



*Research Article*

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## The algorithmic knowledge gap within and between countries: Implications for combatting misinformation

*While understanding how social media algorithms operate is essential to protect oneself from misinformation, such understanding is often unevenly distributed. This study explores the algorithmic knowledge gap both within and between countries, using national surveys in the United States (N = 1,415), the United Kingdom (N = 1,435), South Korea (N = 1,798), and Mexico (N = 784). In all countries, algorithmic knowledge varied across different sociodemographic factors, even though in different ways. Also, different countries had different levels of algorithmic knowledge: The respondents in the United States reported the greatest algorithmic knowledge, followed by respondents in the United Kingdom, Mexico, and South Korea. Additionally, individuals with greater algorithmic knowledge were more inclined to take actions against misinformation.*

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### Research questions

- How are sociodemographic factors (e.g., age, gender, education, income, political ideology, social media use, ethnicity) associated with algorithmic knowledge?
- How is algorithmic knowledge distributed between countries?
- How does algorithmic knowledge shape individuals' reactions to misinformation on social media?

### Essay summary

- This study explored the unequal distribution of algorithmic knowledge both within and between countries, along with its real-world implications, drawing on national surveys in the United States (N = 1,415), the United Kingdom (N = 1,435), South Korea (N = 1,798), and Mexico (N = 784).
- In the four countries with diverse technological, political, and social landscapes, algorithmic knowledge varied across different sociodemographic factors, even though in different ways.
- Different countries had different levels of algorithmic knowledge: the United States respondents reported the greatest algorithmic knowledge, followed by the United Kingdom, Mexico, and South Korea. Notably, South Korean respondents exhibited the lowest levels of algorithmic knowledge,

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despite having highest rates of internet penetration and social media access among the four countries.

- Varying levels of algorithmic knowledge prompted individuals to respond to misinformation differently; those possessing higher algorithmic knowledge were more inclined to undertake actions to combat misinformation on social media than those lacking algorithmic knowledge.
- Our findings indicate that algorithmic knowledge can empower social media users to combat misinformation and address social inequalities. This study also highlights the necessity of tailoring algorithmic literacy initiatives to diverse populations across social and cultural backgrounds.

## **Implications**

The digital divide, originally referring to the gap between people who have access to modern information and communications technology (ICT) and those who don't (Ragnedda & Muschert, 2013), has been a concern since the advent of ICT and the internet. It has gained renewed attention due to the growing role of algorithms. In particular, algorithms increasingly control information flow on social media, determining what users see in their feeds. Social media algorithms are designed to filter and present online content in ways that optimize user engagement and retention (Golino, 2021), often resulting in the dissemination of misinformation that aligns with users' biases and beliefs (Bakshy et al., 2015; Hussein et al., 2020; Pariser, 2011). A notable example is Facebook's algorithm which supported a surge of hate-filled misinformation targeting the Rohingya people, contributing to their genocide by the Myanmar military in 2017 (Mozur, 2018).

Given these dangers, social media users' understanding of algorithms has become crucial for users' agency, public discourse, and democracy (Gran et al., 2021; Zarouali et al., 2021). However, algorithmic knowledge (i.e., understanding of how algorithms filter and present information) may not be equally distributed among people with different sociodemographic backgrounds (i.e., the second-level digital divide, Cotter & Reisdorf, 2020; Gran et al., 2021; Klawitter & Hargittai, 2018). In many respects, algorithmic knowledge may resemble civic, political, or economic knowledge in terms of its uneven distribution, but such a point has only recently begun to attract scholarly attention. With the uneven distribution of algorithmic knowledge, some may possess the ability to scrutinize and make informed judgments about the information presented by algorithms, while others may be more susceptible to the false or biased narratives embedded in algorithmic outputs without questioning them.

Some recent studies (e.g., Cotter & Reisdorf, 2020) have explored the development of the algorithmic knowledge gap across sociodemographic backgrounds and how these gaps intersect with our understanding of digital divides. However, prior studies have primarily focused on this algorithmic knowledge gap within individual countries, neglecting potential variations between countries. Hence, it remains unclear whether the algorithmic knowledge gap found in one country is observable in different national contexts (Oeldorf-Hirsch & Neubaum, 2023). Given that algorithms operate within intricate blends of political, technological, cultural, and social dynamics (Roberge & Melançon, 2017), it is possible that certain factors hold greater influence over individuals' algorithmic knowledge in one country, while exerting less power in other countries. Furthermore, the level of algorithmic knowledge might vary among countries, even if they share similar levels of access to the internet and social media. Lastly, while there is increasing awareness that differences in skills or knowledge of digital resources have inherent consequences in the real world (i.e., the third-level digital divide, Fuchs, 2009; Selwyn, 2004), the specific outcomes of the algorithmic knowledge gap have rarely been empirically examined (Scheerder et al., 2017).

Against this backdrop, this study advances research on the algorithmic knowledge gap across multiple fronts. First, by exploring the association between various sociodemographic factors and algorithmic

knowledge, this study extends prior research on the second-level digital divide. Across four countries with diverse technological, political, and social landscapes, we found a degree of cross-cultural validity indicating that younger individuals and frequent social media users have greater algorithmic knowledge. Additionally, while the specific predictors varied across countries, algorithmic knowledge was unevenly distributed across education level, ethnicity, gender, and political ideology. Of note, over 90% of respondents in all four countries had access to social media (see Table 3 in Appendix B), suggesting that discussion surrounding today's digital divide indeed needs to encompass more than just the binary distinction between individuals with access to the internet or social media and those without (i.e., the first-level digital divide).

This study also expands the existing research on the algorithmic knowledge gap which has predominantly focused on single national populations. Our findings indicate that the predictive power of specific sociodemographic factors may differ between countries. In the United States, political ideology and ethnicity were the primary predictors of algorithmic knowledge. In the United Kingdom, age, political ideology, and social media use were the significant factors. In South Korea, the main predictors included age, gender, education, and social media use, whereas in Mexico, only education and social media use were associated with algorithmic knowledge. Certain country-specific determinants warrant further attention. In economically advanced Western democracies, such as the United States and the United Kingdom, where political polarization has reached high levels in recent years (Dimock & Wike, 2020; Grechyna, 2023), political ideology emerged as the most significant factor in explaining differences in algorithmic knowledge; individuals with more liberal views were more likely to understand how social media algorithms function compared to their conservative counterparts. In contrast, in South Korea where women encounter ongoing disparities and obstacles across various societal domains (Lee, 2024), gender emerged as the most powerful predictor of algorithmic knowledge, with male respondents demonstrating a deeper understanding of algorithmic mechanisms than female respondents. These findings suggest that the algorithmic knowledge gap can manifest across various dimensions beyond traditional socioeconomic factors, such as income and education. Future research exploring additional social or cultural determinants may offer a more comprehensive understanding of the algorithmic knowledge gap, particularly in cross-country explorations.

Moreover, our findings elucidated disparities in algorithmic knowledge among countries. We found significant variations in knowledge levels across the four countries. The United States exhibited the highest overall algorithmic knowledge, followed by the United Kingdom, Mexico, and South Korea. One insight of note is that South Korea boasted the highest rates of internet penetration (98%) among the four countries examined (DataReportal, 2022). This finding once again underscores the notion that the issue of access to digital resources alone cannot offer a comprehensive understanding of the digital divide today. It also highlights the importance of considering national and cultural contexts in future research and potential interventions to enhance algorithmic knowledge.

Another important contribution of this study pertains to the outcomes of the algorithmic knowledge gap. While numerous scholars have proposed that the digital divide contributes to the perpetuation of existing social inequalities (e.g., Helsper, 2010; Van Dijk, 2006), empirical investigations into the real-world outcomes of the algorithmic knowledge gap have been limited. Bridging this gap, our study furnishes empirical evidence indicating that individuals with greater algorithmic knowledge are more inclined to take actions against misinformation. The rationale behind this link is that when people understand that social media algorithms provide information based on their previous interactions and those of similar users, they may be more aware of the risks of being trapped in filter bubbles (Pariser, 2011) that limit exposure to diverse viewpoints and make them more vulnerable to misinformation (Ciampaglia et al., 2018). Recognizing these risks might prompt people to take steps to avoid or mitigate them. Previous research supports this reasoning, indicating that individuals unaware of how algorithms tailor information to match their existing beliefs may mistakenly believe that all content they encounter on social media is

unbiased and accurate (Effron & Raj, 2020), leading them to endorse or share such content without reservations (Shin & Valente, 2020). In particular, those traditionally lagging behind in terms of algorithmic knowledge—such as elderly populations or less educated—were found to be more likely to spread misinformation (Gottfried & Grieco, 2018) and more vulnerable to associated harms (Seo et al., 2021). In this light, the current study suggests the potential role of algorithmic knowledge in empowering those populations to fight misinformation and mitigate the prevailing social inequalities.

Our findings contain significant implications for social media platforms, government, and civil society, as various stakeholders attempt to curb the spread of misinformation. Much of the work to reduce the spread of misinformation has revolved around approaches such as better platform moderation (Chung & Wihbey, 2024), stronger informational labels and cues relating to quality (Chung & Wihbey, 2024), and prebunking or fact-checking (Chung & Kim, 2021; Roozenbeek et al., 2020). Furthermore, civil society and government actors often focus on debunking domain-specific misinformation in spheres such as elections and public health, with varying effectiveness (for a meta-analysis see Walter et al., 2020). However, the findings presented here indicate that developing literacy programs to improve general knowledge around algorithmic mechanisms and flow of information could be a promising alternative.

When designing algorithmic literacy programs, special attention must be given to reaching vulnerable groups identified in this study, such as elderly or less educated populations, who may be more difficult to engage through conventional educational systems (Seo et al., 2021). It is also important to pay careful attention to the varying predictors of the algorithmic knowledge gap across countries, which we have demonstrated in this study, to optimize the effectiveness of algorithmic literacy programs in each country.

Some limitations of this study are worth noting. First, our measurement of algorithmic knowledge focused on knowledge about specific applications (Facebook and X/Twitter) and considered only one type of algorithmic operation (content recommendation for personal feeds). Given that respondents may have different levels of familiarity and experience with other social media platforms and types of algorithms, our findings may not fully represent the breadth and depth of users' algorithmic knowledge. Therefore, we should not assume that algorithmic knowledge is inherently linked to certain sociodemographic features or nationalities discussed in this study, as these populations' understanding of other aspects of social media algorithms may present different pictures. Future research employing a more comprehensive measurement of algorithmic knowledge (e.g., Dogruel et al., 2022) would provide us with a deeper understanding of how various sociodemographic factors and nationalities influence perceptions and understanding of social media algorithms. Second, while the anchor population statistics for each country (see Table 1 in Appendix B) were the latest available at the time of data collection, more up-to-date population statistics would offer a more accurate assessment of the representativeness of the samples.

Overall, this study adds significant nuance to the debate about how to strengthen global citizens' ability to navigate the misinformation-prevalent social media environment. The new frontier in research relating to the algorithmic knowledge gap may in large part relate to some of the factors revealed in this study, such as the apparent role of sociodemographic factors as well as global-cultural embedding. Further research should pursue all these areas, deepening our sense of where new digital divides are emerging, why they might exist, and how interventions might help to close such gaps.

## Findings

*Finding 1: Algorithmic knowledge is not equally distributed across individuals with different socio-demographic backgrounds.*

Consistent with the extant literature on the second-level digital divide in algorithmic knowledge (Cotter & Reisdorf, 2020; Gran et al., 2021; Klawitter & Hargittai, 2018), we found that algorithmic knowledge is

not equally distributed across individuals with different sociodemographic backgrounds. As illustrated in Table 1, age has a statistically significant but modest effect on algorithmic knowledge, with younger individuals exhibiting a better understanding of algorithmic mechanisms compared to older individuals.<sup>2</sup> We also found that social media use has a modest predictive power for algorithmic knowledge, with frequent social media users having a better understanding of algorithmic operations than less active users. Additionally, individuals with higher levels of education exhibit a greater understanding of how social media algorithms curate and present content compared to less educated people in two countries. Political ideology, gender, and ethnicity were also identified as predictors of algorithmic knowledge in certain countries.

It is important to note that the specific pattern of the algorithmic knowledge gap varied among countries. For instance, while age negatively predicted algorithmic knowledge in the United States, the United Kingdom, and South Korea, it did not have any predictive power in Mexico. Conversely, social media use was positively correlated with algorithmic knowledge in the United Kingdom, South Korea, and Mexico, but not in the United States. Education positively predicted algorithmic knowledge in South Korea and Mexico, but did not have any significant influence in the United States and the United Kingdom. Furthermore, in the United States and the United Kingdom, political ideology emerged as the primary predictor of the algorithmic knowledge gap, with individuals leaning more liberal demonstrating a greater understanding of social media algorithms compared to their conservative counterparts. In South Korea, gender was a notable predictor of the algorithmic knowledge gap, with male respondents demonstrating a significantly higher understanding of how social media algorithms operate compared to female respondents.

**Table 1.** Results of Structural Equation Modeling (SEM) analysis.

Variable	United States	United Kingdom	South Korea	Mexico
	$\beta$	$\beta$	$\beta$	$\beta$
Antecedents of Algorithmic Knowledge				
Age	-.01*	-.01**	-.02***	-.00
Gender	-.00	.03	.23**	-.05
Income	.00	-.02	.02	.02
Education	.02	-.00	.17***	.05*
Political ideology	.15***	.11***	.01	.01
Social media use	.04	.08*	.09*	.11*
Ethnicity	-.04*	-.02	N/A	N/A
Outcome of Algorithmic Knowledge				
Corrective actions	2.93**	1.43***	.07***	1.11*

Note: Ethnicity was not measured in Korea and Mexico, as they exhibit comparatively homogeneous racial compositions.

\* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

**Finding 2:** Algorithmic knowledge predicts actions to counter misinformation.

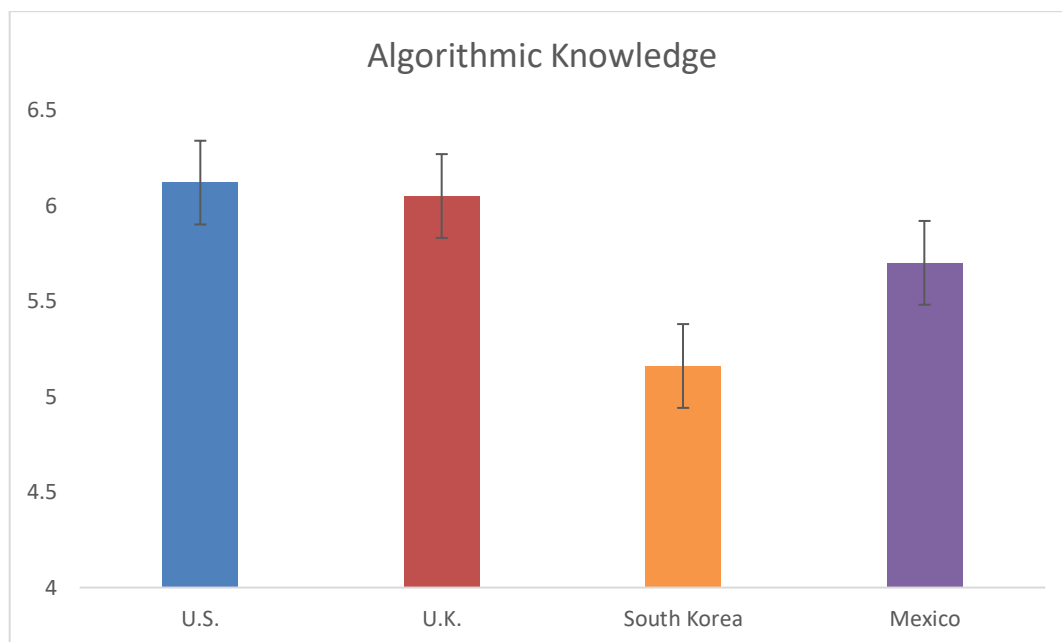
Varying levels of algorithmic knowledge prompt individuals to respond to misinformation differently, elucidating the real-world outcomes of the algorithmic knowledge gap (i.e., the third-level digital divide,

<sup>2</sup> Further analyses of the data revealed that individuals between 18–24 years (the United States and the United Kingdom) and 25–34 years (South Korea) demonstrated the highest levels of algorithmic knowledge (see Table 2 in Appendix A).

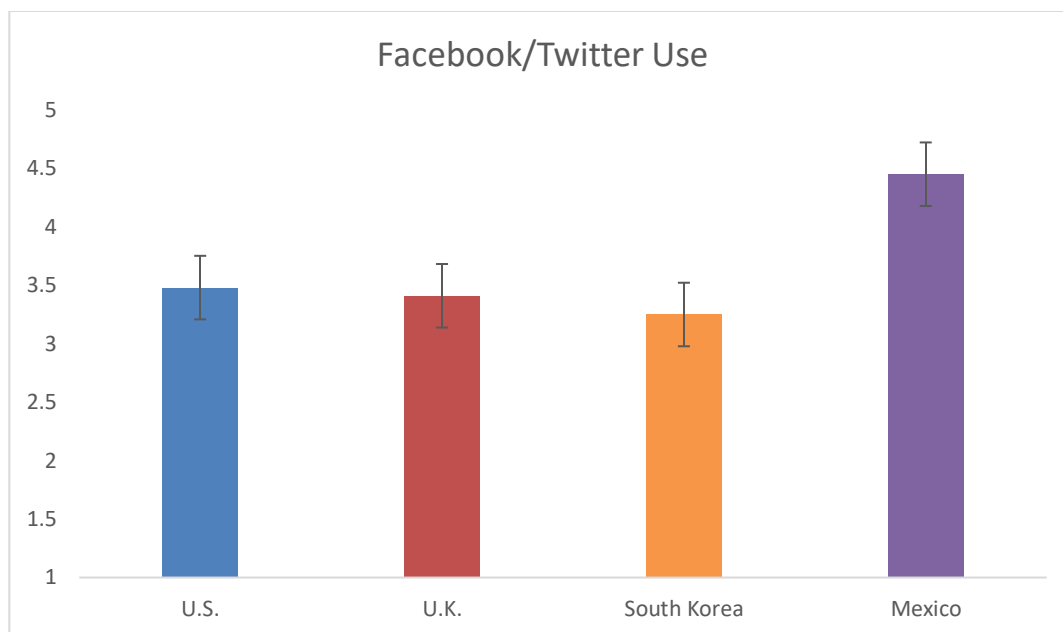
Fuchs, 2009; Scheerder et al., 2017). Specifically, algorithmic knowledge was positively associated with intentions to take corrective actions in all four countries (see Table 1). Those possessing higher algorithmic knowledge were more inclined to undertake actions to combat misinformation, such as commenting to caution against potential biases or risks in media messages, sharing counter-information or opinions, disseminating information exposing the flaws in the provided media content, and reporting a misinformation post to the social media platform, as compared to those lacking algorithmic knowledge.

*Finding 3: There are cross-country disparities in algorithmic knowledge.*

There was unequal distribution of algorithmic knowledge across countries. Respondents from the four countries exhibited significantly different levels of understanding about how social media algorithms work,  $F(3, 5428) = 107.28, p < .001$ . Notably, the U.S. respondents reported the greatest algorithmic knowledge ( $M = 6.12, SD = 1.73$ ), followed by the United Kingdom ( $M = 6.05, SD = 1.74$ ), Mexico ( $M = 5.70, SD = 1.49$ ), and South Korea ( $M = 5.16, SD = 1.76$ ). A Bonferroni post-hoc test indicated that there were no significant differences in the algorithmic knowledge level between respondents from the United States and the United Kingdom, whereas both groups exhibited significantly distinct levels of algorithmic knowledge compared to respondents from South Korea and Mexico, all  $ps < .001$ . Furthermore, respondents from South Korea exhibited notably lower levels of algorithmic knowledge compared to those from all other countries, all  $ps < .001$ .



**Figure 1. Algorithmic knowledge gaps across countries.** Algorithmic knowledge was measured using nine questions that gauged respondents' understanding of social media algorithms with yes/no options (for question items, see Table1 in Appendix C). The number of correct answers constituted the algorithmic knowledge index, with a possible range of 0 to 9.



**Figure 2. Social media (Facebook & X/Twitter) use across countries.** Social media use was measured with a question asking how much time respondents spend on Facebook or X/Twitter in a typical day (1 = never/almost never, 5 = more than 2 hours).

Relatedly, the levels of Facebook and X/Twitter use also differed significantly across countries,  $F(3, 5431) = 216.12, p < .001$ . A Bonferroni post-hoc test revealed significant differences in Facebook and X/Twitter use among respondents from the United States, Korea, and Mexico, all  $ps < .001$ . Notably, respondents from South Korea exhibited significantly lower levels of Facebook and X/Twitter use compared to those from all other countries, all  $ps < .001$ . Respondents from the United States and the United Kingdom did not show distinct levels of Facebook and X/Twitter use from each other. Although the varying levels of Facebook and X/Twitter use (see Figure 2) did not perfectly align with the pattern of the algorithmic knowledge gap between countries (see Figure 1), it is reasonable to suggest that social media use levels contributed to the between-country algorithmic knowledge gap to some extent. Nevertheless, considering that South Korea had higher overall social media access (83%) than the other three countries (see Table 3 in Appendix B), this issue may be related to the limitations of our algorithmic knowledge measurement discussed above.

## Methods

We conducted national surveys in the United States ( $N = 1,415$ ), the United Kingdom ( $N = 1,435$ ), South Korea ( $N = 1,718$ ), and Mexico ( $N = 784$ ) between April and September 2021. We used a non-probability-based quota sample to resemble the demographics of each country (see Table 1 in Appendix B). The four countries were chosen to reflect geographic diversity, a range of Internet experiences, and divergent approaches to digital literacy education (see Table 3 in Appendix B).

Respondents in the four countries were presented with the same questionnaire. We conducted a pre-test of the survey in English with students and faculty members ( $N = 29$ ) from the researchers' university network, approximately one-third of whom were from international/non-U.S. populations. Feedback from

respondents regarding question wording and order was integrated into the final survey questionnaire.<sup>3</sup> The survey questionnaire was administered in English in the United States and the United Kingdom. Respondents in South Korea received a Korean version, while respondents in Mexico received a Spanish version of the survey questionnaire. The English version was translated into Korean by a native Korean speaker and into Spanish by a native Spanish speaker with advanced English skills. We then performed back-translations to ensure accuracy.

*Algorithmic knowledge* was measured with nine questions with yes/no options that gauged participants' understanding of social media algorithms (modified from Brodsky et al., 2020; Powers, 2017; see Table 1 in Appendix C for question items). The number of correct answers constituted the algorithmic knowledge index (possible range of 0 to 9,  $M = 6.12$ ,  $SD = 1.73$  in the United States;  $M = 6.05$ ,  $SD = 1.74$  in the United Kingdom;  $M = 5.16$ ,  $SD = 1.76$  in South Korea;  $M = 5.70$ ,  $SD = 1.49$  in Mexico).

*Intention to take actions to counter misinformation* was measured by asking respondents how likely they are to take the following actions when they encounter misinformation on social media (modified from Barnidge & Rojas, 2014; Lim, 2017, 1 = extremely unlikely, 5 = extremely likely,  $M = 2.82$ ,  $SD = 1.13$ ,  $\alpha = .84$  in the United States;  $M = 2.58$ ,  $SD = 1.07$ ,  $\alpha = .83$  in the United Kingdom;  $M = 2.19$ ,  $SD = .93$ ,  $\alpha = .85$  in South Korea;  $M = 3.58$ ,  $SD = .93$ ,  $\alpha = .77$  in Mexico).

Sociodemographic variables including age, gender, education (1 = less than high school, 9 = doctoral degree), ethnicity (in the United States and the United Kingdom only, see Table 1 in Appendix B), monthly household income (the range varied across countries), and political views (1 = very conservative, 7 = very liberal) were measured.

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<sup>3</sup> Pre-test feedback primarily concerned confusing or unclear language in the survey. For instance, some pre-test respondents noted that "Report the post to the social media platform" was not specific enough to measure a corrective action. Therefore, we revised the item to "Report the post as misinformation to the social media platform."



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**Competing interests**

The authors declare no competing interests.

**Ethics**

The research protocol employed was approved by an institutional review board (IRB#: 21-03-22) at Northeastern University. All survey participants were provided informed consent. Ethnicity/gender categories used in this study were based on the American Community Survey and the U.K. Census survey.

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**Data availability**

All materials needed to replicate this study are available via the Harvard Dataverse:  
<https://doi.org/10.7910/DVN/7EHLMI>

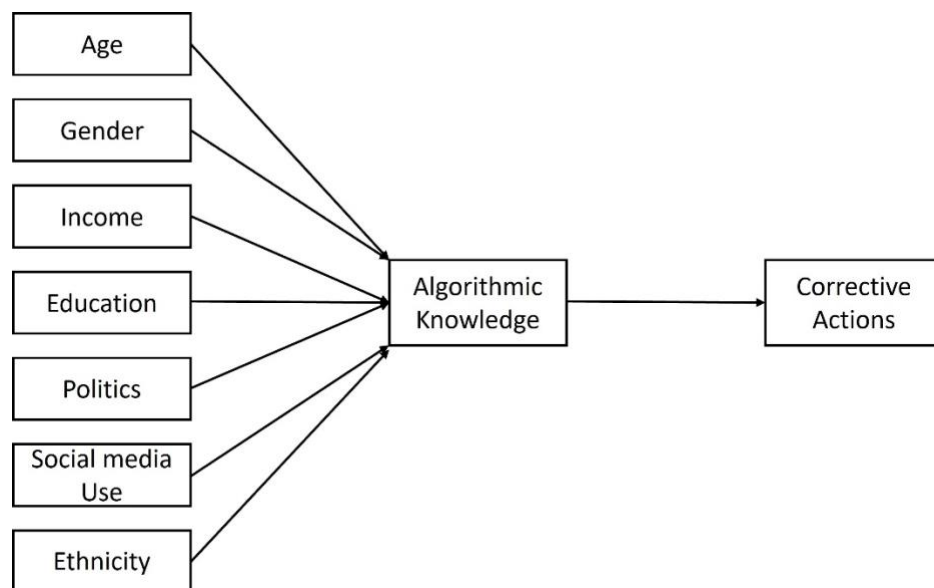
## Appendix A: Statistical analysis

To explore the predictors and the outcome of the algorithmic knowledge gap, we constructed a structural equation modeling (SEM) path model based on the theoretical model (see Figure 1) and carried out SEM analyses using a path analysis approach (SPSS AMOS 28). SEM enables the simultaneous use of multiple indicator variables for each construct, leading to more valid conclusions at the construct level. Alternative analysis methods often result in less clear conclusions and/or require multiple separate analyses.

We checked the fit indices of the SEM model with independent country samples. To ensure satisfactory model fit, the CFI needs to be no less than .95, and the RMSEA estimate should be smaller than .06. The results all met the criteria (see Table 1).

**Table A1.** SEM Model fit indices.

	$\chi^2$	df	p	CFI	RMSEA
United States	10.84	4	.028	.991	.035 (.010, .060)
United Kingdom	18.18	4	.001	.982	.050 (.028, .074)
South Korea	14.02	4	.000	.981	.037 (.017, .059)
Mexico	22.80	4	.000	.992	.026 (.000, .070)



**Figure A1.** Theoretical model for the predictors and the outcome of the algorithmic knowledge gap.

To conduct a more detailed analysis, we performed a series of one-way ANOVAs in the United States, the United Kingdom, and South Korea to determine which age group demonstrates the highest levels of algorithmic knowledge.

**Table A2.** ANOVA results.

Item	Country		
	United States <i>M (SD)</i>	United Kingdom <i>M (SD)</i>	South Korea <i>M (SD)</i>
Age group			
18 – 24	6.36 (1.78)	6.53 (1.63)	5.36 (1.71)
25 - 34	6.26 (1.78)	6.22 (1.63)	5.58 (1.79)
35 – 44	6.00 (1.75)	6.12 (1.66)	5.20 (1.71)
45 – 54	6.15 (1.72)	6.09 (1.73)	5.08 (1.75)
55 – 64	6.18 (1.65)	5.80 (1.85)	4.84 (1.72)
65 or older	5.73 (1.68)	5.78 (1.76)	4.57 (1.67)
ANOVA	$F(1414) = 3.376$ $p = .005$	$F(1434) = 5.327$ $p < .001$	$F(1797) = 9.711$ $p < .001$

*Note: Algorithmic knowledge was measured using nine questions that gauged respondents' understanding of social media algorithms with yes/no options (for question items, see Table 1 in Appendix C). The number of correct answers constituted the algorithmic knowledge index, with a possible range of 0 to 9.*

## Appendix B: Survey sample information

**Table B1.** Non-probability-based quota sampling in each country.

Country	Sample	Population
<b>United States</b>		
Age	43	46.7
Gender	50.8% Female	51.4% Female
Median income	\$50,000 – \$74,999	\$57,652
Ethnicity		
White	74.1%	73%
Black	13.1%	12.7%
Hispanics	4.4%	7.6%
Asian	6.6%	5.4%
<b>United Kingdom</b>		
Age	46	40.5
Gender	51.2% Female	51% Female
Median income	£18,000 – £35,999	£29,400
Ethnicity		
White	85.3%	86.0%
Black	3.5%	3.3%
Asian	7.7%	7.5%
Mixed/multiple ethnic	2.0%	2.2%
<b>South Korea</b>		
Age	44	44.3
Gender	49% Female	48% Female
Median income	KRW48,000,000 – KRW58,800,000	KRW4,384,000
<b>Mexico</b>		
Age	30.81	29.2
Gender	58.4% Female	51.1% Female
Median income	135,000 pesos – 164,999 pesos	158,876 pesos

*Note: The U.S. population information was based on the 2017 American Community Survey. The U.K. population information was based on the 2011 U.K. Census. South Korea population information was based on the 2021 Korean Statistical Information Service. Mexico population information was based on the 2020 World Bank data. The population statistics were the latest available at the time of the study.*

**Table B2.** Income range in each country.

Item	Country			
	United States	United Kingdom	South Korea	Mexico
Income range	0-\$24,999	0-£17,999	0 -KRW1,199,999	0 -180,000 Pesos
	\$25,000-\$49,999	£18,000-£35,999	KRW12,000,000 – KRW23,999,999	180,000 – 359,999 Pesos
	\$50,000-\$74,999	£36,000-£53,999	KRW24,000,000 – KRW35,999,999	360,000 – 539,999 Pesos
	\$75,000-\$99,999	£54,000-£71,999	KRW36,000,000 – KRW47,999,999	540,000 – 899,999 Pesos
	\$100,000-\$149,999	£72,000-£99,999	KRW48,000,000 – KRW5,999,999	900,000 – 1,499,999 Pesos
	\$150,000-\$199,999	£100,000-£124,999	KRW60,000,000 – KRW83,999,999	1,500,000 – 2,399,999 Pesos
	\$200,000 +	£125,000-£149,999	KRW84,000,000 – KRW95 999,999	2,400,000+ Pesos
		£150,000 +	KRW96,000,000 – KRW107,999,999  KRW108,000,000 – KRW119,999,999  KRW120,000,000 +	

**Table B3.** Internet penetration, social media access, digital literacy education across countries.

Item	Country			
	United States	United Kingdom	South Korea	Mexico
Internet penetration <sup>1</sup>	91%	94%	98%	64%
Social media access <sup>2</sup>	70%	66%	83%	67%
Digital literacy education <sup>3</sup>	78.8%	67.6%	49.1%	62.3%

Notes: 1) Internet penetration rate for population as of 2020 (Statistica, n.d.); 2) Social media access rate for population as of 2021 (DataReportal, 2021); 3) Digital literacy education rate for 15-year-old students (OECD, 2021).<sup>4</sup>

**Table B4.** Social media usage across countries.

Question	Country			
	United States	United Kingdom	South Korea	Mexico
In a typical day, how much time do you spend on social media (e.g., Facebook, X/Twitter)?				
Never/almost never	89 (6.3%)	119 (8.3%)	0 (0%)	5 (0.6%)
Less than 30 minutes	253 (17.9%)	266 (18.5%)	575 (32.0%)	30 (3.8%)
Less than 1 hour	282 (19.9%)	293 (20.4%)	521 (29.0%)	59 (7.5%)
1 – 2 hours	465 (32.9%)	417 (29.1%)	386 (21.5%)	201 (25.6%)
More than 2 hours	326 (23.0%)	340 (29.7%)	316 (17.6%)	489 (62.4%)
Total N	1,415 (100%)	1,435 (100%)	1,798 (100%)	784 (100%)

<sup>4</sup> In the United States, robust digital literacy education initiatives like the Digital Literacy Initiatives overseen by the Department of Education have been praised by the public and education experts, along with ongoing discussions and policy proposals concerning algorithmic accountability (Heikkilä, 2022). In the United Kingdom, there has been early consideration of integrating comprehensive digital literacy education into the national curriculum (Polizzi, 2020), alongside various governmental and educational institutions offering programs such as courses like Being a Digitally Literate Student (University of Oxford, 2023). In Mexico, the Network for Media and Information Literacy, a collaborative effort involving institutions, academia, and civil society organizations, has developed courses focused on media and information literacy (UNESCO, 2021). While such efforts were not as prominent at the time of data collection compared to other countries, South Korea's Ministry of Education has since integrated more digital literacy into the 2022 revised national curriculum, with plans to introduce new textbooks starting in 2024 (Ministry of Education, 2021).



## Appendix C: Survey questions

*Table C1. Questions to measure algorithmic knowledge and corrective actions.*

Variable	Questions
Algorithmic knowledge (yes/no)	<ol style="list-style-type: none"> <li>1. Does Facebook’s News Feed always show you every news item posted by the people or organizations you follow?</li> <li>2. Does Facebook allow you to adjust your News Feed preferences to affect the posts you see and in what order?</li> <li>3. Does each of the following affect either the type of news you find on your Facebook News Feed or the order in which posts are displayed? <ul style="list-style-type: none"> <li>- your actions (i.e., search and click history, status updates, liking a post)</li> <li>- actions your friends take (sharing a link, commenting on a post)</li> <li>- actions that users you don’t know take (aggregate page views and shares)</li> <li>- actions taken by engineers, editors, or curators (tweaking the algorithm, considering editorial judgments made by news outlets)</li> </ul> </li> <li>4. Does X/Twitter show you tweets and retweets from people you do not follow, but whom your friends follow?</li> <li>5. Does the X/Twitter timeline show the standard chronological flow of content?</li> <li>6. Does X/Twitter allow you to choose the content you see (e.g., top tweets vs. latest tweets)?</li> </ol>
Corrective actions (1 = extremely unlikely, 5 = extremely likely)	<p>How likely are you to do the following when you encounter misinformation on social media?</p> <ul style="list-style-type: none"> <li>- Leave comments to inform others of the harm of the misinformation</li> <li>- Share news or information that refutes the misinformation</li> <li>- Share news or information that reports the harmful consequences of the misinformation</li> <li>- Report the post as misinformation to the social media platform</li> </ul>