



The impact of social media usage on algorithmic literacy among Chinese adults

Yuheng Ren & Shan Jiang

To cite this article: Yuheng Ren & Shan Jiang (2026) The impact of social media usage on algorithmic literacy among Chinese adults, *Information, Communication & Society*, 29:5, 1514-1543, DOI: [10.1080/1369118X.2025.2557558](https://doi.org/10.1080/1369118X.2025.2557558)

To link to this article: <https://doi.org/10.1080/1369118X.2025.2557558>



Published online: 26 Sep 2025.



Submit your article to this journal [↗](#)



Article views: 642



View related articles [↗](#)



View Crossmark data [↗](#)



The impact of social media usage on algorithmic literacy among Chinese adults

Yuheng Ren  and Shan Jiang 

School of Media and Communication, Shanghai Jiao Tong University, Shanghai, People's Republic of China

ABSTRACT

In an era where algorithms dominate digital platforms, algorithmic literacy has become essential for understanding platform features, reducing informational biases, and empowering informed user decisions. This research investigates how social media use influences algorithmic literacy among Chinese adults (18–45). Using an online convenience sample ($n = 951$), we find that higher education and frequent social media use predict greater algorithmic awareness, which in turn fosters behaviors to counteract algorithmic filtering; age shows no effect. Awareness reduces ambivalence, strengthens positive attitudes, and weakens negative ones – particularly towards prioritizing algorithms. These effects are moderated by accuracy motivation and locus of control (LOC): both amplify awareness's impact by increasing positivity and reducing negativity. Users with higher perceived control exhibit more favorable, less ambivalent attitudes. Though interaction terms modestly improved model fit, motivation and LOC independently outperformed awareness in explaining attitudes. Education and social media use also directly influence evaluations. Models best explained positive attitudes, but poorly predicted ambivalent or negative ones. In comparison to their U.S. and German counterparts, Chinese users report higher engagement but varied awareness. This study shows that motivation and perceived control, beyond awareness, are key to shaping algorithm-related attitudes – underscoring the need for targeted algorithmic literacy in non-Western contexts.

ARTICLE HISTORY

Received 11 October 2024
Accepted 30 August 2025

KEYWORDS

Algorithmic literacy;
algorithmic awareness; social
media; locus of control (LOC);
accuracy motivation;
algorithmic divide

Algorithms are integral to internet infrastructure, shaping decision-making in diverse fields, from music recommendations to critical choices in law enforcement and health-care (Gran et al., 2020). Their influence has spurred growing concern about algorithmic literacy, highlighting the need to explore individuals' understanding of algorithms, their attitudes, and behaviors. The pervasive use of algorithms in social media – where 95.13% of China's internet users were active by December 2022 (Digitaling, 2023) – further emphasizes the importance of algorithmic literacy in the digital age.

Research trends highlight a focus on algorithmic literacy (Shin et al., 2022) and its educational applications (Kampa & Balzer, 2021) as well as algorithm recommendations (Du, 2023; Swart, 2021), information bubbles (Zhou et al., 2021), and AI applications.

Significant work has also been done on social media and algorithmic risk (Brady et al., 2023; Saurwein & Spencer-Smith, 2021). However, there has been limited focus on the specific algorithmic literacy among Chinese adults and the impact of social media use. Driven by the growing importance of algorithmic literacy, our study examines its relationship with social media use among Chinese adults aged 18–45, focusing on perceptions, interactions, and the factors influencing their awareness, attitudes, and behaviors. We will also explore how locus of control, defensive motivation, and accuracy motivation moderate these perceptions, within the context of China’s unique culture – characterized by a dynamic, state-regulated yet highly innovative digital environment shaped by both governmental control and market-driven creativity (Craig et al., 2021; Fitzgerald et al., 2022; Yang, 2009).

Understanding algorithms and algorithmic literacy

Algorithms are human-made constructs that embed value judgments in their design, shaping how information is prioritized and filtered (Powers, 2017). Scholars hold differing views on the nature and role of algorithms: some regard them as purely technical tools that establish material and technical structures (Beer, 2017), while others emphasize their broader influence in shaping, transforming, and governing social life (Masso & Kasapoglu, 2020). These perspectives reflect an ongoing debate about how algorithms construct reality. For instance, some studies frame algorithms as extensions of traditional and social media processes (Introna, 2016), while others argue they are products of networked media logic (Klinger & Svensson, 2018).

Despite theoretical debates, algorithms have tangible effects on users’ daily interactions with digital media. Operating as a ‘black box,’ they remain opaque even to researchers (Hargittai et al., 2020), yet users recognize their impact. Even without knowing the term *algorithm*, social media users perceive personalization through their experiences (Swart, 2021). These interactions help individuals form personal experiences and derive meaning from how content is filtered and prioritized on social media. Users perceive algorithms in diverse ways, ranging from personalized content tools to unclear, hard-to-explain concepts (Dogruel et al., 2022). This variability underscores the need for algorithmic literacy to bridge the gap between user experiences and the technical realities of algorithms, fostering more critical engagement with algorithm-driven content.

Algorithmic literacy has emerged as a critical skill for navigating the digital world. Traditionally, it has been defined through computational thinking and computer literacy, emphasizing the mathematical aspects of algorithms (Katai, 2015; Stiller & LeBlanc, 2006). However, given the widespread influence of algorithms in everyday life, a broader conceptualization is necessary (Ridley & Pawlick-Potts, 2021). Expanding on Bruns (2019), Swart (2021) identifies four key components of algorithmic literacy: awareness, knowledge, imaginaries, and tactics. Similarly, DeVito (2021) views it as the ability to recognize algorithmic impact and apply that understanding, while Dogruel et al. (2021) describe it as awareness of algorithms, understanding their operations, critically evaluating algorithmic decisions, and managing or influencing them. While these perspectives differ in emphasis, they collectively highlight both the awareness and practical dimensions of algorithmic literacy.

Algorithmic literacy protects individuals from algorithmic risks (Gran et al., 2020; Kemper & Kolkman, 2019) and enables critical engagement, particularly in social media, where algorithms shape user experiences. Given their role in shaping user experiences, understanding two key types of algorithms is crucial: (a) *filtering algorithms*, which select content based on user activity, and (b) *prioritizing algorithms*, which rank content according to user preferences (Oeldorf-Hirsch & Neubaum, 2023).

Algorithmic literacy framework

We will use the research framework developed by Oeldorf-Hirsch and Neubaum (2023), based on Swart's (2021) framework of algorithmic literacy, which categorizes understanding and engagement with algorithms into **awareness, affective, and behavioral dimensions**. By examining these components, the study aims to provide a comprehensive understanding of how users perceive and engage with algorithms in social media environments.

Algorithmic awareness refers to recognizing the dynamic systems that shape online content exposure (Hargittai et al., 2020; Swart, 2021). It plays a crucial role in how individuals engage with and interpret social media algorithms, influencing their digital interactions (Zarouali et al., 2021). This study defines algorithmic awareness as users' understanding of content curation, automated decision-making, human-algorithm interactions, ethical implications, and user control (Oeldorf-Hirsch & Neubaum, 2023). As Du (2023) notes, algorithmic awareness strongly predicts algorithmic literacy, underscoring its importance in fostering informed digital engagement.

The affective dimension captures users' emotional responses to algorithms, ranging from appreciation to skepticism (Swart, 2021). On social media, users often perceive algorithms as beneficial – for instance, by enabling personalized content – but also problematic, such as when they reinforce filter bubbles. This duality fosters attitudinal ambivalence (Oeldorf-Hirsch & Neubaum, 2023), which this study conceptualizes as the core of the affective dimension. Importantly, such ambivalence is further amplified by users' specific motivations for engaging with algorithmic platforms.

The behavioral dimension examines how individuals interact with and influence algorithms (Swart, 2021). Users employ algorithmic skills – such as understanding how algorithms curate content – to strategically shape their digital experiences (Oeldorf-Hirsch & Neubaum, 2023). Active engagement strategies include liking specific posts, adjusting posting times, or using keywords to steer algorithmic outputs. Conversely, avoidance tactics involve measures like browsing incognito or limiting data sharing (Gruber & Hargittai, 2023). This study defines the behavioral dimension as user-driven actions aimed at counteracting algorithms' restrictive effects.

Factors determining algorithmic awareness

Factors such as prior knowledge, personality traits, and demographics significantly influence algorithmic awareness (Fang & Jin, 2022). Research highlights age and education as key demographic predictors. For instance, Gran et al. (2020) found significant age- and education-based differences in Norway, while Zarouali et al. (2021) observed that older, less-educated, and female individuals in the Netherlands are more likely to misunderstand media algorithms. Similarly, in China, Huang (2019) noted that educational

background shapes attitudes towards algorithmic news, with Zhao and Lin (2022) reporting that higher education levels correlate with greater algorithmic awareness, while associate degree holders exhibit significantly lower awareness. Brodsky et al. (2020) further emphasized the need for algorithmic awareness education, particularly among college students, who often overlook how algorithms filter and customize information. Collectively, these findings underscore the role of demographic factors, particularly age and education, in shaping algorithmic awareness. The following hypotheses explore these relationships:

Hypothesis 1: (a) Algorithmic awareness is negatively associated with age and (b) positively associated with education.

Previous studies have shown that social media usage frequency correlates with algorithmic awareness, though often indirectly. For example, YouTube users recognize that video suggestions are influenced by prior actions, strengthening the link between usage and awareness (Alvarado et al., 2020). Similarly, increased activity on TikTok corresponds to a better understanding of its algorithm (Klug et al., 2021), and frequent social media users in the U.S. and Germany demonstrate greater algorithmic awareness (Oeldorf-Hirsch & Neubaum, 2023). In China, longer usage durations on algorithmic news platforms are associated with a better understanding of algorithms and heightened awareness of the ‘information cocoon’ effect (Huang, 2019). These findings collectively suggest that more frequent social media use enhances algorithmic awareness. Building on this, we propose:

Hypothesis 2: Algorithmic awareness is positively associated with the frequency of social media use.

Impact of algorithmic awareness on ambivalence towards algorithms

Social media algorithms personalize content through *filtering* (excluding irrelevant material) and *prioritizing* (ranking based on user preferences) mechanisms (Eg et al., 2023; Hart et al., 2009). While these algorithmic functions are often bundled within recommender systems (Haim et al., 2018), distinguishing them analytically helps clarify their respective roles in shaping user experience. These systems help reduce information overload and mitigate certain technical biases (Bozdag, 2013; Swart, 2021). However, rather than eliminating all biases, they may inadvertently reinforce selective exposure, leading to echo chambers that limit content diversity (Du, 2023; Thurman et al., 2019). Understanding how such algorithms work has been shown to influence users’ attitudes towards them (Silva et al., 2024). As users recognize both the benefits – such as reduced cognitive load – and the drawbacks – such as restricted information diversity – of filtering and prioritizing algorithms, they may experience conflicting evaluations. This aligns with *attitudinal ambivalence theory* (Armitage & Conner, 2000), which posits that individuals can hold strong positive and negative attitudes towards the same entity. Building on this framework, we adopted an exploratory approach by measuring positive and negative attitudes separately in order to calculate ambivalence and capture the full spectrum of algorithm-related perceptions.

Hypothesis 3: Algorithmic awareness positively correlates with attitudinal ambivalence towards (a) filtering and (b) prioritizing algorithms.

Algorithmic awareness influences user attitudes (Oeldorf-Hirsch & Neubaum, 2023), but its effects vary based on individual traits such as locus of control (LOC) – a psychological construct describing individuals’ beliefs about their ability to influence life events (Inoue, 2013). LOC reflects individuals’ attributional tendencies: those with an internal LOC perceive outcomes as contingent on their own actions, while those with an external LOC attribute events to external forces such as luck, chance, or social influence (Spector, 1982). Perceived control over online interactions plays a crucial role in shaping algorithmic awareness (Morrison et al., 2023). Users who feel a greater sense of control may pay less attention to the ways algorithms shape their experiences (Dogruel et al., 2022). LOC may moderate this process: individuals with a stronger external LOC, perceiving outcomes as externally determined, may feel more uncertain about algorithms, fostering ambivalence. In contrast, those with a stronger internal LOC may navigate algorithmic environments with greater confidence, leading to clearer and more stable attitudes.

Silva et al. (2024) measured control using power usage scores, reflecting users’ proactivity in managing social media. They found that higher scores correlated with more negative attitudes towards algorithms after interacting with Instagram’s ad system, suggesting that perceived control shapes user attitudes and may moderate the awareness-ambivalence link. Building on these insights, we propose that LOC moderates the relationship between algorithmic awareness and attitudinal ambivalence, with individuals who have a stronger internal LOC exhibiting lower ambivalence due to greater confidence in navigating algorithms.

Hypothesis 4: LOC moderates the relationship between algorithmic awareness and attitudinal ambivalence, such that individuals with a stronger internal LOC exhibit lower ambivalence toward (a) filtering algorithms and (b) prioritizing algorithms.

Attitudes towards filtering and prioritizing algorithms are influenced not only by algorithmic awareness but also by users’ underlying motivational orientations, such as *defensive* and *accuracy* motivations (Hart et al., 2009; Liu, 2017). Defensive motivation drives individuals to seek information that reinforces their preexisting beliefs, leading them to favor environments that maintain content consistency (Winter et al., 2016). Since filtering algorithms curate content by selectively including or excluding information, their function aligns with belief-preserving goals, reinforcing positive attitudes towards them (Oeldorf-Hirsch & Neubaum, 2023). Similarly, prioritizing algorithms, by ranking content based on past interactions, further structure the information environment in a way that supports preexisting preferences, potentially strengthening favorable perceptions among defensively motivated individuals.

Accuracy motivation, on the other hand, emphasizes the acquisition of objective and comprehensive information (Kunda, 1990). Early research suggested that accuracy-motivated users criticized filtering algorithms for restricting perspective diversity while favoring prioritizing algorithms for their emphasis on factual accuracy (Hart et al., 2009). However, recent studies indicate that highly accuracy-motivated users view filtering algorithms more positively as efficient information tools, whereas those with low accuracy motivation and algorithmic awareness tend to hold negative attitudes (Oeldorf-Hirsch & Neubaum, 2023). These conflicting findings underscore the complex interaction between algorithmic awareness and motivation, shaping attitudinal ambivalence. This study therefore proposes that:

Hypothesis 5: Defense motivation negatively moderates the relationship between algorithmic awareness and attitudinal ambivalence toward (a) filtering and (b) prioritizing algorithms.

Hypothesis 6: Accuracy motivation negatively moderates the relationship between algorithmic awareness and attitudinal ambivalence toward (a) filtering and (b) prioritizing algorithms.

Attitude's influence on algorithmic behavior to counteract filtering

The latest study by Oeldorf-Hirsch and Neubaum (2023) found that algorithmic awareness predicts behaviors to counteract algorithmic filtering, as evidenced by the correlation between greater algorithmic awareness and increased use of measures like private browsing or do-not-track options. Researchers developed an algorithm resistance model, finding that in rural China, algorithmic literacy significantly enhances teenagers' willingness and intention to resist algorithms, while age plays a significant role in algorithm resistance (Yang & Xing, 2022). Based on these findings, we assume:

Hypothesis 7: Algorithmic awareness among Chinese adults predicts overall behaviors to counteract algorithmic filtering in China.

Cross-country variations in algorithmic awareness

Research on cross-country differences in algorithmic awareness underscores the critical role of contextual factors in shaping users' perceptions and behaviors (Chung, 2023; Shin, 2021). In particular, China's dynamic social media environment, characterized by a vast and diverse user base, presents a distinctive context for examining these factors (Graham, 2014; Pearson, 2015). As of June 2024, China had nearly 1.1 billion internet users, with a penetration rate of 78%. Among these users, 52.5% are aged 18–45, 21.1% can modify security and privacy settings, and 33.7% possess a basic understanding of how to do so (CINIC, 2024). Despite the country's high adult literacy rate of 97% (National Bureau of Statistics, 2021; UNESCO Institute for Statistics, 2023), the social media landscape in China differs significantly from global norms, primarily due to government censorship. This censorship shapes both the content available on platforms and users' interactions with algorithms, presenting an important distinction from other countries' social media landscapes.

This study extends Oeldorf-Hirsch and Neubaum's (2023) research on algorithmic awareness in the U.S. and Germany by incorporating data from China. While their study highlights how social media use and privacy expectations influence attitudes towards algorithms in the U.S. and Germany, this research explores how these patterns might differ in China's unique cultural and social environment. Specifically, China's functional culture – a pragmatic, goal-oriented orientation towards technology that emphasizes usefulness over ethical skepticism, as observed in Di (2023) – and government governance (Plantin & Seta, 2019; Wu & Fitzgerald, 2021) may shape attitudes towards algorithms differently, leading to the following research question:

Research Question: How does algorithmic awareness among social media users in China differ from that of users in the United States and Germany?

Method

An online survey was conducted in China using the SoJump platform, with participants receiving a monetary incentive ranging from 1 to 10 yuan. The sample was limited to social media users aged between 18 and 45 years old. Data collection occurred in March 2024 and the survey had a median completion time of 7 min ($M = 6.97$, $SD = 5.24$). Six participants over the age of 45 were excluded, resulting in a final sample size of 951. The research model is presented in Figure 1. The study adhered to the ethical principles outlined in the Belmont Report, ensuring respect for participants, beneficence, and justice. Informed consent was obtained prior to participation, and full voluntary engagement was ensured throughout the process.

Sample

Within the sample, 30.6% identified as female, 69.0% as male, and 0.4% as other genders. Participants' ages ranged from 18 to 45 ($M = 24.51$, $SD = 4.38$). Regarding education, 17.2% had less than a bachelor's degree, 72.7% were undergraduates or held a bachelor's degree, and 10.1% had education beyond a bachelor's degree. Due to convenience sampling, gender distribution deviated from a 50/50 ratio, so gender was included as a control variable.

Measures

Demographics

Participants' gender responses were grouped into three categories: female, male, and other. Ages were provided in an open-ended format. Educational backgrounds were categorized into five levels, ranging from 'less than high school' to 'doctoral candidate or doctoral.' Considering the Chinese educational system, these were further divided into two

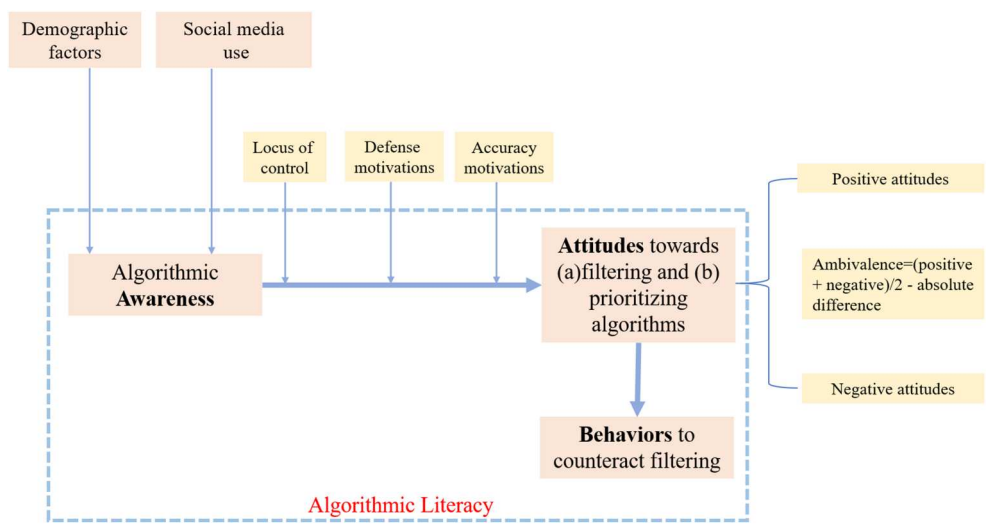


Figure 1. Research model.

broad categories: lower education levels (high school or below, associate's degree) and higher education levels (undergraduate or bachelor's degree, master's candidate or master's degree, doctoral candidate or doctoral).

Social media use

Participants indicated how often they used various social media platforms (1 = 'never' to 6 = 'several times a day'), including WeChat, Douyin, QQ, Weibo, Kuaishou, Bilibili, Xiaohongshu, Zhihu, Douban, Baidu Tieba, LinkedIn/Maimai, and overseas platforms. The average score across platforms was calculated to produce a composite score for overall usage ($M = 4.01$, $SD = .85$).

Algorithmic awareness

Following the approach of Oeldorf-Hirsch and Neubaum (2023), the Algorithmic Media Content Awareness Scale (AMCA) by Zarouali et al. (2021) was employed to assess overall comprehension of 'social media' algorithms, scored on a scale from 1 (not at all aware) to 5 (completely aware). The scale includes four dimensions: (a) *content filtering* (4 items, e.g., 'Algorithms tailor content to me'); (b) *automated decisions* (3 items, e.g., 'Algorithms decide what content I see'); (c) *human-algorithm interplay* (3 items, e.g., 'Recommendations depend on my online behavior'); (d) *ethical considerations* (3 items, e.g., 'Algorithm decisions lack transparency'). Additionally, we included a fifth dimension: (e) *control over one's own content* (4 items, e.g., 'Algorithms decide if my content is shown to others'). The overall scale demonstrated high reliability ($\alpha = .94$, $M = 3.70$, $SD = .70$), as did all sub-dimensions ($\alpha = .72$ to $.84$). To minimize bias, we used general statements about algorithms rather than explicit definitions and asked participants to rate their awareness, avoiding the influence of unprompted thoughts. However, as Swart (2021) notes, algorithmic literacy does not require understanding the term 'algorithm,' so the AMCA scale may underestimate awareness among users unfamiliar with technical language.

Attitudes towards filtering algorithms and prioritizing algorithms

Attitudes towards filtering and prioritizing algorithms were measured using a scale from Oeldorf-Hirsch and Neubaum (2023). After separately introducing filtering algorithms and prioritizing algorithms in social media contexts briefly, participants rated their agreement with six adjectives (good, bad, beneficial, harmful, desirable, and undesirable) on a 1 (completely disagree) to 4 (strongly agree) scale. Positive attitudes towards filtering were calculated by averaging scores for positive adjectives (good, beneficial, desirable; $M = 3.16$, $SD = .56$, $\alpha = .77$), and negative attitudes were based on negative adjectives (bad, harmful, undesirable; $M = 2.19$, $SD = .82$, $\alpha = .88$). The same approach was used for prioritizing algorithms (positive attitudes: $M = 3.16$, $SD = .56$, $\alpha = .78$; negative attitudes: $M = 2.15$, $SD = .82$, $\alpha = .89$). The algorithm explanations were provided only after assessing participants' algorithmic awareness, minimizing potential bias in their responses.

Attitudinal ambivalence

Ambivalence towards algorithms was calculated using a multi-step process (Thompson et al., 1995), reflecting the tension between the coexistence of positive and negative

evaluations and the dominance of one attitude over the other (polarization). First, the absolute difference between positive and negative attitudes was determined. Then, the formula: $(positive + negative)/2 - absolute\ difference$ was applied. The resulting value quantified ambivalence towards filtering ($M = 1.47$, $SD = 1.15$) and prioritizing algorithms ($M = 1.47$, $SD = 1.52$).

Locus of control

The internet locus of control was measured using a scale by Oeldorf-Hirsch and Neubaum (2023), rated from 1 (strongly disagree) to 5 (strongly agree). It encompasses two items: ‘Whether algorithms determine what content I see, it mostly depends on my skills’, and ‘Whether algorithms prioritize content, it depends on me,’ with higher scores indicating a more internal locus of control. The scale showed acceptable reliability ($\alpha = .64$, $M = 3.80$, $SD = .79$).

Defense and accuracy motivations

Utilizing Winter et al.’s (2016) information-seeking motivation measures, participants rated their motivation on a five-point scale during their use of social media for information searching (e.g., news). Four items, such as ‘... find arguments or data that support your viewpoint,’ measured *defense motivations* ($\alpha = .72$, $M = 3.94$, $SD = .59$). Another set, such as ‘... avoid inaccurate information,’ measured *accuracy motivations* ($\alpha = .71$, $M = 3.93$, $SD = .61$).

Behaviors to counteract algorithmic filtering

Participants were surveyed to determine (yes/no) if they employed specific behaviors to mitigate the impact of algorithmic filtering while online (Oeldorf-Hirsch & Neubaum, 2023), including: (a) browsing web pages using incognito or private mode, (b) clearing their browsing history regularly, (c) clearing their cache regularly, (d) deleting cookies regularly, or (e) enabling the ‘Do Not Track’ option in the browser. Responses were averaged ($M = .69$, $SD = .29$). Additional data were collected for future analyses beyond the current study.

Analysis

Initially, zero-order correlations were conducted for all predictor and outcome variables (see Table 16). H1a, H1b, and H2 were tested through linear regression analyses, using age, education, and social media use as predictors, algorithmic awareness as the outcome, and gender as a control. For H3 and H4, linear regression models included algorithmic awareness, locus of control, and their interaction term as predictors, along with age, gender, education, and social media use as controls; outcomes were ambivalent, negative, and positive attitudes towards filtering and prioritizing algorithms.

H5 and H6 were tested via linear regression, with algorithmic awareness, defense motivation (H5), accuracy motivation (H6), and their respective interactions with algorithmic awareness as predictors. Outcomes remained attitudes towards algorithms, with age, gender, education, social media use, and locus of control as controls. For comparison purposes, we also tested a combined model including locus of control, defense motivation, accuracy motivation, and all their interactions with algorithmic awareness (Table 14).

H7 was examined through linear regression analysis, with algorithmic awareness as the predictor and behavioral outcomes as the dependent variable. The research question (RQ) compared demographic differences in algorithmic awareness across age-matched samples from the U.S. ($n = 685$) and Germany ($n = 593$), as obtained from Oeldorf-Hirsch and Neubaum (2023), with the Chinese sample. A one-way ANOVA assessed cross-country differences.

Results

Contrary to predictions, age (**H1a**) was not significantly related to algorithmic awareness ($\beta < .01$, $p = .805$), suggesting no significant differences in algorithmic awareness among social media users aged 18–45 in China. In contrast, education (**H1b**) showed a significant positive relationship with algorithmic awareness ($\beta = .16$, $p < .001$), indicating that individuals with higher education levels have greater algorithmic awareness. Similarly, more frequent social

Table 1. Linear regression analysis on algorithmic awareness (H1a/b, H2).

Model	Unstandardized coefficients		Standardized coefficients		<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β							
(Constant)	1.95	.20			9.77	<.001		41.56	.15	1.94
Age	<.01	<.01	.01		.25	0.805	1.01			
Gender	.06	.04	.04		1.31	0.190	1.01			
Education	.30	.06	.16		5.30	<.001	1.03			
Social media use	.27	.02	.33		10.75	<.001	1.03			

Notes: Dependent variable: Algorithmic Awareness. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 2. Linear regression analysis of the moderating effects of locus of control on attitudinal ambivalence towards filtering algorithms (H3a, H4a).

Model	Unstandardized coefficients		Standardized coefficients		<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β							
1 (Constant)	2.22	.35			6.28	<.001		2.93	.01	
Age	−.01	.01	−.02		−.60	.547	1.01			
Gender	.01	.08	.01		.17	.865	1.01			
Education	−.32	.10	−.11		−3.26	.001	1.03			
Social media use	−.02	.04	−.01		−.33	.739	1.03			
2 (Constant)	1.91	.37			5.19	<.001		3.36	.02	
Age	−.01	.01	−.02		−.57	.568	1.01			
Gender	.03	.08	.01		.32	.749	1.01			
Education	−.28	.10	−.09		−2.77	.006	1.06			
Social media use	.04	.05	.03		.73	.464	1.19			
AMCA	−.14	.07	−.08		−2.06	.040	1.54			
Locus of control	−.04	.06	−.03		−.77	.442	1.48			
3 (Constant)	1.95	.36			5.35	<.001		6.50	.05	1.99
Age	.00	.01	−.01		−.25	.800	1.01			
Gender	.00	.08	.00		.00	.998	1.01			
Education	−.29	.10	−.10		−2.93	.003	1.06			
Social media use	.05	.05	.03		.98	.327	1.19			
AMCA	−.22	.07	−.14		−3.33	.001	1.66			
Locus of control	−.07	.06	−.05		−1.21	.229	1.49			
AMCA × Locus of control	−.26	.05	−.17		−4.99	<.001	1.17			

Notes: Dependent variable: Attitudinal ambivalence towards filtering algorithms. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

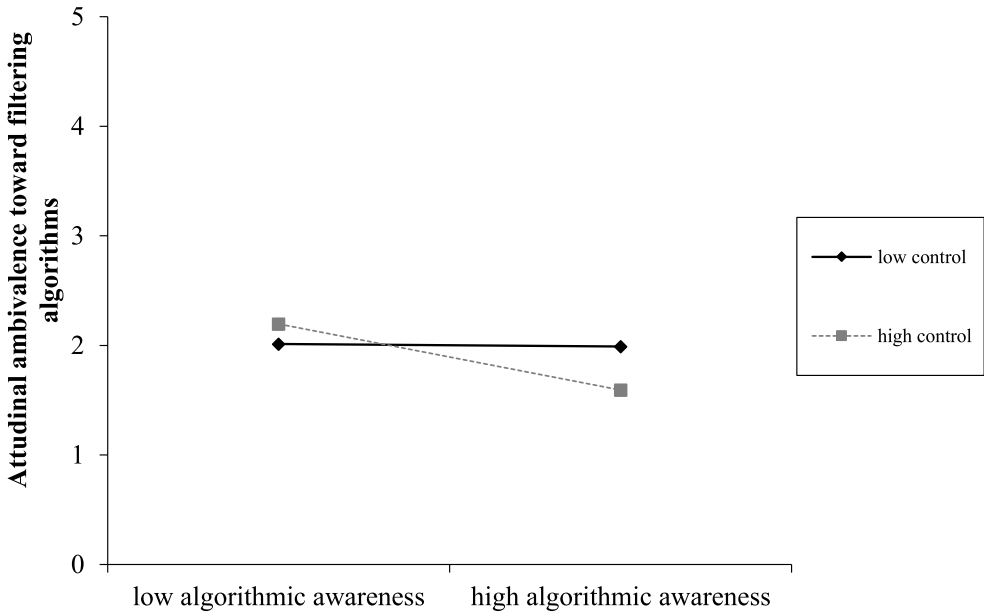


Figure 2. Simple slope plot of locus of control $\times$ Algorithmic awareness interaction on attitudinal ambivalence towards filtering algorithms (H4a).

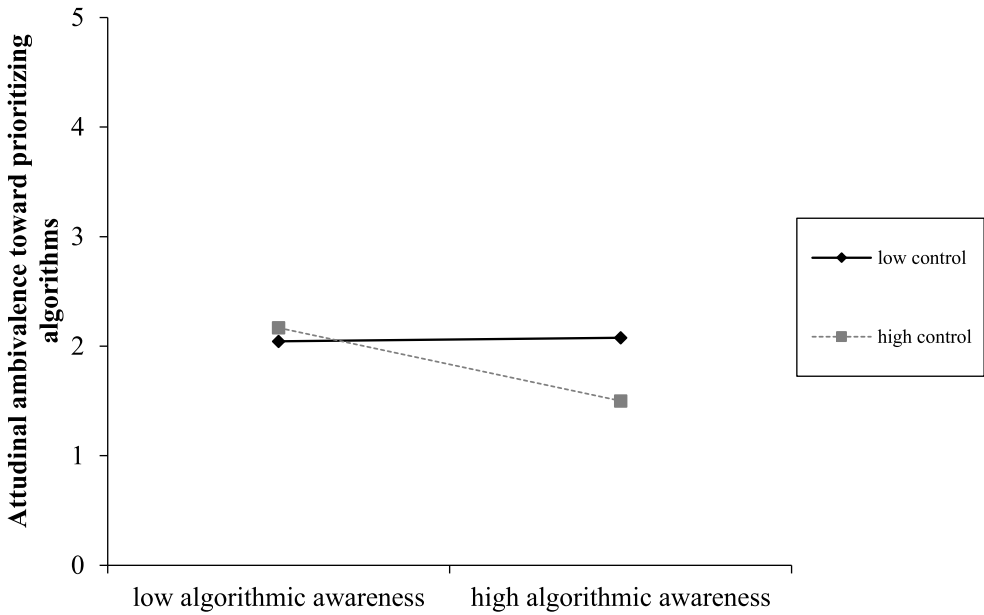


Figure 3. Simple slope plot of locus of control $\times$ Algorithmic awareness interaction on attitudinal ambivalence towards prioritizing algorithms (H4b).

media use (H2) was positively associated with higher algorithmic awareness ($\beta = .33$, $p < .001$). The regression model testing H1-H2 demonstrated a good fit ($R^2 = .15$, $F(4, 946) = 41.56$, $p < .001$), as shown in Table 1.

Table 3. Linear regression analysis of the moderating effects of locus of control on negative filter attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.53	.25		10.04	<.001		2.33	.01	
Age	.00	.01	–.01	–.15	.880	1.01			
Gender	.04	.06	.02	.64	.523	1.01			
Education	–.21	.07	–.10	–2.93	.004	1.03			
Social media use	.00	.03	.00	.01	.996	1.03			
2 (Constant)	2.44	.26		9.27	<.001		2.53	.02	
Age	.00	.01	.00	–.11	.910	1.01			
Gender	.04	.06	.02	.76	.450	1.01			
Education	–.21	.07	–.10	–2.89	.004	1.06			
Social media use	.02	.03	.02	.58	.563	1.19			
AMCA	.04	.05	.03	.76	.448	1.54			
Locus of control	–.10	.04	–.09	–2.37	.018	1.48			
3 (Constant)	2.45	.26		9.39	<.001		4.10	.03	1.95
Age	.00	.01	.00	.12	.902	1.01			
Gender	.03	.06	.02	.52	.601	1.01			
Education	–.21	.07	–.10	–3.00	.003	1.06			
Social media use	.03	.03	.03	.76	.449	1.19			
AMCA	–.01	.05	–.01	–.23	.820	1.66			
Locus of control	–.11	.04	–.11	–2.69	.007	1.49			
AMCA $\times$ Locus of control	–.14	.04	–.13	–3.65	<.001	1.17			

Notes: Dependent variable: Negative filter attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 4. Linear regression analysis of the moderating effects of locus of control on positive filter attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.39	0.17		14.15	<.001		16.67	.07	
Age	.01	.00	.05	1.66	.098	1.01			
Gender	–.03	.04	–.03	–.81	.419	1.01			
Education	.00	.05	.00	–.09	.929	1.03			
Social media use	.17	.02	.25	7.89	<.001	1.03			
2 (Constant)	2.94	.16		18.01	<.001		39.23	.20	
Age	.01	.00	.05	1.59	.112	1.01			
Gender	–.06	.04	–.05	–1.61	.108	1.01			
Education	–.06	.05	–.04	–1.41	.158	1.06			
Social media use	.07	.02	.11	3.35	.001	1.19			
AMCA	.12	.03	.15	4.12	<.001	1.54			
Locus of control	.21	.03	.30	8.34	<.001	1.48			
3 (Constant)	2.92	.16		18.34	<.001		42.78	.24	1.88
Age	.00	.00	.03	1.16	.245	1.01			
Gender	–.04	.03	–.03	–1.19	.236	1.01			
Education	–.06	.04	–.04	–1.26	.207	1.06			
Social media use	.06	.02	.10	3.09	.002	1.19			
AMCA	.18	.03	.22	5.98	<.001	1.66			
Locus of control	.23	.03	.32	9.15	<.001	1.49			
AMCA $\times$ Locus of control	.17	.02	.22	7.18	<.001	1.17			

Notes: Dependent variable: Positive filter attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Algorithmic awareness significantly reduced ambivalence towards both filtering and prioritizing algorithms (filtering: $\beta = -.14$, $p = .001$; prioritizing: $\beta = -.14$, $p = .001$; see Tables 2 and 5), contrary to H3. This suggests that higher awareness is associated with

Table 5. Linear regression analysis of the moderating effects of locus of control on attitudinal ambivalence towards prioritizing algorithms (H3b, H4b).

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.48	.35		7.00	<.001		3.74	.02	
Age	−.01	.01	−.03	−.76	.448	1.01			
Gender	−.01	.08	.00	−.09	.925	1.01			
Education	−.33	.10	−.11	−3.34	.001	1.03			
Social media use	−.06	.04	−.04	−1.27	.204	1.03			
2 (Constant)	2.08	.37		5.66	<.001		4.92	.03	
Age	−.01	.01	−.02	−.71	.479	1.01			
Gender	.01	.08	.00	.12	.901	1.01			
Education	−.29	.10	−.09	−2.83	.005	1.06			
Social media use	.01	.05	.01	.22	.827	1.19			
AMCA	−.12	.07	−.07	−1.83	.068	1.54			
Locus of control	−.11	.06	−.08	−2.01	.045	1.48			
3 (Constant)	2.12	.36		5.88	<.001		9.62	.07	1.95
Age	.00	.01	−.01	−.33	.743	1.01			
Gender	−.02	.08	−.01	−.27	.791	1.01			
Education	−.30	.10	−.10	−3.04	.002	1.06			
Social media use	.02	.05	.02	.51	.607	1.19			
AMCA	−.23	.07	−.14	−3.40	.001	1.66			
Locus of control	−.14	.06	−.10	−2.56	.011	1.49			
AMCA × Locus of control	−.32	.05	−.21	−6.06	<.001	1.17			

Notes: Dependent variable: Attitudinal ambivalence towards prioritizing algorithms. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 6. Linear regression analysis of the moderating effects of locus of control on negative prioritize attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.62	0.25		10.41	.000		2.21	.01	
Age	.00	.01	−.02	−.45	.650	1.01			
Gender	−.02	.06	−.01	−.26	.792	1.01			
Education	−.21	.07	−.10	−2.91	.004	1.03			
Social media use	.00	.03	.00	.03	.978	1.03			
2 (Constant)	2.42	.26		9.25	.000		3.36	.02	
Age	.00	.01	−.01	−.40	.690	1.01			
Gender	.00	.06	.00	−.07	.941	1.01			
Education	−.19	.07	−.09	−2.68	.008	1.06			
Social media use	.04	.03	.04	1.11	.269	1.19			
AMCA	−.01	.05	−.01	−.11	.909	1.54			
Locus of control	−.12	.04	−.11	−2.87	.004	1.48			
3 (Constant)	2.44	.26		9.41	.000		5.63	.04	1.92
Age	.00	.01	.00	−.12	.904	1.01			
Gender	−.02	.06	−.01	−.36	.723	1.01			
Education	−.20	.07	−.09	−2.81	.005	1.06			
Social media use	.04	.03	.05	1.33	.185	1.19			
AMCA	−.06	.05	−.05	−1.26	.209	1.66			
Locus of control	−.13	.04	−.13	−3.26	.001	1.49			
AMCA × Locus of control	−.16	.04	−.15	−4.34	.000	1.17			

Notes: Dependent variable: Negative prioritize attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

more definitive attitudes, diverging from earlier findings in Western contexts (Oeldorf-Hirsch & Neubaum, 2023). Correlation analyses confirmed that algorithmic awareness was negatively related to ambivalent attitudes (filtering: $r = -.12$; prioritizing: $r = -.13$),

Table 7. Linear regression analysis of the moderating effects of locus of control on positive prioritize attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.39	0.17		14.15	<.001		16.67	.07	
Age	.01	.00	.05	1.66	.098	1.01			
Gender	−.03	.04	−.03	−.81	.419	1.01			
Education	.00	.05	.00	−.09	.929	1.03			
Social media use	.17	.02	.25	7.89	<.001	1.03			
2 (Constant)	2.94	.16		18.01	<.001		39.23	.20	
Age	.01	.00	.05	1.59	.112	1.01			
Gender	−.06	.04	−.05	−1.61	.108	1.01			
Education	−.06	.05	−.04	−1.41	.158	1.06			
Social media use	.07	.02	.11	3.35	.001	1.19			
AMCA	.12	.03	.15	4.12	<.001	1.54			
Locus of control	.21	.03	.30	8.34	<.001	1.48			
3 (Constant)	2.92	.16		18.34	<.001		42.78	.24	1.88
Age	.00	.00	.03	1.16	.245	1.01			
Gender	−.04	.03	−.03	−1.19	.236	1.01			
Education	−.06	.04	−.04	−1.26	.207	1.06			
Social media use	.06	.02	.10	3.09	.002	1.19			
AMCA	.18	.03	.22	5.98	<.001	1.66			
Locus of control	.23	.03	.32	9.15	<.001	1.49			
AMCA × Locus of control	.17	.02	.22	7.18	<.001	1.17			

Notes: Dependent variable: Positive prioritize attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 8. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on attitudinal ambivalence towards filtering algorithms (H5a, H6a).

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.44	0.37		6.61	<.001		3.18	.02	
Age	−.01	.01	−.02	−.57	.569	1.01			
Gender	.02	.08	.01	.28	.776	1.01			
Education	−.31	.10	−.10	−3.15	.002	1.03			
Social media use	.02	.05	.01	.34	.736	1.14			
Locus of control	−.10	.05	−.07	−2.03	.043	1.13			
2 (Constant)	1.59	.41		3.87	<.001		7.19	.06	
Age	.00	.01	−.01	−.19	.853	1.01			
Gender	.01	.08	.00	.13	.897	1.02			
Education	−.28	.10	−.09	−2.80	.005	1.06			
Social media use	.03	.05	.03	0.71	.478	1.19			
Locus of control	.07	.06	.05	1.23	.218	1.66			
AMCA	.03	.07	.02	.48	.634	1.85			
Defense motivation	−.31	.09	−.16	−3.32	.001	2.35			
Accuracy motivation	−.20	.09	−.11	−2.16	.031	2.47			
3 (Constant)	1.68	.41		4.11	<.001		7.36	.07	2.00
Age	.00	.01	.00	.12	.903	1.02			
Gender	.01	.08	.01	.16	.869	1.02			
Education	−.29	.10	−.09	−2.91	.004	1.06			
Social media use	.04	.05	.03	.78	.438	1.20			
Locus of control	.05	.06	.03	.83	.409	1.68			
AMCA	.02	.07	.01	.21	.835	1.86			
Defense motivation	−.28	.10	−.14	−2.92	.004	2.48			
Accuracy motivation	−0.25	0.094	−.13	−2.66	.008	2.53			
AMCA × Defense motivation	.13	.10	.06	1.30	.195	2.37			
AMCA × Accuracy motivation	−.37	.11	−.17	−3.43	.001	2.42			

Notes: Dependent variable: Attitudinal ambivalence towards filtering algorithms. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

positively related to positive attitudes ($r = .34$ for both), and only weakly negatively (prioritizing: $r = -.07$) or unrelated (filtering) to negative attitudes. The effect was slightly stronger for prioritizing algorithms, especially regarding negative attitudes.

Locus of control (LOC) moderated these effects. Significant interaction between algorithmic awareness and LOC emerged for ambivalence towards both filtering ($\beta = -.17, p < .001$; Table 2) and prioritizing ($\beta = -.21, p < .001$; Table 5) algorithms, supporting H4. Simple slope analyses (Figures 2 and 3) indicated these effects were significant only among high-LOC respondents, who reported lower ambivalence with higher awareness (filtering: $b = -.43, p < .001$; prioritizing: $b = -.48, p < .001$). LOC also moderated the effect of algorithmic awareness on attitudes, reducing negative attitudes (filtering: $\beta = -.13, p < .001$; Table 3; prioritizing: $\beta = -.15, p < .001$; Table 6), and amplifying positive attitudes ($\beta = .22$ for both, $p < .001$; Tables 4 and 7). This moderating effect was slightly stronger for negative attitudes towards prioritizing algorithms, suggesting heightened sensitivity to control in evaluations of prioritization systems. Although interaction terms modestly increased model R^2 , explanatory power for ambivalent and negative attitudes remained low ($R^2 = .05$ and $.03$ for filtering; $.07$ and $.04$ for prioritizing). In contrast, models predicting positive attitudes showed moderate explanatory strength ($R^2 = .24$ for both algorithm types; see Tables 2–7).

Table 9. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on negative filter attitude.

Model	Unstandardized coefficients		Standardized coefficients		<i>t</i>	<i>p</i>	VIF	<i>F</i>	R^2	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β							
1 (Constant)	2.71	.26			10.29	<.001		2.92	.02	
Age	.00	.01	.00	–.11	.910	1.01				
Gender	.04	.06	.03	.77	.442	1.01				
Education	–.20	.07	–.09	–2.80	.005	1.03				
Social media use	.03	.03	.03	.74	.459	1.14				
Locus of control	–.08	.04	–.08	–2.29	.023	1.13				
2 (Constant)	2.53	.30			8.58	<.001		4.56	.04	
Age	.00	.01	.01	.19	.854	1.01				
Gender	.04	.06	.02	.62	.537	1.02				
Education	–.21	.07	–.10	–2.90	.004	1.06				
Social media use	.02	.03	.02	.56	.574	1.19				
Locus of control	–.03	.04	–.03	–.76	.446	1.66				
AMCA	.13	.05	.11	2.52	.012	1.85				
Defense motivation	–.17	.07	–.12	–2.46	.014	2.35				
Accuracy motivation	–.11	.07	–.09	–1.70	.090	2.47				
3 (Constant)	2.58	.29			8.76	<.001		4.56	.05	1.97
Age	.00	.01	.01	.42	.675	1.02				
Gender	.04	.06	.02	.65	.519	1.02				
Education	–.21	.07	–.10	–2.98	.003	1.06				
Social media use	.02	.03	.02	.61	.542	1.20				
Locus of control	–.05	.04	–.04	–1.07	.286	1.68				
AMCA	.12	.05	.10	2.31	.021	1.86				
Defense motivation	–.15	.07	–.11	–2.16	.031	2.48				
Accuracy motivation	–.14	.07	–.11	–2.08	.038	2.53				
AMCA × Defense motivation	.07	.07	.05	.97	.334	2.37				
AMCA × Accuracy motivation	–.20	.08	–.13	–2.60	.009	2.42				

Notes: Dependent variable: Negative filter attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

No significant interactions emerged between algorithmic awareness and defensive motivation on any outcome variable, across both filtering and prioritizing algorithms (Tables 8–14), providing no support for **H5**. In contrast, accuracy motivation significantly moderated the effect of algorithmic awareness on ambivalence towards filtering algorithms ($\beta = -.17, p = .001$; Table 8), supporting **H6(a)**. Simple slope analyses revealed a crossover interaction (Figure 4): under low accuracy motivation, higher algorithmic awareness predicted greater ambivalence ($b = .24, p = .008$), whereas under high accuracy motivation, it predicted lower ambivalence ($b = -.21, p = .041$). Accuracy motivation also moderated the effects of awareness on discrete attitudes, reducing negative attitudes ($\beta = -.13, p = .009$; Table 9), and amplifying positive ones ($\beta = .17, p < .001$; Table 10). These findings diverge from Oeldorf-Hirsch and Neubaum (2023), who found no significant moderating effect on the awareness-positive attitude link.

Similar patterns emerged for prioritizing algorithms, supporting **H6(b)**. Algorithmic awareness interacted with accuracy motivation to predict ambivalent ($\beta = -.17, p < .001$; Table 11), negative ($\beta = -.20, p < .001$; Table 12), and positive ($\beta = .17, p < .001$; Table 13) attitudes. The moderating effect on negative attitudes was slightly stronger for prioritizing ($\beta = -.20$) than filtering algorithms ($\beta = -.13$), suggesting that motivational factors may play a more pronounced role in shaping attitudes towards content prioritization.

Table 10. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on positive filter attitude.

Model	Unstandardized coefficients		Standardized coefficients		<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β							
1 (Constant)	1.82	.17			11.07	.000		42.94	.19	
Age	.01	.00	.05	1.58	.115	1.01				
Gender	–.05	.04	–.05	–1.53	.128	1.01				
Education	–.03	.04	–.02	–0.74	.461	1.03				
Social media use	.09	.02	.13	4.20	.000	1.14				
Locus of control	.26	.02	.37	11.76	.000	1.13				
2 (Constant)	2.40	.18			13.32	.000		37.37	.24	
Age	.00	.00	.03	1.16	.246	1.01				
Gender	–.05	.03	–.04	–1.43	.154	1.02				
Education	–.06	.04	–.04	–1.47	.142	1.06				
Social media use	.07	.02	.11	3.46	.001	1.19				
Locus of control	.15	.03	.21	5.76	.000	1.66				
AMCA	.03	.03	.04	1.02	.309	1.85				
Defense motivation	.16	.04	.17	3.80	.000	2.35				
Accuracy motivation	.11	.04	.12	2.70	.007	2.47				
3 (Constant)	2.36	.18			13.20	.000		33.08	.26	1.90
Age	.00	.00	.02	.77	.443	1.02				
Gender	–.05	.03	–.04	–1.51	.132	1.02				
Education	–.06	.04	–.04	–1.37	.172	1.06				
Social media use	.07	.02	.10	3.40	.001	1.20				
Locus of control	.16	.03	.23	6.25	.000	1.68				
AMCA	.04	.03	.05	1.34	.179	1.86				
Defense motivation	.15	.04	.15	3.47	.001	2.48				
Accuracy motivation	.14	.04	.15	3.31	.001	2.53				
AMCA × Defense motivation	–.04	.05	–.04	–.98	.327	2.37				
AMCA × Accuracy motivation	.19	.05	.17	3.98	.000	2.42				

Notes: Dependent variable: positive filter attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 11. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on attitudinal ambivalence towards prioritizing algorithms (H5b, H6b).

Model	Unstandardized coefficients		Standardized coefficients		<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β							
1 (Constant)	2.84	.37			7.70	<.001		5.22	.03	
Age	−.01	.01	−.02	−.71	.479	1.01				
Gender	.01	.08	.00	.09	.926	1.01				
Education	−.32	.10	−.10	−3.17	.002	1.03				
Social media use	−.01	.05	−.01	−.14	.888	1.14				
Locus of control	−.17	.05	−.11	−3.32	.001	1.13				
2 (Constant)	1.98	.41		4.85	<.001		9.57	.08		
Age	.00	.01	−.01	−.28	.780	1.01				
Gender	−.01	.08	.00	−.12	.906	1.02				
Education	−.29	.10	−.09	−2.90	.004	1.06				
Social media use	.01	.05	.01	.17	.867	1.19				
Locus of control	.02	.06	.01	.27	.790	1.66				
AMCA	.07	.07	.04	.93	.355	1.85				
Defense motivation	−.37	.09	−.19	−3.96	<.001	2.35				
Accuracy motivation	−.20	.09	−.11	−2.12	.034	2.47				
3 (Constant)	2.06	.40		5.10	<.001		9.82	.10	1.98	
Age	.00	.01	.00	.09	.932	1.02				
Gender	.00	.08	.00	−.06	.956	1.02				
Education	−.30	.10	−.10	−3.03	.003	1.06				
Social media use	.01	.05	.01	.26	.793	1.20				
Locus of control	−.01	.06	−.01	−.15	.884	1.68				
AMCA	.05	.07	.03	.65	.514	1.86				
Defense motivation	−.35	.10	−.18	−3.68	<.001	2.48				
Accuracy motivation	−.25	.09	−.13	−2.66	.008	2.53				
AMCA × Defense motivation	.07	.10	.04	.73	.466	2.37				
AMCA × Accuracy motivation	−.37	.11	−.17	−3.51	<.001	2.42				

Notes: Dependent variable: Attitudinal ambivalence towards prioritizing algorithms. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Despite theoretical expectations, interaction terms provided limited practical value. Across outcome variables, models incorporating interaction terms between algorithmic awareness and motivation (both defense and accuracy) failed to substantially improve model fit beyond the main effects. In some cases (e.g., [Tables 10](#) and [13](#)), model performance even declined, as indicated by lower *F*-statistics, suggesting minimal added value from these interactions.

In the full model ([Table 14](#)), accuracy motivation moderated the relationship between algorithmic awareness and negative attitudes only for prioritizing algorithms ($\beta = .17$, $p = .001$), reinforcing the context-specific nature of motivation's role. Interaction effects between awareness and LOC remained significant even after accounting for motivational variables (ambivalence: filtering $\beta = -.12$, $p = .008$; prioritizing $\beta = -.15$, $p = .001$; positive attitudes: filtering and prioritizing $\beta = .17$, $p < .001$), further supporting **H4**.

No significant main effects of algorithmic awareness were found for ambivalent attitudes towards filtering ($\beta = .01$, $p = .835$) or prioritizing ($\beta = .03$, $p = .514$) algorithms, for negative attitudes towards prioritizing algorithms ($\beta = .06$, $p = .164$), or for positive attitudes towards either filtering or prioritizing algorithms (both $\beta = .05$, $p = .179$). The only significant effect was found for negative attitudes towards filtering algorithms ($\beta = .10$, $p = .021$). In contrast, motivational factors consistently showed stronger

Table 12. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on negative prioritize attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	2.87	.26		10.99	.000		4.03	.02	
Age	.00	.01	–.01	–.40	.689	1.01			
Gender	.00	.06	.00	–.08	.940	1.01			
Education	–.19	.07	–.09	–2.74	.006	1.03			
Social media use	.04	.03	.04	1.11	.269	1.14			
Locus of control	–.12	.04	–.12	–3.35	.001	1.13			
2 (Constant)	2.59	.29		8.85	.000		5.45	.04	
Age	.00	.01	.00	–.09	.931	1.01			
Gender	–.02	.06	–.01	–.28	.777	1.02			
Education	–.19	.07	–.09	–2.73	.007	1.06			
Social media use	.04	.03	.04	1.05	.293	1.19			
Locus of control	–.05	.04	–.05	–1.18	.237	1.66			
AMCA	.09	.05	.07	1.70	.089	1.85			
Defense motivation	–.21	.07	–.15	–3.14	.002	2.35			
Accuracy motivation	–.07	.07	–.06	–1.10	.270	2.47			
3 (Constant)	2.67	.29		9.19	.000		6.83	.07	1.94
Age	.00	.01	.01	.30	.762	1.02			
Gender	–.01	.06	–.01	–.23	.816	1.02			
Education	–.20	.07	–.09	–2.87	.004	1.06			
Social media use	.04	.03	.04	1.15	.250	1.20			
Locus of control	–.07	.04	–.07	–1.67	.095	1.68			
AMCA	.07	.05	.06	1.39	.164	1.86			
Defense motivation	–.19	.07	–.14	–2.74	.006	2.48			
Accuracy motivation	–.12	.07	–.09	–1.73	.085	2.53			
AMCA × Defense motivation	.09	.07	.06	1.29	.197	2.37			
AMCA × Accuracy motivation	–.31	.08	–.20	–4.10	.000	2.42			

Notes: Dependent variable: Negative prioritize attitude. Gender: 1 = Female, 2 = Male. Education: 1 = low to moderate, 2 = High.

Table 13. Linear regression analysis of the moderating effects of defense motivation and accuracy motivation on positive prioritize attitude.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	1.82	.17		11.07	.000		42.94	.19	
Age	.01	.00	.05	1.58	.115	1.01			
Gender	–.05	.04	–.05	–1.53	.128	1.01			
Education	–.03	.04	–.02	–0.74	.461	1.03			
Social media use	.09	.02	.13	4.20	.000	1.14			
Locus of control	.26	.02	.37	11.76	.000	1.13			
2 (Constant)	2.40	.18		13.32	.000		37.37	.24	
Age	.00	.00	.03	1.16	.246	1.01			
Gender	–.05	.03	–.04	–1.43	.154	1.02			
Education	–.06	.04	–.04	–1.47	.142	1.06			
Social media use	.07	.02	.11	3.46	.001	1.19			
Locus of control	.15	.03	.21	5.76	.000	1.66			
AMCA	.03	.03	.04	1.02	.309	1.85			
Defense motivation	.16	.04	.17	3.80	.000	2.35			
Accuracy motivation	.11	.04	.12	2.70	.007	2.47			
3 (Constant)	2.36	.18		13.20	.000		33.08	.26	1.90
Age	.00	.00	.02	.77	.443	1.02			
Gender	–.05	.03	–.04	–1.51	.132	1.02			
Education	–.06	.04	–.04	–1.37	.172	1.06			
Social media use	.07	.02	.10	3.40	.001	1.20			
Locus of control	.16	.03	.23	6.25	.000	1.68			
AMCA	.04	.03	.05	1.34	.179	1.86			
Defense motivation	.15	.04	.15	3.47	.001	2.48			
Accuracy motivation	.14	.04	.15	3.31	.001	2.53			
AMCA × Defense motivation	–.04	.05	–.04	–.98	.327	2.37			
AMCA × Accuracy motivation	.19	.05	.17	3.98	.000	2.42			

Notes: Dependent variable: positive prioritize attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

Table 14. Linear regression analysis of three moderating effects on attitudes.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
1 (Constant)	1.88	.36		5.24	.000		7.38	.08	2.01
Age	.00	.01	.01	.14	.887	1.02			
Gender	–.01	.08	.00	–.06	.953	1.03			
Education	–.29	.10	–.10	–2.95	.003	1.06			
Social media use	.04	.05	.03	.91	.364	1.20			
AMCA	–.05	.07	–.03	–.62	.536	2.06			
Locus of control	.04	.06	.02	.60	.549	1.70			
Defense motivation	–.25	.10	–.13	–2.54	.011	2.53			
Accuracy motivation	–.24	.09	–.13	–2.54	.011	2.53			
AMCA $\times$ Locus of control	–.18	.07	–.12	–2.67	.008	1.95			
AMCA $\times$ Defense motivation	.12	.10	.06	1.19	.235	2.38			
AMCA $\times$ Accuracy motivation	–.21	.12	–.09	–1.69	.091	3.18			
2 (Constant)	2.42	.26		9.29	.000		4.46	.05	1.97
Age	.00	.01	.01	.43	.665	1.02			
Gender	.03	.06	.02	.49	.623	1.03			
Education	–.21	.07	–.10	–3.00	.003	1.06			
Social media use	.02	.03	.02	.70	.484	1.20			
AMCA	.09	.05	.08	1.65	.100	2.06			
Locus of control	–.05	.04	–.05	–1.22	.223	1.70			
Defense motivation	–.13	.07	–.10	–1.89	.058	2.53			
Accuracy motivation	–.14	.07	–.10	–1.99	.047	2.53			
AMCA $\times$ Locus of control	–.09	.05	–.08	–1.81	.070	1.95			
AMCA $\times$ Defense motivation	.07	.07	.04	.89	.373	2.38			
AMCA $\times$ Accuracy motivation	–.12	.09	–.08	–1.38	.168	3.18			
Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
3 (Constant)	2.96	.16		18.89	.000		32.51	.28	1.90
Age	.00	.00	.02	.74	.458	1.02			
Gender	–.04	.03	–.03	–1.14	.254	1.03			
Education	–.06	.04	–.04	–1.34	.181	1.06			
Social media use	.07	.02	.10	3.21	.001	1.20			
AMCA	.09	.03	.11	2.67	.008	2.06			
Locus of control	.17	.03	.24	6.67	.000	1.70			
Defense motivation	.12	.04	.13	2.87	.004	2.53			
Accuracy motivation	.13	.04	.14	3.12	.002	2.53			
AMCA $\times$ Locus of control	.13	.03	.17	4.48	.000	1.95			
AMCA $\times$ Defense motivation	–.04	.04	–.03	–.81	.421	2.38			
AMCA $\times$ Accuracy motivation	.07	.05	.06	1.30	.193	3.18			
4 (Constant)	2.06	.36		5.79	.000		10.07	.11	1.99
Age	.00	.01	.00	.11	.911	1.02			
Gender	–.03	.08	–.01	–.34	.735	1.03			

(Continued)

Table 14. Continued.

Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
Education	–.30	.10	–.10	–3.08	.002	1.06			
Social media use	.02	.05	.02	.43	.667	1.20			
AMCA	–.03	.07	–.02	–.41	.679	2.06			
Locus of control	–.03	.06	–.02	–.43	.664	1.70			
Defense motivation	–.31	.10	–.16	–3.21	.001	2.53			
Accuracy motivation	–.23	.09	–.12	–2.50	.013	2.53			
AMCA × Locus of control	–.22	.07	–.15	–3.39	.001	1.95			
AMCA × Defense motivation	.06	.10	.03	.59	.553	2.38			
AMCA × Accuracy motivation	–.17	.12	–.08	–1.41	.160	3.18			
Model	Unstandardized coefficients		Standardized coefficients	<i>t</i>	<i>p</i>	VIF	<i>F</i>	<i>R</i> ²	Durbin–Watson
	<i>B</i>	<i>SE B</i>	β						
5 (Constant)	2.41	.26		9.38	.000		6.33	.07	1.94
Age	.00	.01	.01	.31	.755	1.02			
Gender	–.02	.06	–.01	–.33	.743	1.03			
Education	–.20	.07	–.09	–2.88	.004	1.06			
Social media use	.04	.03	.04	1.21	.228	1.20			
AMCA	.05	.05	.04	.98	.329	2.06			
Locus of control	–.07	.04	–.07	–1.76	.078	1.70			
Defense motivation	–.18	.07	–.13	–2.56	.011	2.53			
Accuracy motivation	–.11	.07	–.08	–1.67	.096	2.53			
AMCA × Locus of control	–.05	.05	–.05	–1.14	.256	1.95			
AMCA × Defense motivation	.09	.07	.06	1.24	.215	2.38			
AMCA × Accuracy motivation	–.26	.09	–.17	–3.01	.003	3.18			
6 (Constant)	2.96	.16		18.89	.000		32.51	.28	1.90
Age	.00	.00	.02	.74	.458	1.02			
Gender	–.04	.03	–.03	–1.14	.254	1.03			
Education	–.06	.04	–.04	–1.34	.181	1.06			
Social media use	.07	.02	.10	3.21	.001	1.20			
AMCA	.09	.03	.11	2.67	.008	2.06			
Locus of control	.17	.03	.24	6.67	.000	1.70			
Defense motivation	.12	.04	.13	2.87	.004	2.53			
Accuracy motivation	.13	.04	.14	3.12	.002	2.53			
AMCA × Locus of control	.13	.03	.17	4.48	.000	1.95			
AMCA × Defense motivation	–.04	.04	–.03	–.81	.421	2.38			
AMCA × Accuracy motivation	.07	.05	.06	1.30	.193	3.18			

Notes: Dependent variable: Model 1 = Attitudinal ambivalence towards filtering algorithms, Model 2 = Negative filter attitude, Model 3 = Positive filter attitude, Model 4 = Attitudinal ambivalence towards prioritizing algorithms, Model 5 = Negative prioritize attitude, Model 6 = Positive prioritize attitude. Gender: 1 = Female, 2 = Male. Education: 1 = Low to moderate, 2 = High.

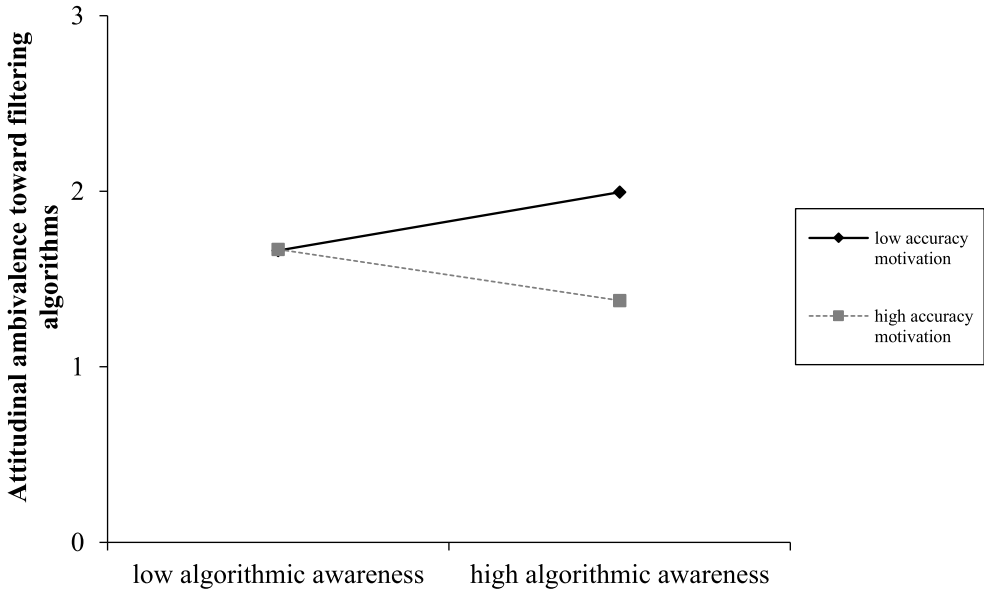


Figure 4. Simple slope plot of accuracy motivations × Algorithmic awareness interaction on attitudinal ambivalence towards filtering algorithms (H5b).

Table 15. Cross-country differences of variables between US and Germany (RQ).

		China		United States		Germany		F	p
		M	SD	M	SD	M	SD		
Education level		1.83	0.38	1.53	0.50	1.33	0.47	243.60	<.001
Social media use		4.01	0.85	2.92	0.71	2.83	0.74	574.06	<.001
Algorithmic awareness dimension	Content filtering	3.75	0.77	4.51	0.69	3.82	1.05	184.54	<.001
	Automated decisions	3.67	0.79	4.24	0.80	3.63	1.05	104.66	<.001
	Human-algorithm interplay	3.76	0.78	4.43	0.73	3.77	1.08	141.58	<.001
	Ethical considerations	3.63	0.80	4.00	0.84	3.50	1.04	58.34	<.001
	Own content	3.66	0.76	3.98	0.99	3.30	1.11	82.95	<.001

Notes: US and German data in this table are adapted from Oeldorf-Hirsch and Neubaum (2023).

predictors across all models (Tables 8–14), surpassing algorithmic awareness and control-related constructs.

Model explanatory power (R^2) varied by outcome: positive attitudes showed the highest R^2 (.24–.28), followed by ambivalence (.05–.11), while models for negative attitudes explained the least variance (.00–.07; Tables 12 and 14). These patterns suggest that cognitive and motivational variables are more predictive of favorable evaluations than of negative or ambivalent reactions. Additionally, education and social media as distinct predictors of algorithmic attitudes. While higher education was linked to reduced ambivalence and negativity, frequent social media use predicted more positive evaluations (Tables 2–13). These effects remained robust after controlling for algorithmic awareness.

Consistent with H7, algorithmic awareness significantly predicts users’ behavioral intentions to mitigate algorithmic filtering ($R^2 = .04$, $F(1, 949) = 34.35$, $p < .001$). Finally, comparing with data from Oeldorf-Hirsch and Neubaum (2023) reveal that Chinese

Table 16. Zero-order correlations of all study variables.

	1. Age	2	3	4	5	6	7	8	9	10	11	12	13
2. Education	-.01												
3. Social media use	-.02	.15**											
4. Algorithmic awareness	-.00	.21**	.35**										
5. Filter attitude positive	.05	.04	.25**	.34**									
6. Filter attitude negative	-.01	-.10**	-.01	-.03	-.42**								
7. Filter attitude ambivalence	-.02	-.11**	-.03	-.12**	-.31**	.87**							
8. Prioritize attitude positive	.05	.04	.26**	.34**	1.00**	-.42**	-.31**						
9. Prioritize attitude negative	-.01	-.10**	-.01	-.07*	-.28**	.79	.77**	-.28**					
10. Prioritize attitude ambivalence	-.02	-.12**	-.06	-.13**	-.31**	.76	.85**	-.31**	.92				
11. Defense motivation	.06	.09**	.21**	.53**	.40**	-.15**	-.21**	.40**	-.18**	-.25**			
12. Accuracy motivation	.04	.14**	.26**	.57**	.39**	-.13**	-.19**	.39**	-.15**	-.23**	.73**		
13. Behaviors to counteract algorithmic filtering	.07*	.09**	.14**	.19**	.06	-.07*	-.10**	.06	-.09**	-.12**	.12**	.16**	
14. Locus of control	.00	.10**	.33**	.55**	.41**	-.08*	-.08*	.41**	-.11**	-.13**	.51**	.51**	.16**

Note: * $p < .05$, ** $p < .01$.

participants surpass their American and German peers in both education level ($F(2, 2226) = 243.60, p < .001$) and social media usage frequency ($F(2, 2226) = 574.06, p < .001$). However, Americans demonstrated significantly higher algorithmic awareness across all five sub-dimensions ($F(2, 2226) = 135.40, p < .001$), answering our research question. Detailed statistics can be found in [Table 15](#).

Discussion

This study offers a context-sensitive examination of how cognitive, motivational, and sociocultural factors jointly shape algorithmic literacy in the Chinese digital environment. Our findings contribute to theoretical refinement and empirical elaboration of existing models of algorithmic awareness and evaluation, highlighting the importance of cultural specificity in algorithm-related research ([Table 16](#)).

Consistent with prior research, education emerged as a significant predictor of algorithmic awareness (Gran et al., 2020; Petrovčič et al., 2024). However, in the Chinese context, social media use was an equally strong – if not stronger – explanatory factor. This finding supports research suggesting that multi-platform engagement fosters algorithmic understanding through broader exposure to diverse platform functionalities (Espinoza-Rojas et al., 2023). Unlike Western studies reporting age-based divides in awareness (Gran et al., 2020; Oeldorf-Hirsch & Neubaum, 2023), we found no significant correlation between age and awareness among Chinese adults aged 18–45. This may reflect the digitally saturated environment of our sample, in which age variation within the cohort becomes less salient. Our findings align with Dogruel et al. (2022), who observed similarly negligible age effects in a German sample. These results highlight digital familiarity and routine engagement rather than demographic structure, are primary drivers of algorithmic knowledge, consistent with global trends (Chung & Wihbey, 2024).

In terms of attitudinal outcomes, algorithmic awareness significantly reduced ambivalence towards both filtering and prioritizing algorithms, encouraging more definitive evaluations. This contrasts with prior Western findings that awareness often increases attitudinal polarization (Oeldorf-Hirsch & Neubaum, 2023). The Chinese regulatory and pragmatic approach to digital technology (Cai, 2023) may contribute to a more stable interpretive framework, wherein increased awareness fosters clarity rather than division. However, the influence of awareness varied by algorithm type. Awareness improved attitudes towards prioritizing algorithms – often perceived as more transparent and responsive – while having limited impact on negative attitudes towards the more opaque filtering algorithms (Vaassen, 2022). This discrepancy likely reflects differences in perceived user agency. Prioritizing algorithms allow users to shape content ranking through visible interactions, reinforcing a sense of control and reducing concerns over manipulation (Cen et al., 2024). Conversely, filtering algorithms often involve hidden forms of content suppression, offering users minimal control. This aligns with research showing that opacity reduces user trust and engagement (Eslami et al., 2019). Beyond awareness, both education and social media use independently shaped user attitudes. Higher education reduced ambivalence and negativity, while frequent social media use predicted more positive views, suggesting that critical thinking and habitual exposure influence evaluations beyond cognitive understanding.

Psychological factors further conditioned the effect of algorithmic awareness. Internal locus of control (LOC) moderated the relationship between awareness and ambivalence: individuals with strong control beliefs formed more consistent and definitive attitudes. This finding aligns with earlier work showing that internal control enhances confidence in navigating algorithmic systems (Hong & Chen, 2022; Zhao & Lin, 2022), underscoring the importance of perceived agency in algorithmic engagement (Silva et al., 2024).

Motivational factors also played a significant role. Accuracy motivation moderated the relationship between awareness and user attitudes, particularly by reducing negative views of prioritizing algorithms. This effect appears driven by epistemic beliefs: users who value evidence-based knowledge are more likely to appreciate algorithmic processes that organize content by relevance or personalization (Choung et al., 2020). In contrast, defensive motivation had no significant effect, challenging earlier claims that belief-consistent filtering enhances algorithm appeal (Oeldorf-Hirsch & Neubaum, 2023). This discrepancy may reflect a cultural context in which the pursuit of goal-relevant information takes precedence over belief maintenance. Supporting this interpretation, Hart et al. (2009) found congeniality bias weakens when epistemic goals prevail.

Beyond moderation, accuracy motivation independently predicted more favorable attitudes across models, indicating its direct influence regardless of users' algorithmic awareness levels. In contrast, defensive motivation exhibited weaker and more inconsistent effects, suggesting that the drive to protect existing beliefs may be less influential in this cultural context. These findings affirm the independent role of motivation in shaping algorithm-related evaluations and reinforce its theoretical importance in models of algorithmic engagement.

Our analysis further showed that algorithmic awareness and user motivation explained more variance in positive evaluations than in ambivalent or negative ones. When users are aware of how algorithms work and are driven by accuracy or goal-oriented motives, they are more likely to form clear and consistent evaluations – resulting in higher model predictability. In contrast, ambivalent or negative attitudes may stem from broader sources of uncertainty, such as perceived opacity, lack of control, or institutional mistrust, which are less easily captured by individual-level variables. This divergence highlights that cognitive and motivational predictors are more effective in explaining positive responses, whereas critical or uncertain attitudes likely require broader structural or contextual explanations beyond user psychology.

While algorithmic awareness predicted some behavioral intentions to counteract filtering, its overall explanatory power remained modest – consistent with cross-cultural findings that awareness alone rarely translates into sustained resistance (Oeldorf-Hirsch & Neubaum, 2023; Swart, 2021). The persistence of this gap challenges assumptions about a linear relationship between algorithmic knowledge and user empowerment. Instead, structural barriers such as opaque user interfaces and discouraging platform norms may constrain effective response. Addressing these issues requires incorporating algorithmic literacy into formal education systems (Powers, 2017) and advancing inclusive media initiatives for populations with limited access to digital resources (Roth, 2019). Long-term progress further depends on regulatory reforms that promote equitable participation across different age groups (Koenig, 2020; Wei & Yan, 2023).

Cross-national comparisons further contextualize our findings. Chinese respondents aged 18–45 reported the higher levels of education and social media use, yet exhibited

lower algorithmic awareness than their American counterparts. German users scored lowest across all three dimensions. These disparities likely reflect underlying differences in media infrastructure, educational priorities, and civic discourse. In China, technology is often positioned as a functional tool for governance and regional development (Cai, 2023), which may foster utilitarian engagement rather than critical reflection (Di, 2023). In contrast, American public discourse tends to emphasize individual rights and systemic accountability, which may increase sensitivity to algorithmic risks (Oeldorf-Hirsch & Neubaum, 2023). These observations emphasize the importance of situating algorithmic literacy within specific cultural frameworks rather than treating it as a universally linear or generational phenomenon.

This study has several limitations. First, the use of convenience sampling and gender imbalance may limit generalizability of findings. Second, reliance on self-reported measures may not fully capture behavioral or implicit algorithmic literacy, particularly given the opacity of many algorithmic systems (Hargittai et al., 2020). Third, the observed interaction effects were modest and sensitive to model specification, warranting cautious interpretation. Future research should adopt systematic sampling, integrate behavioral data, and utilize longitudinal or experimental designs to establish causality. Qualitative approaches may uncover cultural variations in algorithmic awareness for deeper insights.

Conclusion

This study provides a culturally attuned account of algorithmic literacy by disentangling how users in China engage with filtering and prioritizing algorithms. Rather than treating algorithms as a monolithic construct, our findings show that differentiated awareness reduces attitudinal ambivalence and fosters more favorable perceptions – particularly when users feel a sense of control. However, awareness alone appears insufficient to shape evaluations and behaviors. Instead, motivational orientations (especially accuracy motivation), perceived control, and platform experience play more decisive roles. While positive attitudes are cognitively grounded, ambivalent and negative responses appear more emotionally driven, shaped by distrust or perceived opacity. This asymmetry suggests that algorithmic evaluation is shaped not only by technical understanding but also by users' psychological traits and affective contexts. Moreover, cross-national comparisons between China, the US, and Germany reveal structural differences in media environments, educational access, and algorithmic sense-making. These disparities underscore the presence of an emerging algorithmic divide and highlight the need for culturally responsive strategies to mitigate digital inequalities.

Author contributions

CRediT: **Yuheng Ren:** Conceptualization, Data curation, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing; **Shan Jiang:** Data curation, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Yuheng Ren is a PhD candidate at the School of Media and Communication, Shanghai Jiao Tong University. She holds both a Bachelor's and a Master's degree in Communication. Her research interests include social media usage, digital technology, digital stress, and role conflict [email: renyuheng@sjtu.edu.cn].

Shan Jiang is a PhD candidate at Shanghai Jiao Tong University School of Media and Communication. She holds a Master's degree in Cultural Industry and Management and a Bachelor's degree in New Media. Her research focuses on the intersection of culture, media and digital technology [email: jiangshan2018@sjtu.edu.cn].

Data availability statement

The data supporting this article will be made available upon reasonable request to the corresponding author.

ORCID

Yuheng Ren  <http://orcid.org/0000-0002-9383-9053>

Shan Jiang  <http://orcid.org/0000-0002-7807-2317>

References

- Alvarado, O., Heuer, H., Vanden Abeele, V., Breiter, A., & Verbert, K. (2020). Middle-aged video consumers' beliefs about algorithmic recommendations on YouTube. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW2), 121:1–121:24. <https://doi.org/10.1145/3415192>
- Armitage, C. J., & Conner, M. (2000). Attitudinal ambivalence: A test of three key hypotheses. *Personality and Social Psychology Bulletin*, 26(11), 1421–1432. <https://doi.org/10.1177/0146167200263009>
- Beer, D. (2017). The social power of algorithms. *Information, Communication & Society*, 20(1), 1–13. <https://doi.org/10.1080/1369118X.2016.1216147>
- Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics and Information Technology*, 15(3), 209–227. <https://doi.org/10.1007/s10676-013-9321-6>
- Brady, W. J., Jackson, J. C., Lindström, B., & Crockett, M. J. (2023). Algorithm-mediated social learning in online social networks. *Trends in Cognitive Sciences*, 27(10), 947–960. <https://doi.org/10.1016/j.tics.2023.06.008>
- Brodsky, J. E., Zomberg, D., Powers, K. L., & Brooks, P. J. (2020). Assessing and fostering college students' algorithm awareness across online contexts. *Journal of Media Literacy Education*, 12(3), 43–57. <https://doi.org/10.23860/JMLE-2020-12-3-5>
- Bruns, A. (2019). *Are filter bubbles real?* Wiley. <https://www.wiley.com/en-us/Are+Filter+Bubbles+Real%3F-p-9781509536443>
- Cai, T. (2023). Administrative regulation of social media algorithms in the European Union and America and their implications for China. *Journal of Management and Humanity Research*, 09, 01–10. <https://doi.org/10.22457/jmhr.v09a012355>
- Cen, S. H., Ilyas, A., Allen, J., Li, H., & Madry, A. (2024). *Measuring strategization in recommendation: Users adapt their behavior to shape future content.* <https://doi.org/10.48550/ARXIV.2405.05596>
- Choung, H., Newman, T. P., & Stenhouse, N. (2020). The role of epistemic beliefs in predicting citizen interest and engagement with science and technology. *International Journal of Science Education, Part B*, 10(3), 248–265. <https://doi.org/10.1080/21548455.2020.1774094>

- Chung, M. (2023). What's in the black box? How algorithmic knowledge promotes corrective and restrictive actions to counter misinformation in the USA, the UK, South Korea and Mexico. *Internet Research*, 33(5), 1971–1989. <https://doi.org/10.1108/INTR-07-2022-0578>
- Chung, M., & Wihbey, J. (2024). The algorithmic knowledge gap within and between countries: Implications for combatting misinformation. *Harvard Kennedy School Misinformation Review*, 5(4), 1–17. <https://doi.org/10.37016/mr-2020-155>
- CINIC. (2024). *The 54th statistical report on the development of the internet in China*. China Internet Network Information Center. <https://www.cnnic.cn/n4/2024/0828/c208-11063.html>
- Craig, D., Lin, J., & Cunningham, S. (2021). *Wanghong as social media entertainment in China*. Springer. <https://doi.org/10.1007/978-3-030-65376-7>
- DeVito, M. A. (2021). Adaptive folk theorization as a path to algorithmic literacy on changing platforms. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2), 339:1–339:38. <https://doi.org/10.1145/3476080>
- Di, D. (2023). Ethical ambiguity and complexity: Tech workers' perceptions of big data ethics in China and the US. *Information, Communication & Society*, 26(5), 957–973. <https://doi.org/10.1080/1369118X.2023.2166357>
- Digitaling. (2023, April 17). KAWO releases the 2023 China social media platform guide. *Digitaling*. <https://www.digitaling.com/articles/916901.html>
- Dogruel, L., Facciorusso, D., & Stark, B. (2022). 'I'm still the master of the machine.' internet users' awareness of algorithmic decision-making and their perception of its effect on their autonomy. *Information, Communication & Society*, 25(9), 1311–1332. <https://doi.org/10.1080/1369118X.2020.1863999>
- Dogruel, L., Masur, P., & Joeckel, S. (2021). Development and validation of an algorithm literacy scale for internet users. *Communication Methods and Measures*, 16(2), 115–133. <https://doi.org/10.1080/19312458.2021.1968361>
- Du, Y. R. (2023). Personalization, echo chambers, news literacy, and algorithmic literacy: A qualitative study of AI-powered news app users. *Journal of Broadcasting & Electronic Media*, 67(3), 246–273. <https://doi.org/10.1080/08838151.2023.2182787>
- Eg, R., Demirkol Tønnesen, Ö, & Tennfjord, M. K. (2023). A scoping review of personalized user experiences on social media: The interplay between algorithms and human factors. *Computers in Human Behavior Reports*, 9, 100253. <https://doi.org/10.1016/j.chbr.2022.100253>
- Eslami, M., Vaccaro, K., Lee, M. K., Elazari Bar On, A., Gilbert, E., & Karahalios, K. (2019). *User attitudes towards algorithmic opacity and transparency in online reviewing platforms*. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19). Association for Computing Machinery. <https://doi.org/10.1145/3290605.3300724>
- Espinoza-Rojas, J., Siles, I., & Castelain, T. (2023). How using various platforms shapes awareness of algorithms. *Behaviour & Information Technology*, 42(9), 1422–1433. <https://doi.org/10.1080/0144929X.2022.2078224>
- Fang, W., & Jin, J. (2022). Unpacking the effects of personality traits on algorithmic awareness: The mediating role of previous knowledge and moderating role of internet use. *Frontiers in Psychology*, 13, 953892. <https://doi.org/10.3389/fpsyg.2022.953892>
- Fitzgerald, R., Sandel, T., & Wu, X. (2022). Chinese social media: Technology, culture and creativity. *Discourse, Context & Media*, 48, 100610. <https://doi.org/10.1016/j.dcm.2022.100610>
- Graham, N. (2014). *Culture Mandala: The bulletin of the Centre for East-West Cultural and Economic Studies*. <https://www.semanticscholar.org/paper/Culture-Mandala%3A-Th-e-Bulletin-of-the-Centre-for-Graham/a683d934d7737758ab560a1de112cf33148665ca>
- Gran, A.-B., Booth, P., & Bucher, T. (2020). To be or not to be algorithm aware: A question of a new digital divide? *Information, Communication & Society*, 24(12), 1779–1796. <https://doi.org/10.1080/1369118X.2020.1736124>
- Gruber, J., & Hargittai, E. (2023). The importance of algorithm skills for informed internet use. *Big Data & Society*, 10(1), 20539517231168100. <https://doi.org/10.1177/20539517231168100>
- Haim, M., Graefe, A., & Brosius, H.-B. (2018). Burst of the filter bubble?: Effects of personalization on the diversity of Google news. *Digital Journalism*, 6(3), 330–343. <https://doi.org/10.1080/21670811.2017.1338145>

- Hargittai, E., Gruber, J., Djukaric, T., Fuchs, J., & Brombach, L. (2020). Black box measures? How to study people's algorithm skills. *Information, Communication & Society*, 23(5), 764–775. <https://doi.org/10.1080/1369118X.2020.1713846>
- Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., & Merrill, L. (2009). Feeling validated versus being correct: A meta-analysis of selective exposure to information. *Psychological Bulletin*, 135(4), 555–588. <https://doi.org/10.1037/a0015701>
- Hong, J., & Chen, R. (2022). Consciousness arousal and rule imagination: Tactics and practical paths for users resisting algorithms. *Journalism and Communication Research*, 29(8), 38–56 +126–127.
- Huang, X. (2019). The influence mechanism of users' algorithm perception on feedback behavior: An analysis based on social cognitive theory. *News and Writing*, 39(6), 63–68. <https://doi.org/10.13786/j.cnki.cn14-1066/g2.2019.6.011>
- Inoue, N. (2013). *Locus of control*. <https://onlinelibrary.wiley.com/doi/10.1002/9781118339893.wbeccp334>
- Introna, L. D. (2016). Algorithms, governance, and governmentality: On governing academic writing. *Science, Technology, & Human Values*, 41(1), 17–49. <https://doi.org/10.1177/0162243915587360>
- Kampa, P., & Balzer, F. (2021). Algorithmic literacy in medical students – Results of a knowledge test conducted in Germany. *Health Information & Libraries Journal*, 38(3), 224–230. <https://doi.org/10.1111/hir.12392>
- Katai, Z. (2015). The challenge of promoting algorithmic thinking of both sciences- and humanities-oriented learners. *Journal of Computer Assisted Learning*, 31(4), 287–299. <https://doi.org/10.1111/jcal.12070>
- Kemper, J., & Kolkman, D. (2019). Transparent to whom? No algorithmic accountability without a critical audience. *Information, Communication & Society*, 22(14), 2081–2096. <https://doi.org/10.1080/1369118X.2018.1477967>
- Klinger, U., & Svensson, J. (2018). The end of media logics? On algorithms and agency. *New Media & Society*, 20(12), 4653–4670. <https://doi.org/10.1177/1461444818779750>
- Klug, D., Qin, Y., Evans, M., & Kaufman, G. (2021). Trick and please. A mixed-method study on user assumptions about the TikTok algorithm. In O. Seneviratne, V. Singh, A. Freire, & J.-D. Luo (Eds.), *Proceedings of the 13th ACM web science conference 2021 (WebSci '21)* (pp. 84–92). Association for Computing Machinery. <https://doi.org/10.1145/3447535.3462512>
- Koenig, A. (2020). The algorithms know me and i know them: Using student journals to uncover algorithmic literacy awareness. *Computers and Composition*, 58, 102611. <https://doi.org/10.1016/j.compcom.2020.102611>
- Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, 108(3), 480–498. <https://doi.org/10.1037/0033-2909.108.3.480>
- Liu, C. (2017). Evaluating arguments during instigations of defence motivation and accuracy motivation. *British Journal of Psychology*, 108(2), 296–317. <https://doi.org/10.1111/bjop.12196>
- Masso, A., & Kasapoglu, T. (2020). Understanding power positions in a new digital landscape: Perceptions of Syrian refugees and data experts on relocation algorithm. *Information, Communication & Society*, 23(8), 1203–1219. <https://doi.org/10.1080/1369118X.2020.1739731>
- Morrison, B. W., Kelson, J. N., Morrison, N. M. V., Innes, J. M., Zelic, G., Al-Saggaf, Y., & Paul, M. (2023). You're not the boss of me, algorithm: Increased user control and positive implicit attitudes Are related to greater adherence to an algorithmic aid. *Interacting with Computers*, 35(3), 452–460. <https://doi.org/10.1093/iwc/iwad028>
- National Bureau of Statistics. (2021, May 11). *The 7th National Census Bulletin* (No. 6). National Bureau of Statistics of China. https://www.stats.gov.cn/xxgk/sjfb/zxfb2020/202105/t20210511_1817201.html
- Oeldorf-Hirsch, A., & Neubaum, G. (2023). Attitudinal and behavioral correlates of algorithmic awareness among German and U.S. social media users. *Journal of Computer-Mediated Communication*, 28(5), zmad035. <https://doi.org/10.1093/jcmc/zmad035>
- Pearson, A. (2015, January 14). *China's social and mobile companies set to shake the tech world*. <https://www.semanticscholar.org/paper/China%E2%80%99s-social-and-mobile-companies-set-to-shake-Pearson/f324edee32da5418653345aea2fb7845998e210c>

- Petrovčič, A., Reisdorf, B. C., Vehovar, V., & Bartol, J. (2024). Disentangling the role of algorithm awareness and knowledge in digital inequalities: An empirical validation of an explanatory model. *Information, Communication & Society*, 28(4), 557–574. <https://doi.org/10.1080/1369118X.2024.2363896>
- Plantin, J.-C., & Seta, G. d. (2019). WeChat as infrastructure: The techno-nationalist shaping of Chinese digital platforms. *Chinese Journal of Communication*, 12(3), 257–273. <https://www.tandfonline.com/doi/abs/10.1080/17544750.2019.1572633>
- Powers, E. (2017). My news feed is filtered?: Awareness of news personalization among college students. *Digital Journalism*, 5(10), 1315–1335. <https://doi.org/10.1080/21670811.2017.1286943>
- Ridley, M., & Pawlick-Potts, D. (2021). Algorithmic literacy and the role for libraries. *Information Technology and Libraries*, 40(2), Article 2. <https://doi.org/10.6017/ital.v40i2.12963>
- Roth, C. (2019). Algorithmic distortion of informational landscapes. *Intellectica. Revue de l'Association pour la Recherche Cognitive*, 70(1), 97–118. <https://doi.org/10.3406/intel.2019.1895>
- Saurwein, F., & Spencer-Smith, C. (2021). Automated trouble: The role of algorithmic selection in harms on social media platforms. *Media and Communication*, 9(4), Article 4. <https://doi.org/10.17645/mac.v9i4.4062>
- Shin, D. (2021). A cross-national study on the perception of algorithm news in the east and the west. *Journal of Global Information Management*, 29(2), 77–101. <https://doi.org/10.4018/JGIM.2021030105>
- Shin, D., Rasul, A., & Fotiadis, A. (2022). Why am I seeing this? Deconstructing algorithm literacy through the lens of users. *Internet Research*, 32(4), 1214–1234. <https://doi.org/10.1108/intr-02-2021-0087>
- Silva, D. E., Chen, C., & Zhu, Y. (2024). Facets of algorithmic literacy: Information, experience, and individual factors predict attitudes toward algorithmic systems. *New Media & Society*, 26(5), 2992–3017. <https://doi.org/10.1177/14614448221098042>
- Spector, P. E. (1982). Behavior in organizations as a function of employee's locus of control. *Psychological Bulletin*, 91(3), 482–497. <https://doi.org/10.1037/0033-2909.91.3.482>
- Stiller, E., & LeBlanc, C. (2006). From computer literacy to cyber-literacy. *J. Comput. Sci. Coll.*, 21(6), 4–13.
- Swart, J. (2021). Experiencing algorithms: How young people understand, feel about, and engage With algorithmic news selection on social media. *Social Media + Society*, 7(2), 20563051211008828. <https://doi.org/10.1177/20563051211008828>
- Thompson, M. M., Zanna, M. P., & Griffin, D. W. (1995). Let's not be indifferent about (attitudinal) ambivalence. In R. E. Petty & J. A. Krosnick (Eds.), *Attitude strength: Antecedents and consequences* (pp 361–386). Lawrence Erlbaum.
- Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2019). My friends, editors, algorithms, and I: Examining audience attitudes to news selection. *Digital Journalism*, 7(4), 447–469. <https://doi.org/10.1080/21670811.2018.1493936>
- UNESCO Institute for Statistics. (2023). *World bank open data*. World Bank Open Data. <https://data.worldbank.org>
- Vaassen, B. (2022). AI, opacity, and personal autonomy. *Philosophy & Technology*, 35(4), 88. <https://doi.org/10.1007/s13347-022-00577-5>
- Wei, S., & Yan, P. (2023). Measuring users' awareness of content recommendation algorithm: A survey on Douyin users in rural China. In I. Sserwanga, A. Goulding, H. Moulaison-Sandy, J. T. Du, A. L. Soares, V. Hessami, & R. D. Frank (Eds.), *Information for a better world: Normality, virtuality, physicality, inclusivity* (pp. 197–220). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-28035-1_15
- Winter, S., Metzger, M. J., & Flanagin, A. J. (2016). Selective Use of news cues: A multiple-motive perspective on information selection in social media environments. *Journal of Communication*, 66(4), 669–693. <https://doi.org/10.1111/jcom.12241>
- Wu, X., & Fitzgerald, R. (2021). 'Hidden in plain sight': Expressing political criticism on Chinese social media. *Discourse Studies*, 23(3), 365–385. <https://doi.org/10.1177/1461445620916365>
- Yang, C., & Xing, L. (2022). The dialectics of control: Resistance of rural adolescents to recommendation algorithms on short video platforms: A study based on the dual mediation path of

- rationality–irrationality. *The Journalist*, 40(7), 71–87. <https://doi.org/10.16057/j.cnki.31-1171/g2.2022.07.004>
- Yang, G. (2009). *The power of the internet in China: Citizen activism online*. Columbia University Press.
- Zarouali, B., Helberger, N., & De Vreese, C. H. (2021). Investigating algorithmic misconceptions in a media context: Source of a New digital divide? *Media and Communication*, 9(4), 134–144. <https://doi.org/10.17645/mac.v9i4.4090>
- Zhao, L., & Lin, C. (2022). Youth in the “black box”: College students’ algorithmic awareness, attitudes, and manipulation. *China Youth Study*, 34(7), 20–30. <https://doi.org/10.19633/j.cnki.11-2579/d.2022.0089>
- Zhou, T., Zhou, Y., & Zhao, Y. (2021). On the relationship among user’s reading behavior, algorithm recommendation mechanism and the manufactured filter bubbles effect. *CONVERTER*, 2021(3), 730–744. <https://doi.org/10.17762/converter.107>