social Influence	SI	SI1	0.838	0.619	0.866	0.795
		SI2	0.841			
		SI3	0.755			
		SI4	0.705			

The Fornell - Larcker Criterion and cross - loadings were employed to evaluate discriminant validity (see Table 2). For each factor, the square roots of the AVE (presented as bold data on the diagonal of Table 2) not only surpassed the established threshold of 0.70 (Henseler et al., 2009), but were also greater than the correlation coefficients with other factors. These results indicated that the measurement model exhibited good discriminant validity (Fornell & Larcker, 1981).

Table 2. Fornell-Larcker criterion.

	ARA	**ARI**	**CFP**	**CLP**	**CTP**	**EE**	**FC**	**PE**	**SI**	**SPPC**
ARA	**0.803**									
ARI	0.546	**0.813**								
CFP	-0.094	0.226	**0.850**							
CLP	0.072	0.19	0.29	**0.920**						
CTP	0.005	0.274	0.465	0.305	**0.809**					
EE	-0.721	-0.492	0.065	-0.065	0.04	**0.758**				
FC	-0.618	-0.354	0.087	-0.011	-0.008	0.474	**0.777**			

PE	-0.438	-0.338	-0.046	-0.078	-0.123	0.351	0.399	**0.878**		
SI	-0.676	-0.388	0.068	-0.065	-0.015	0.443	0.517	0.303	**0.787**	
SPPC	-0.281	-0.096	0.128	0.047	0.154	0.216	0.325	0.151	0.352	**0.843**

4.2 Structural Model

As the second step of PLS-SEM, The structural model was examined with bootstrapping sampling set to 5000 (Preacher & Hayes 2008). The structural model is presented in Fig. 2, presenting path coefficients, significance levels of paths, and R2 values. The results showed that the R2 values of ARA and ARI were 0.721 and 0.445 respectively, indicating that both could be well predicted (Hair et al., 2017a).

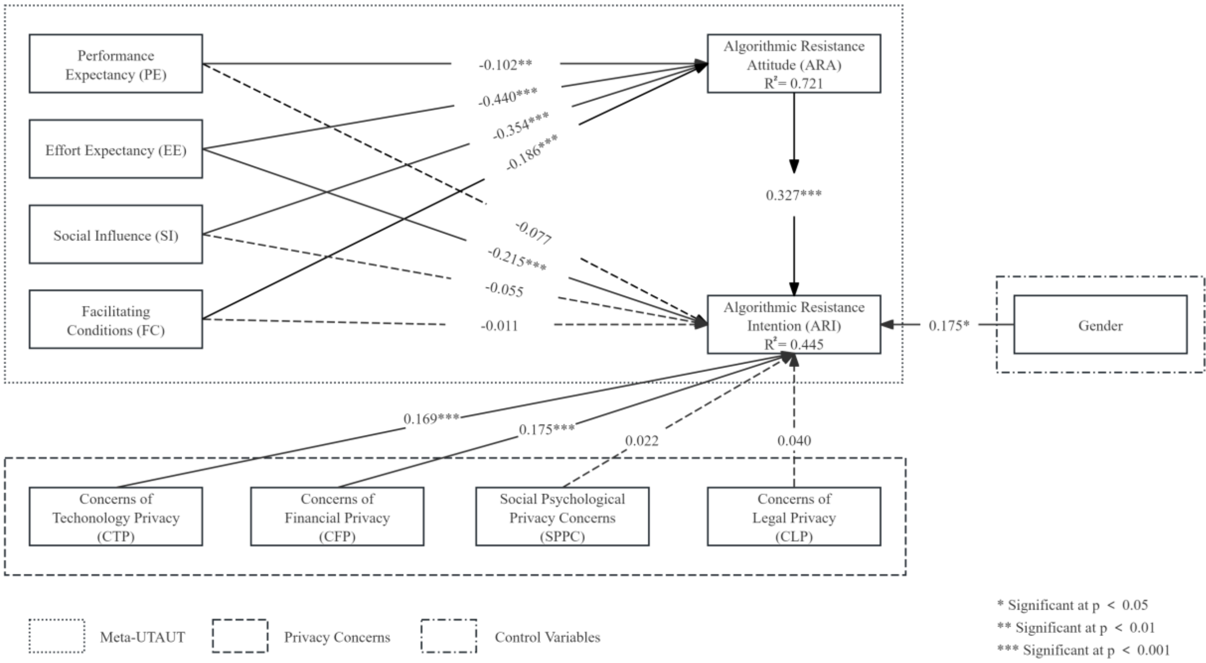

Figure 2. Results of research hypothesis testing.

All hypothesized paths are presented in Table 3. Specifically, these results reveal a significant and positive correlation between ARA and ARI, providing robust backing for H1. Regarding the relationship between particular privacy concerns and ARI, CTP, and CFP exhibited noteworthy positive correlations with ARI, H2a, and H2b were confirmed. Nevertheless, SPPC and CLP did not have a significant effect on ARI. Thus, H2c and H2d were invalid. Furthermore, among H3a - H3d, only H3b was validated; indicating a negative correlation between EE and ARI. H3a, H3c, and H3d did not yield significant results, indicating an absence of a significant relationship between PE, SI, FC, and ARI. Besides, four perceived benefits (PE, EE, SI, and FC) displayed substantial and positive associations with ARA, supporting H4a-H4d. Additionally, among the control variables, only gender correlated significantly with ARA; the rest did not.

Table 3. Assessment of structural model with bootstrapping procedure.

	β	***SD***	***t***	***p***	**Confidence Interval**	VIF	f square	Result
ARA -> ARI	0.338	0.075	**4.499*****	＜0.001	(0.186,0.481)	3.544	0.056	Supported
PE -> ARA	-0.103	0.030	**3.368****	0.001	(-0.163, -0.044)	1.246	0.030	Supported
EE -> ARA	-0.441	0.043	**10.308*****	＜0.001	(-0.521, -0.352)	1.43	0.476	Supported
SI -> ARA	-0.355	0.037	**9.669*****	＜0.001	(-0.426, -0.282)	1.473	0.300	Supported
FC -> ARA	-0.185	0.035	**5.302*****	＜0.001	(-0.255, -0.117)	1.609	0.076	Supported
PE -> ARI	-0.063	0.040	1.619	0.105	(-0.179, -0.019)	1.312	0.006	(Not) Supported
EE -> ARI	-0.220	0.053	**4.122*****	＜0.001	(-0.455, -0.271)	2.127	0.040	Supported
SI -> ARI	-0.051	0.052	1.056	0.291	(-0.272,-0.08)	2.004	0.003	(Not) Supported
FC -> ARI	-0.006	0.048	0.197	0.844	(-0.167, 0.016)	1.786	0.000	(Not) Supported

CTP -> ARI	0.176	0.047	**3.694*****	＜0.001	(0.075, 0.258)	1.381	0.038	Supported
CFP -> ARI	0.183	0.041	**4.352*****	＜0.001	(0.094, 0.257)	1.344	0.042	Supported
SPPC -> ARI	0.014	0.04	0.685	0.494	(-0.037, 0.12)	1.218	0.001	(Not) Supported
CLP -> ARI	0.038	0.039	0.941	0.347	(-0.044, 0.109)	1.153	0.002	(Not) Supported
Coefficient of Determination, R square								
ARA	0.721							
ARI	0.445							

Note:

* Significant at p ＜ 0.05

** Significant at p ＜ 0.01

*** Significant at p ＜ 0.001

4.3 Mediation Analysis

Bootstrapping with 5000 subsamples was used to analyze the mediating effect (Hayes et al., 2017). As shown in Table 4, the *p*-value and Confidence Interval were used to test the significance of the path. According to the results, the mediating effect of ARA was confirmed. It mediated the relationships between all perceived benefits (PE, EE, SI, and FC) and ARI.

Table 4. Mediation calculation.

	β	***SD***	***t***	***p***	**Confidence Interval**
PE -> ARA -> ARI	-0.035	0.013	**2.603***	0.009	(-0.064, -0.012)
EE -> ARA -> ARI	-0.149	0.036	**4.07*****	＜0.001	(-0.225, -0.081)
SI -> ARA -> ARI	-0.120	0.030	**4.017*****	＜0.001	(-0.181, -0.063)
FC -> ARA -> ARI	-0.063	0.019	**3.328****	0.001	(-0.105, -0.029)

Note:

* Significant at p ＜ 0.05

** Significant at p ＜ 0.01

*** Significant at p ＜ 0.001

5. Discussion

The positive correlation between ARA and ARI was confirmed (H1). Path coefficients reveal a positive correlation between ARA and ARI, aligning with previous algorithmic resistance studies (Lv et al., 2022; Mahmud et al., 2023) and contradicting the privacy paradox hypothesis (Gerber et al., 2018). This result suggests that a positive attitude towards algorithmic resistance makes individuals more likely to resist algorithms, extending the application of the attitude-behavioral intention structure from the Meta-UTAUT model to algorithm research.

Regarding the relationship between privacy concerns (CTP, CFP, SPPC, and CLP) and ARI (H2a - H2d), not all hypotheses were supported. H2a and H2b were validated, showing that both CTP and CFP are related to ARI. CTP pertains to individuals' concerns about information disclosure by technologies like communication devices, social networking sites, and Internet platforms. Our finding that individuals tend to intervene in algorithm operation when perceiving technology-related privacy vulnerabilities aligns with previous algorithmic resistance research (Wu et al., 2023; Zhang et al., 2024a; Zhang & Zhang, 2024). CFP refers to concerns about financial information disclosure. The result indicates that when individuals sense the risk of personal economic information leakage (such as income, deposit, and expenditure), they are likely to interfere with algorithm operation, consistent with prior studies (Hanif & Lallie, 2021; Widyanto et al., 2022; Merhi et al., 2019). The validation of H2a and H2b implies that the CTP and CFP measurement items in the CPIP scale can be utilized to measure privacy concerns triggered by algorithmic recommendations.

H2c and H2d were not supported, indicating the non-significant relationship between SPPC, CLP and ARI. This phenomenon may be attributed to two potential explanations. Firstly, in the Chinese cultural context, individuals may not commonly experience SPPC and CLP. Durnell et al. (2020) emphasized the cultural context's significant influence on privacy concerns when proposing the CPIP scale. Culture is a crucial factor affecting privacy concerns

(Milberg et al., 2000), and different cultural groups show varying attitudes toward privacy in IT use (Liu & Wang, 2018; Fan et al., 2018; Trepte et al., 2017). Since this study's participants were mainly Chinese, and recent research shows that Chinese individuals tend to exhibit collectivist cultural traits in algorithm-related privacy issues (Zhou & Liu, 2023), it may explain the results. For SPPC, collectivist cultures value social cohesion and mutual trust (Bandyopadhyay, 2011), so participants may not be overly worried about the disclosure of their psychological and social information. Regarding CLP, Chinese individuals are relatively less sensitive to private information (Ying et al., 2023), meaning participants may not be highly aware of or concerned about the leakage of legally protected information and its potential risks. It is worth noting that gender differences might also play a role. Most participants in this study were female (66.82%), and women are thought to have a stronger collectivist tendency than men (Zhang & Han, 2023), which could contribute to the observed results.

Another possible explanation is that, even if individuals are concerned about the security of their psychosocial and legally protected information, they may not intend to resist algorithms. This indicates that individuals might not care if algorithms access their psychosocial information like preferences and cultural tendencies, nor about algorithms collecting their legally protected data. This interpretation is supported by research on the privacy paradox. Prior studies on this paradox have shown that many individuals do not highly prioritize their psychosocial privacy (Boyd & Ellison, 2007; Taddicken, 2014; Tufekci, 2008; Ying et al., 2023). If this is the case, it implies that the privacy paradox persists to some degree in the context of adopting algorithm technology.

In terms of the relationship between perceived benefits (PE, EE, SI, and FC) and ARI (H3a - H3d), the findings of this study deviate from the hypothesized paths in the Meta-UTAUT model. Only EE was found to have a negative correlation with ARI, validating H3b. However, PE, SI, and FC did not exhibit a significant correlation with ARI.

EE represents an individual's expectation of the effort needed to understand and utilize algorithmic recommendations. The validation of H3b suggests that when users deem the effort for understanding and using algorithms acceptable, they are less likely to interfere with the algorithm's operation. Previous exploratory research has concurred that understanding and using algorithms does not demand excessive conscious effort. Compared to other IS/IT, the process of individuals learning and applying the algorithmic recommendation mechanism is distinct. For one, the algorithmic recommendation system is integrated into Internet platforms, allowing users to access the service with minimal effort. Additionally, most users are aware of algorithms' existence. Research on algorithm imagination has indicated that individuals often notice algorithmic recommendations in daily use and gradually develop specific perceptions (Bucher, 2017; Schellewald, 2022). Moreover, understanding algorithms does not require arduous effort. Folk theory research in HCI has widely shown that users' understanding of algorithms is more of an interpretive process than a traditional learning one (Ytre-Arne & Moe, 2021). During daily interactions with algorithms, users can continuously update their understanding and adjust the algorithms' strategies in real time (Cotter, 2024). Consequently, understanding and utilizing algorithmic recommendations is not a process of strict learning but an experience of coexisting ingrained in daily life and work. The minimal effort cost makes users more inclined to comply with and accept the effects of algorithmic recommendations rather than intervene in their operation.

PE, SI, and FC are not directly related to ARI (H3a, H3c, H3d). A possible explanation is related to the application scenarios of algorithmic recommendation. For ordinary users, algorithmic recommendations are mainly used for information screening in the entertainment field (Shin et al., 2020), which is often deemed less crucial. Thus, when individuals engage in algorithmic resistance behavior, they may not consider the convenience provided by algorithms (H3a). Secondly, the use of algorithms is relatively private (Siles et al., 2020), making it hard for users to directly observe how others interact with algorithms. Consequently, users can't realize which changes in others' behavior are due to algorithmic recommendations. As a result, individuals may not be able to rely on others' usage experiences when deciding to resist algorithms (H3c). Finally, while FC is generally recognized as an important predictor of technology acceptance (Dwivedi et al., 2019; Venkatesh et al., 2003; Venkatesh et al., 2012), research on algorithm folk theory indicates that the algorithmic recommendation system is highly integrated for users and doesn't demand special resources (Ytre-Arne & Moe, 2021). Therefore, when taking algorithmic resistance behaviors, individuals may not consider supporting factors and may even be unaware of the resources needed for algorithm operation (H3d).

Regarding the relationship between perceived benefits (PE, EE, SI, and FC) and ARA (H4a - H4d), all hypothesized paths were validated. PE, EE, SI, and FC were negatively correlated with ARA. The mediating effect results showed that, under the mediation of ARA, all perceived benefits were negatively related to ARI. This implies that perceived benefits can weaken an individual's attitude towards algorithmic resistance, thereby reducing their inclination to engage in algorithmic resistance behavior. This finding is generally in line with research using the Meta-UTAUT model (Alkhowaiter, 2022; Chatterjee et al., 2023; Patil et al., 2020). The unique aspect of this study is that ARA was found to completely mediate the relationships between PE, SI, FC and ARI. This indicates that attitude plays a crucial role in the interaction between individuals and algorithms, enabling perceived benefits to influence individual behavior.

6. Implications and limitations

Theoretically, this research enriches the existing literature in multiple ways. Firstly, it uses quantitative empirical methods to theorize algorithmic resistance. By validating the theoretical model, it offers an alternative framework for future algorithmic resistance research. Incorporating four technology acceptance-related perceived benefits from the Meta-UTAUT model and four privacy concerns relevant to individuals, the study demonstrates their rationality. Most hypothesized paths in the model were confirmed, suggesting that the Meta-UTAUT model can underpin subsequent algorithmic resistance studies. It also validates Dwivedi et al.'s (2019) inclusion of attitude in the UTAUT model. In human-algorithm interactions, attitude is a crucial variable, mediating or fully mediating between perceived benefits and behavioral intention. Second, this study extends the Meta-UTAUT model by incorporating specific privacy concerns. It pinpoints which privacy concerns can trigger individuals' algorithmic resistance intentions, showing that technology and financial privacy concerns can be significant external factors in future algorithmic resistance research. Finally, the study verifies the applicability of the Meta-UTAUT model in algorithm research, broadening its application scenarios. The results confirm that individual attitudes and behavioral intentions are influenced by two opposing external factors: perceived benefits and privacy concerns.

This study's findings offer practical insights for enhancing the interaction between individuals and algorithms. Firstly, it uncovers the relationships between specific privacy concerns and algorithmic resistance intentions. The research shows that users are prompted to intervene in algorithm operation when they perceive privacy vulnerabilities in the algorithm system or fear economic information leakage. Secondly, it emphasizes the distinctiveness of algorithms within the context of technology acceptance. This study underlines the mediating role of attitude between perceived benefits and behavioral intentions, suggesting that individuals are more influenced by emotions during their interaction with algorithmic recommendations. These results can guide the development and implementation of algorithm-related policies, the improvement of algorithm systems, and the enhancement of the user experience.

However, this study has certain limitations. First, it fails to account for variations in resistance behaviors. Algorithmic folk theory research indicates that individuals may intervene in algorithm operations to different extents and in various ways, like algorithm domestication, platform migration, and controlling information disclosure (Chen, 2024; Cotter, 2024). In this study, though, resistance intention was defined and measured globally. This might cause the external factors identified to inaccurately predict users' algorithmic resistance behavior intentions, introducing biases in confirmatory experiments and practical applications. Second, the study treats the individual algorithm interaction as a static strategy. Being a cross-sectional study, it only captures participants' attitudes and behavioral intentions toward algorithmic recommendations at a specific moment. Yet, an individual's interaction strategies with algorithms can change over time and across contexts (Ytre-Arne & Moe, 2021). This restricts the exploration of the dynamic nature of such interactions. Finally, the study overlooks differences in algorithmic recommendation mechanisms across specific platforms. Algorithmic recommendation is widely applied on diverse digital platforms, each collecting distinct user information based on different requirements. Here, algorithmic recommendation was defined and measured generically. As a result, it may miss the unique features of recommendation mechanisms on different platforms, leading to biases in research and practices related to specific platforms.

7. Conclusion

From the individual-algorithm interaction perspective, this study delves into the correlation between perceived benefits, privacy concerns and individual algorithmic resistance. It proposes an extended Meta-UTAUT model integrating privacy concerns, drawing on prior research in algorithmic resistance and privacy. The study's results are a mix of confirmations and refutations, uncovering interesting phenomena. Only certain privacy concerns—about technology vulnerabilities and financial disclosure—significantly correlate with algorithmic resistance. Among perceived benefits, only effort expectancy has a negative correlation with algorithmic resistance, highlighting the unique technology acceptance characteristics of algorithms compared to other information technologies. Additionally, the study emphasizes the mediating role of the attitude towards algorithmic resistance between perceived benefits and the intention of algorithmic resistance, underscoring the importance of personal factors in algorithm research. These findings offer novel insights and an alternative theoretical model for algorithmic resistance and online privacy research. They also have practical implications for formulating algorithm governance policies, improving algorithm systems, and enhancing the user experience.

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Appendix A. Participants’ Socio-Demographic Characteristics.

Variable	Categories	N	%
Gender	Male	144	33.18%
	Female	290	66.82%
	Total	434	100%
Age group	Less than 18	4	0.92%
	18 ~ 25	138	31.80%
	26 ~ 30	138	31.80%
	31 ~ 40	91	20.97%
	41 ~ 50	48	11.06%
	51 ~ 60	12	2.76%
	More than 60	3	0.69%
	Total	434	100%
Education	Junior high school or below	8	1.84%
	Technical secondary education	7	1.61%
	High school education	14	3.23%
	College degree	59	13.59%
	Bachelor degree	311	71.66%
	Postgraduate degree	35	8.06%
	Total	434	100%
Net age	Less than 1 year	1	0.23%
	1 to 5 years	44	10.14%
	6 to 10 years	156	35.94%
	10 to 15 years	127	29.26%
	16 to 20 years	72	16.59%
	21 years and above	34	7.83%
	Total	434	100%

Appendix B. Study constructs

Validity	Code	Question (Engilsh Version)	Citations
	CTP2	I cannot accept that Internet companies monitor what I do on their platforms.	Durnell et al., 2020

Concerns for Technology Privacy (CTP)	CTP3	I feel that my private information on communication software (such as wechat, QQ) should not be disclosed.	
	CTP4	I feel that my private information on social media (such as Tiktok, Weibo) should not be disclosed.	
Concerns for Financial Privacy (CFP)	CFP1	I feel that the amount of money I spend online should be kept secret.	Durnell et al., 2020
	CFP3	I feel that my online spending history should be kept private.	
	CFP4	I feel that my online sales should be kept secret.	
Social Psychological Privacy Concerns (SPPC)	SPPC1	I make it a practice to take action at work to protect my right to maintain my personal and cultural values, such as cultural beliefs.	Durnell et al., 2020
	SPPC2	I make it a practice to take action when it comes to protecting my personal and cultural values, such as inner feelings.	
Concern for Legal Privacy (CLP)	CLP1	I feel that the ability to prevent the nonconsensual disclosure of sensitive information is a right for all people that are currently involved in any form of civil litigation.	Durnell et al., 2020
	CLP2	I feel that the ability to prevent the nonconsensual disclosure of confidential information is a right for all people that are currently involved in any form of civil litigation.	
Performance Expectancy (PE)	PE1	Algorithm recommendations can facilitate my access to the information I desire.	Dwivedi et al., 2019; Vimalkumar et al., 2021
	PE2	Algorithmic recommendations can enable me to access the information I want more rapidly.	
	PE4	I find algorithmic recommendations useful in my daily life.	
	PE5	If I use algorithmic recommendations, I believe it will enhance my academic performance.	
Effort Expectancy (EE)	EE1	I understand how algorithms utilize my information to provide me with personalized content?	Dwivedi et al., 2019; Chopdar, 2022
	EE2	Am I familiar with how to use the algorithm recommendation mechanism?	
	EE3	I consider the algorithm easy to understand and employ.	
	EE4	Learning how to use App with algorithm recommendation system is easy for me	
Social Influence (SI)	SI1	People who influence my behavior think that I should use algorithm recommendation.	Dwivedi et al., 2019; Rana et al., 2024
	SI2	People who are vital to me suggest that I exchange more personal information for the convenience of algorithms.	
	SI3	People around me who use algorithmic recommendations have easy, accurate access to information	
	SI4	People around me helped me learn how to use algorithmic recommendations	

Facilitating Condition (FC)	FC2	I know that it is necessary to use algorithm recommendations.	Dwivedi et al., 2019; Rana et al., 2024
	FC3	It is necessary to acquire information through the use of algorithm recommendation.	
	FC4	Algorithmic recommendations do not confuse my sources.	
Algorithmic Resistance Attitude (ARA)	ARA2	Even though the algorithm can assist me in filtering information, I am not concerned about this feature.	Kim & Kankanhalli, 2009; Patil et al., 2020
	ARA3	Using algorithm recommendations is not a wise idea	
	ARA4	I would never accept a service that incorporates an algorithm.	
	ARA6	I will not accept services that involve algorithms unless there is no alternative.	
Algorithmic Resistance Intention (ARI)	ARI2	I will not recommend others to use App with algorithm recommendation system	Kim & Kankanhalli, 2009
	ARI4	I am not going to click on something that appears to be an algorithmic recommendation.	
	ARI5	I will not rely on the content recommended by the algorithm in my study and work	