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Assessing and fostering college students' algorithm awareness across online contexts

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ABSTRACT

Internet users may fail to recognize how algorithms filter and personalize information. Two studies explored college students' algorithm awareness across varying contexts. Study 1 examined Facebook users' awareness of its algorithms (N = 222). Only about half recognized that Facebook does not show all their friends' posts. These students more often reported making adjustments to News Feed settings than students lacking algorithm awareness. Study 2 compared students' (N = 244) algorithm awareness for online shopping and search, and the efficacy of video instruction to increase awareness. Students were more algorithm aware for online shopping. Compared to those who watched a video on Internet storage, students who watched a video on Internet algorithms showed greater understanding of how search results are personalized. Across studies, students demonstrated high media literacy knowledge, yet knowledge was inconsistently related to algorithm awareness. This suggests the need to incorporate instruction about algorithms into media literacy curricula.

Keywords: *algorithm awareness, media literacy, Facebook, online instruction.*

INTRODUCTION

Students today spend an unprecedented amount of time on the Internet (Anderson & Jiang, 2018). Despite their familiarity with the Internet's varied affordances for socializing, shopping, searching, and the like, students lack technical understanding of its underlying structure and the mechanisms that govern its search functions (Yan, 2009). Current media literacy curricula do not focus on how algorithms personalize online information feeds. Traditionally, media literacy knowledge is characterized as students' understanding of how media messages are constructed and interpreted (Hobbs & Jensen, 2009). However, several scholars have called for more direct instruction in algorithm literacy (Cohen, 2018; Head et al., 2020) to develop students' awareness of how algorithms shape online experiences and the implications of relying on these algorithms. To inform these efforts, we conducted two studies that examined undergraduates' awareness of personalization algorithms across different online contexts: social media feeds, shopping, and search results.

Personalization algorithms

Popular information "gatekeeping" websites, such as Facebook and Google, use multiple algorithms to select what information Internet users see (Bozdag, 2013). Among these algorithms is the personalization algorithm, which aims to increase the relevance of each user's content based on data collected from them and others with similar profiles. While users may explicitly provide some data (e.g., demographics, preferences), other data are collected more subtly by tracking online behavior (e.g., queries, clicks). By accumulating massive quantities of profiling data from Internet users, in conjunction with other factors (e.g., paying advertisers), companies develop algorithms that filter what users see in their social media feeds, shopping recommendations, and search results.

Broadly defined, an algorithm is a model for transforming input (i.e., data) into output (e.g., a decision, classification, or prediction). Scholars (e.g., Bozdag, 2013; Bucher, 2018) have warned that the computational nature of algorithms does not make algorithm-generated decisions objective. Rather, algorithms reflect the choices made by their developers, from the types of data collected to the types of outputs desired. As a profit-driven company, Facebook's developers may design the News Feed algorithm to increase the visibility of advertisements by prioritizing information that will keep users on their site (Tufekci, 2017). Similarly, Google's developers may design search algorithms to prioritize results from large companies and advertisers (Grind et al., 2019). As products of human decisions, algorithms may reflect individual and societal biases, including discriminatory biases based on race or sex (Noble, 2018; O'Neil, 2016).

Algorithms are not passive mechanisms. Rather, they directly influence users' online behaviors and are directly influenced by users' behaviors (Bucher, 2018). Personalization algorithms have been criticized for creating "filter bubbles" (Pariser, 2011) where users only encounter information and interactions that echo their own views and preferences. At the same time, users demonstrate varying levels of engagement with algorithms. Based on a survey of 3441 social media users (M_{age} = 44 years), Min (2019) identified four types of users varying in how they controlled their social media information feeds: those unaware of algorithms and doing nothing, those curating through negative actions (e.g., blocking, unfollowing) to receive less news, those curating through positive actions (e.g., liking, following) to receive more news, and those aware and actively trying to manipulate the algorithm. Time spent on social media sites, size of social networks, political efficacy, and Internet skills were positive predictors of algorithm engagement, while age was a negative predictor.

College students' algorithm awareness and engagement

Min (2019)'s findings suggest that younger social media users may have greater awareness of algorithms and make greater efforts to manipulate them than older users. Yet, in an online survey of U.S. college students (N = 147), Powers (2017) found that most were unaware that information on Facebook's News Feed and Google News was personalized via algorithms. As in Min (2019), users who spent more time on the sites more often reported knowing how to adjust what they saw. Similarly, another study with a small, diverse sample (N = 40) reported that most were unaware that Facebook's algorithm customizes content in the News Feed (Eslami et al., 2015). Algorithm awareness was associated with frequency of Facebook usage and active behaviors such as posting, adjusting News Feed settings, and managing a Facebook group. In contrast to these negative findings, a recent study utilizing focus groups of U.S. college students (N = 103; Head et al., 2020) suggested that many young adults are aware that companies like Facebook, Amazon, and Google collect data to target advertisements and personalize users' experiences. While students recognized the convenience of these companies' services, they expressed concerns about the use of algorithms, including violations of privacy, perpetuation of social inequalities, and filter bubbles. Students also reported using strategies such as ad blockers to protect their privacy.

In focus groups conducted by Head et al. (2020), students described learning about algorithms through their own online experiences and interactions with peers, rather than through formal instruction. This finding is in keeping with previous research that social media users generate informal understanding (i.e., "folk theories") about how algorithms work through abductive reasoning (Eslami et al., 2016), meaning that their understanding is formed through observation and synthesis of their daily experiences with platforms (Devito et al., 2018). Bucher (2018) describes this algorithmic awareness and engagement as the *algorithmic imaginary*, i.e., the "ways of thinking about what algorithms are, what they should be, how they function, and what these imaginations, in turn, make possible" (p. 113).

Increasing algorithmic literacy as part of media literacy instruction

Media literacy instruction seeks to improve students' ability to access, analyze, evaluate, create, reflect, and act on media content (Hobbs, 2010). Such instruction often emphasizes that content is created for target audiences, may be biased and interpreted from multiple perspectives, and varies in its representation of reality (Hobbs & Jensen, 2009). Previous research (Brodsky et al., 2020) suggests that undergraduates have high general media literacy knowledge, though this knowledge is unlikely to include knowledge about how algorithms work. Cohen (2018) argues that traditional media literacy instruction in the "deconstruction and analysis" of specific media content be expanded to teach students to think critically about the ever-changing, personalized media environment or "echo-system" created by algorithms. Students should recognize that personal data are collected and shared, learn about inferences that algorithms make about users from that data, and critically consider decisions made by algorithm developers. Valtonen and colleagues (2019) argue that media literacy education should incorporate instruction about the computational mechanisms themselves (e.g., tracking, filtering, recommendation). Similarly, Head and colleagues (2020) call for developing, "critical awareness of what algorithms are, how they interact with human behavioral data in information systems, and an understanding of the social and ethical issues related to their use" (p. 49).

Research objectives

We present results from two online surveys investigating undergraduates' algorithm awareness across three popular online contexts. Study 1 examined the relationship between algorithm awareness and engagement on a social media site (Facebook), while Study 2 delved deeper into students' algorithm awareness in the contexts of online shopping and of searches. Given calls to expand the focus of media literacy curricula beyond media content to include media environments, we assessed whether algorithmic awareness was related to students' general media literacy knowledge, using validated scales adapted from studies of media literacy in relation to advertising (Bier et al., 2011) and news production (Ashley et al., 2013). In keeping with recommendations for direct instruction on how algorithms personalize their online experiences, we assessed the efficacy of a brief video for increasing students' algorithm awareness and understanding.

STUDY 1

Study 1 asked whether college Facebook users are algorithm aware, defined as knowing that content in their News Feed is filtered, and whether awareness is related to algorithm engagement, defined as making News Feed adjustments, Facebook usage, and general media literacy knowledge. Our research questions were as follows:

- Is algorithm awareness related to algorithm engagement?
- Is algorithm awareness related to Facebook usage?
- Is algorithm awareness related to general media literacy knowledge?

METHOD

Participants

Undergraduates were recruited through a subject pool at a large, urban public university in the northeastern United States. The subject pool comprised students taking Introductory Psychology, a 100-level general education course with a research participation requirement. As an open enrollment institution, the university has a diverse student body, including many students from underrepresented communities. As of Fall 2019, undergraduate enrollment was 54.5% female, with 39.3% under 20 years old, 42.2% 20 to 24 years old, 9.2% 25 to 29 years old, 5.6% 30 to 39 years old, and 3.6% over 40 years old (Office of Institutional Research, n.d.). Students' race/ethnicity was 44.3% White, 26.5% Hispanic/Latinx, 13.1% Black/African American, 11.0% Asian, and 5.1% Other.

Participation was open to students who reported using Facebook accounts at least rarely (N = 222, 59.3% female, M_{age} 20.0 years, SD 2.8, range 18 to 34). Students self-reported race/ethnicity as follows: 39.8% White, 26.7% Hispanic/Latinx, 16.3% Black/African American, 13.6% Asian, 3.6% Other. Students reported their mother's highest level of education as follows: 21.9% some high school, 31.1% finished high school, 20.6% some college/special schooling after high school, 16.9% finished college, 5.5% schooling beyond college, 4.1% did not have someone with the role of mother in their family. In addition to the 222 participants, 19 survey entries were removed due to duplicate or missing fields (n = 3), insufficient/excessive time (< 10 minutes, n = 3; > 6 hours, n = 7), or lack of variability on Likert scales (i.e., careless responses, n = 6).

Materials

Facebook algorithm awareness. Students were presented with questions, adapted from Eslami et al. (2015), assessing awareness of Facebook's News Feed algorithm. Students saw the prompt *One of your Facebook friends posts a story to her timeline. The post is set to be visible to all her friends. Will her story appear in your News Feed?* paired with response options "Yes," "No," or "Maybe."

They then indicated "Yes" or "No" for each of a set of reasons why they would not see their friend's story: *I scroll too quickly through my News Feed*; *I do not check Facebook often enough*; *Facebook does not show me all the stories that my friends post*; and *Other*. For *Other,* students could enter a text explanation.

Facebook News Feed adjustment. Students were shown methods for adjusting settings for their Facebook News Feed, such as switching from seeing most popular stories to most recent stories first, and asked if they had ever adjusted settings using that method. Items were adapted from Eslami et al. (2015), see Table 1 for items.

Facebook usage. Students responded to the question *How often do you go to Facebook?* on a 5-point Likert scale ranging from "never" (1) to "constantly" (5). The scale included the option "I do not use Facebook" (–9) which along with "never" (1) served as a means of excluding students who did not meet inclusion criteria. Students who indicated that they go to Facebook at least "rarely" (2) were asked to indicate *How often do you post stories on Facebook?* on a 5-point Likert scale ranging from "never" (1) to "constantly" (5). Students were also asked if they managed a Facebook page or group and if they had ever created a Facebook account and then deleted or deactivated it.

Media literacy scale. This scale, adapted from Powers et al. (2018), presented 16 statements assessing general media literacy knowledge (see Table 3 for items). Students indicated the extent to which they agreed or disagreed with each statement using a 4-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (4). To assess media literacy knowledge, responses were re-coded for accuracy, with responses of "agree" (3) and "strongly agree" (4) re-coded as "correct" (1) and responses of "strongly disagree" (1) and "disagree" (2) recoded as "incorrect" (0). Of the 16 items, 3 were reverse-scored. Missing data (< 2%) were imputed using item means. The scale showed high internal consistency (α = .83).

Procedure

Institutional Review Board approval was granted to gather de-identified responses via the Qualtrics online platform with the survey link posted to the SONA Systems experiment management system. Students received research participation credits by entering the survey and could exit at any time with no consequence. The survey was expected to take approximately 45 minutes to complete. Median length of time for completion was 38.4 minutes.

Materials were presented in the following order: first set of demographic questions, Facebook usage, Facebook algorithm awareness, Facebook News Feed adjustment, history of managing a Facebook group and deleting or deactivating a Facebook account, media literacy scale, second set of demographic questions.

RESULTS

For each research question, we present descriptive statistics followed by inferential statistics addressing the question. All analyses were run in *R* (R Core Team, 2018; RStudio Team, 2016).

Is algorithm awareness related to algorithm engagement? We first examined different ways that students might indicate awareness of the Facebook algorithm.

When asked if a public story posted by their Facebook friend would appear in their News Feed, 55.4% responded "Yes," 38.3% "Maybe," and 6.3% "No." When asked why they might not see the story, we coded "algorithm aware" as responding "Yes" to *Facebook does not show me all the stories that my friends post*, with 51.4% of students coded as aware. Students who indicated "Maybe" to the first question were more likely to be algorithm aware, X^2 (1, N = 222) = 22.98, p < .001.

Table 1. *Percentages of students making Facebook News Feed adjustments for Study 1 (N = 222)*

Adjustment type	**Percentage**
Snoozed or unfollowed a person, Page or group to hide their posts from my News Feed	57.2%
Prioritized whose stories to see first in my News Feed	30.5%
Liked or followed a person, Page, or group to show their posts in my News Feed	71.8%
Switched from seeing most popular stories to most recent stories first in my News Feed	39.8%
Hidden a story from a person, Page, or group in my News Feed	45.5%
Used lists to organize friends	26.4%

Table 2. *Percentage of students who made News Feed adjustments and used Facebook by whether or not students responded "maybe" to the News Feed prompt or were classified as algorithm aware (N = 222)*

	Responded "Maybe"		**Algorithm aware**	
	%	X^2 (df = 1)	%	X^2 (df = 1)
Made no adjustments to News Feed (N = 39)	48.7%	2.18	33.3%	6.15*
Made at least one adjustment to News Feed (N = 183)	36.1%		55.2%	
Low user (N = 109)	47.7%	8.04**	47.7%	1.14
High user (N = 113)	29.2%		54.9%	
Passive user (N = 197)	40.6%	5.21*	51.8%	0.30
Active user (N = 24)	16.7%		45.8%	
Does not manage a page or group (N = 166)	38.0%	0.03	50.6%	0.15
Manages a page or group (N = 56)	39.3%		53.6%	
Has not deleted or deactivated an account (N = 112)	35.7%	0.63	49.1%	0.46
Deleted or deactivated an account (N = 110)	40.9%		53.6%	

*p < .05; **p < .01

We then examined different ways that students might engage with the Facebook algorithm by adjusting News Feed settings. Most students (82.4%) reported making at least one adjustment to their News Feed. They made an average of 2.70 out of six possible adjustments (*SD* 1.92); see Table 1 for percentages of students making each adjustment.

To examine the relationship between algorithm awareness and engagement, we ran Chi-square tests to determine if responding "Maybe" to the News Feed prompt or being classified as algorithm aware was related to adjusting News Feed settings. The top section of Table 2 indicates that students who made at least one adjustment to their News Feed settings were not more likely to respond "Maybe" than students who made no adjustments.

However, students who made at least one adjustment to their News Feed settings were more likely to be classified as algorithm aware than students who made no adjustments.

Table 3. *Media literacy scale for Study 1 (N = 222)*

Item	***M***	

Item	$M_{\text{agreement}}$ ***(SD)*** ***Max = 4***	M_{accuracy} ***(SD)***
Most of the time, when people advertise products they are more concerned about making a profit than giving correct information.	3.21 (.59)	90.5% (29.3)
When you see something on the Internet you can always believe that it is true. (reverse-scored)	3.26 (.83)	80.3% (39.5)
Photos your friends post on social media are an accurate representation of what is going on in their life. (reverse-scored)	2.84 (.81)	68.8% (46.3)
Sending a document or picture to one friend on the Internet means no one else will ever see it. (reverse-scored)	3.15 (.77)	80.9% (39.2)
Movies and TV shows don't usually show life like it really is.	3.10 (.67)	86.9% (33.8)
Advertisements usually leave out a lot of important information.	3.05 (.64)	81.4% (38.9)
When you see an ad, it is very important to think about what was left out of the ad.	2.96 (.67)	78.6% (40.9)
When you see something on the Internet you look at the source before deciding if it is trustworthy.	2.99 (.67)	81.3% (38.8)
Two people may see the same movie or TV show and get very different ideas about it.	3.33 (.60)	93.6% (24.3)
Two people may see the same advertisement and get very different ideas about it.	3.26 (.54)	95.9% (19.8)
When people make movies and TV shows, every camera shot is very carefully planned.	3.28 (.61)	91.3% (28.0)
When people make advertisements, every camera shot is very carefully planned.	3.23 (.60)	91.0% (28.7)
People are influenced by TV and movies whether they realize it or not.	3.29 (.56)	94.5% (22.7)
People are influenced by advertisements whether they realize it or not.	3.20 (.63)	91.8% (27.3)
When you see something on the Internet the creator is trying to convince you to agree with their point of view.	3.05 (.55)	87.7% (32.7)
People who advertise think very carefully about the people they want to buy their product.	3.16 (.67)	85.0% (35.6)
Mean	3.15 (.35)	86.2% (13.0)

Note: Regular items should be interpreted on a scale of *1* = strongly disagree to *4* = strongly agree. Reverse-scored items should be interpreted on a scale of *1* = strongly agree to *4* = strongly disagree.

Next, we ran independent-samples *t*-tests to determine if responding "Maybe" to the News Feed prompt or being classified as algorithm aware was associated with the number of News Feed adjustments. Responding "Maybe" to the News Feed prompt was unrelated to the number of adjustments made, $t(220)= 0.87$, $p = .384$. In contrast, algorithm-aware students used more methods of adjustment (*M* 2.97, *SD* 1.87) than unaware students (*M* 2.40, *SD* 1.88), $t(220)= –2.28$, $p = .023$.

Is algorithm awareness related to Facebook usage? As a first step in exploring whether algorithm awareness was related to Facebook usage, we examined different ways that students might use Facebook. Students (50.9%) who reported using Facebook often or constantly were categorized as high users; those (49.1%) who reported going to Facebook rarely or sometimes were categorized as low users. High users (M_{age} 20.5 years, *SD* 3.4) tended to be older than low users (M_{age} 19.5 years, *SD* 1.8), $t(166.9) = –2.98$, $p = .003$. Students (89.1%) who reported never, rarely, or sometimes posting stories on Facebook were grouped together as passive users. The remaining 10.9% who reported often or constantly posting stories on Facebook were grouped as active users. High users were more likely to be active users, X^2 $(1, N = 221) = 18.10$, $p < .001$. The percentage of students who had managed a Facebook group was 25.2% and 49.6% had deactivated or deleted a Facebook account at some point.

Next, we ran Chi-square tests to determine if responding "Maybe" to the News Feed prompt or being classified as algorithm aware was related to different types of Facebook usage, see Table 2. Low Facebook users and passive users were more likely to respond "Maybe" to the News Feed prompt than high Facebook users and active users. Facebook usage was unrelated to being classified as algorithm aware.

Is algorithm awareness related to general media literacy knowledge? Lastly, we examined students' general media literacy knowledge. Students demonstrated high media literacy knowledge ($M_{\text{agreement}}$ 3.15 out of 4, *SD* 0.35; M_{correct} 86.2%, *SD* 13.0%); see Table 3 for item means. We ran independent samples *t*-tests to determine if responding "Maybe" to the News Feed prompt or being classified as algorithm aware was associated with general media literacy knowledge. Students who did and did not respond "Maybe" to the News Feed prompt did not differ in media literacy knowledge (86.0% v. 86.3%, $t(220)=0.20$, $p = .844$). Algorithm-aware and unaware students also did not differ in media literacy knowledge (85.4% v. 87.0%, $t(220)=0.91$, $p = .36$).

Discussion

Study 1 examined Facebook users' awareness that content in their News Feed is filtered and how this awareness related to their News Feed adjustments, Facebook usage, and general media literacy knowledge. Replicating Eslami et al. (2015), only about half of students recognized that Facebook does not display all their friends' posts. Such awareness was associated with higher algorithm engagement by making greater numbers of adjustments to Facebook settings. However, since these findings are correlational, we cannot conclude that increased awareness led students to make more News Feed adjustments. Additional qualitative research is needed to understand students' motivations for adjusting News Feed settings.

Unlike previous findings showing algorithm-aware individuals to be heavier Facebook users (Eslami et al., 2015; Powers, 2017), awareness that Facebook curates users' News Feeds was unrelated to frequency of Facebook visits and behaviors including posting, managing a page or group, or deactivating or deleting an account. Heavy Facebook engagers may be underrepresented in our sample, as it comprised mostly infrequent posters with only a quarter managing Facebook pages or groups. With other social media sites gaining in popularity, it is unclear how many undergraduates qualify as heavy Facebook users. We found high users to be somewhat older than low users, aligning with Shane-Simpson et al.'s (2018) finding that students who reported Facebook as their preferred social media site tended to be older than those who preferred Instagram or Twitter.

Both algorithm-aware and unaware groups demonstrated high media literacy knowledge and did not differ in knowledge. This conceptual divide is not surprising; as Cohen (2018) highlights, media literacy instruction has traditionally focused on interrogating how specific media content is created and perceived, while understanding algorithms involves thinking about how the entire media environment is formed.

STUDY 2

In addition to social media sites, algorithms shape online experiences across a variety of other contexts. Study 2 explored undergraduates' algorithm awareness in online shopping and search contexts while assessing the efficacy of a brief instructional video in increasing understanding. Our research questions were as follows:

- To what extent are students aware of the role of algorithms in online shopping?
- Does watching a video about algorithms increase awareness of the role of algorithms in online searches?
- Is algorithm awareness for online searches related to algorithm awareness for online shopping?
- Is algorithm awareness for online shopping and online searches related to media literacy knowledge?

METHOD

Participants

Undergraduates were recruited through the same subject pool as Study 1. Participation was open to 18- to 34-year-olds (*N* = 244, 60.3% female, M_{age} 19.7 years, *SD* 2.6). Students self-reported race / ethnicity as follows: 33.2% White, 27.8% Hispanic/Latinx, 18.7% Black/African American, 13.3% Asian, 7.1% Other. Students reported maternal education as follows: 18.7% some high school, 29.5% finished high school, 19.1% some college/special schooling after high school, 21.2% finished college, 7.9% schooling beyond college, 3.7% did not have someone with the role of mother in their family. An additional 66 survey entries were removed due to non-consent (*n* = 4), duplicate or missing fields (*n* = 7), insufficient/excessive time (< 10 minutes, *n* = 15; > 6 hours, *n* = 31), or lack of variability on Likert scales (*n* = 9).

Materials

Instructional videos. Students watched custom-made animated videos about the Internet. Each video is approximately five minutes long. The treatment group watched *How do algorithms help you search the Internet?*[1], which explained algorithms using the example of male and female shoppers experiencing different search results based on gender stereotypes. The control group watched *How does the Internet work?*[2], which explained how the Internet stores information using the example of photo-sharing on social media.

Algorithm awareness questions. Students responded to five open-ended questions: Three questions assessed understanding of how algorithms customize online shopping and two assessed understanding of how algorithms customize search results.

We adopted a keyword approach to code the open-ended responses; see Table 4. Relevant terms were identified from Powers (2017) and by scanning responses for additional keywords related to tracking search histories, tailoring information to match user profiles, and geolocation. Responses containing at least one relevant keyword were scored as 1; responses with no relevant keywords were scored as 0. Scores were manually reviewed and verified. On average, the agreement between keyword and manual scoring was 81.5% (*SD* 7.2%, *Range* 71.3% - 91.4%).

Media literacy scale. We adapted the media literacy scale from Study 1 to include items about news media literacy (Ashley et al., 2013) and add more reverse-scored items. We also changed the Likert scale from 4 points to 5 points to increase validity, since the 4-point scale may have forced students with a neutral attitude to indicate a level of agreement. Students indicated the extent to which they agreed/disagreed with each of 18 statements using a 5-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (5). Responses of “agree” (4) and “strongly agree” (5) were recoded as “correct” (1) and responses of “strongly disagree” (1), “disagree” (2), and no opinion (3) as “incorrect” (0). Six items were reverse-scored. The 18-item scale showed adequate internal consistency (α = .73); reliability increased after removing an item with low item-rest correlation (–.02) (α = .76). The 17-item scale was used in analyses.

Procedure

Materials were presented in the following order: first set of demographic questions, algorithm awareness for online shopping, media literacy scale, instructional video, algorithm awareness for online searches, second set of demographic questions. The survey was expected to take approximately 45 minutes to complete. Median length of time for completion was 44.0 minutes.

Results

For each research question, we present descriptive statistics followed by inferential statistics addressing the question. All analyses were run in *R* (R Core Team, 2018; RStudio Team, 2016).

[1] https://youtu.be/_iLBHp-ITPo

[2] https://youtu.be/lnaXEk37Fmk

Table 4. *Keywords for scoring online shopping and online search questions and examples of responses for Study 2*

Theme	Keywords	Examples for online shopping questions	Examples for online search questions
Search history	search*; history; past; previous; track; collect; cache; save; store; cookie	"The internet uses its own search engines and cookies to develop an idea and history of the kind of shopping habits one develops."	"Due to history and past searches it knows what to show you and what most people have searched."
Tailored information	algorithm; filter	"They have algorithms that suggest products similar to products you've looked up or bought."	"The internet uses an algorithm that tracks your interest and shows you what they think you want to see."
Geo-location	location	"The internet can limit products we see through features like our location and demographics."	"By checking where your location is, determining your potential net worth, political affiliation, etc."
Interests / preferences	interest	"The internet follows what you like and don't like. They know interests from what you search up."	"The internet is made to share the same types of content to the same types of people, so if you are interested in cars, the internet is set up so that you come into contact with people and posts that include cars and everything to do with them."

* "Search" was not used as a keyword for online search questions because the keyword appeared in the prompt.

To what extent are students aware of the role of algorithms in online shopping? We first examined algorithm awareness in the context of online shopping. The top section of Table 5 presents percentages of algorithm-aware students by question and group and the top section of Table 6 presents examples of responses. Chi-square tests indicated that treatment and control groups did not differ in their responses to the online shopping questions administered prior to the videos (see Table 5 for results of Chi-Square tests). Across groups, most students demonstrated awareness that the Internet tracks what they have been shopping for (84.4%) and uses the information to recommend products (91.0%). Only about half (50.4%) referenced algorithms or personalization when asked how the Internet limits what products they see.

Does watching a video about algorithms increase awareness of the role of algorithms in online searches? Next, we examined algorithm awareness in the context of online searches. The bottom section of Table 5 presents percentages of algorithm-aware students by question and group and the bottom section of Table 6 presents examples of responses. Chi-square tests indicated that, for each online search question, students in the treatment group who watched the video about algorithms were more likely to demonstrate algorithm awareness than students in the control group (see Table 5 for Chi-Square test results).

Is algorithm awareness for online searches related to algorithm awareness for online shopping? To address our third aim, we examined associations between students' algorithm awareness for online shopping and online searches by conducting a series of McNemar's tests. When running these tests, we were interested in the proportion of students in the treatment group who showed algorithm awareness on an online shopping question but not on an online search question, and vice versa.

Students in the treatment group were more likely to express algorithm awareness in response to either of the first two online shopping questions than for either question about online search results ($p < .001$). For the third, and most difficult, shopping question *How does the Internet limit what products you see online?*, students were more likely to answer this question correctly than the search question *How does the Internet help you find information you need?* ($p < .001$).

Table 5. *Percentage of students demonstrating algorithm awareness in Study 2*

Question	Control ($N = 127$)	Treatment ($N = 117$)	X^2 ($df = 1$)
Online Shopping			
After shopping online, you might see an ad for the product you bought somewhere else on the Internet, like on your social networking site or on YouTube. How does the Internet know what you have been shopping for?	83.5%	85.5%	0.19
How does the Internet figure out what products to recommend to you?	90.6%	91.5%	0.06
How does the Internet limit what products you see online?	48.8%	52.1%	0.27
Online Searches			
How does the Internet help you find information you need?	12.7%	27.6%	8.42**
When you search for information, how does the Internet decide what results to show you first?	30.6%	60.0%	20.79***

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

Table 6. *Examples of responses to algorithm awareness questions in Study 2*

Prompt	Participant A	Participant B
How does the Internet know what you have been shopping for?	"When you do anything on the internet your activity is being monitored by the company that owns the device you are accessing through and they then use this information to send you ads to make money."	"I guess through memory it saves what the user was looking at previously and tries to grab his/her attention again."
How does the Internet figure out what products to recommend to you?	"The internet figures this out by looking at your recent activity and what you like on social media and compiles a list of related items or activities."	"It takes information from things you've previously searched."
How does the Internet limit what products you see online?	"The internet does this by looking at your past activity and what you like and dislike to limit your exposure to the things that you dislike."	"It can ask for proof of identity or age before allowing you to see something."
How does the Internet help you find information you need?	"The internet is helpful for getting information by making it easier to obtain any information shared but also to share information with others."	"It helps you by exposing others information to you."
When you search for information, how does the Internet decide what results to show you first?	"The internet decides what to show you when you search for information by showing the most popular results first or the result that got the most clicks."	"It analyzes the words you use in your search."

This difference was not significant for the second search question, *When you search for information, how does the Internet decide what results to show you first?* (p = .272). Thus, the results of five of six McNemar's tests suggest that students may recognize that the Internet uses tracking mechanisms to promote products via advertisements that match users' interests and previous searches, but fail to detect similar processes at work in delimiting search results. As shown in Table 6, students who used terms like "past activity" and "previously searched" in relation to online shopping often failed to use these terms in relation to online search results.

Is algorithm awareness for online shopping and online searches related to media literacy knowledge? To address our final aim, we examined whether algorithm awareness for online shopping and searches was related to general media literacy knowledge. Students demonstrated high media literacy knowledge, with $M_{agreement}$ 3.99 out of 5 (SD 0.40) and $M_{accuracy}$ 78.7% (SD 17.3); see Table 7.

An independent samples t-test indicated that treatment (M 77.7%, SD 18.5) and control groups (M 79.6%, SD 16.2) did not differ in media literacy knowledge, $t(242) = 0.87$, p = .383.

Table 7. *Media literacy scale for Study 2 (N = 244)*

Item	$M_{agreement}$ (SD) Max = 5	$M_{accuracy}$ (SD)
A news story that has good pictures is less likely to get published. (reverse-scored)	3.37 (.93)	48.0% (50.1)
People who advertise think very carefully about the people they want to buy their product.	4.00 (.98)	80.7% (39.5)
When you see something on the Internet the creator is trying to convince you to agree with their point of view.	3.82 (.83)	77.9% (41.6)
People are influenced by news whether they realize it or not.	4.15 (.71)	88.9% (31.4)
Two people might see the same news story and get different information from it.	4.25 (.72)	92.2% (26.9)
Photos your friends post on social media are an accurate representation of what is going on in their life. (reverse-scored)	3.97 (1.03)	76.2% (42.7)
People pay less attention to news that fits with their beliefs than news that doesn't. (reverse-scored)	2.85 (1.14)	30.7% (46.2)
Advertisements usually leave out a lot of important information.	3.93 (.92)	76.2% (42.7)
News makers select images and music to influence what people think.	4.12 (.73)	86.5% (34.3)
Sending a document or picture to one friend on the Internet means no one else will ever see it. (reverse-scored)	4.26 (.89)	87.7% (32.9)
Individuals can find news sources that reflect their own political values.	4.09 (.80)	86.1% (34.7)
*A reporter's job is to tell the truth.	3.17 (1.26)	42.6% (49.6)
News companies choose stories based on what will attract the biggest audience.	4.28 (.73)	88.9% (31.4)
When you see something on the Internet you should always believe that it is true. (reverse-scored)	4.48 (.78)	91.0% (28.7)
Two people may see the same movie or TV show and get very different ideas about it.	4.41 (.66)	95.1% (21.7)
News coverage of a political candidate does not influence people's opinions. (reverse-scored)	3.75 (1.05)	66.8% (47.2)
People are influenced by advertisements, whether they realize it or not.	4.12 (.73)	88.5% (31.9)
Movies and TV shows don't usually show life like it really is.	3.98 (1.00)	76.2% (42.7)
Mean (17 items)	3.99 (.40)	78.7% (17.3)

*Item removed due to low item-rest correlation.

Note: Regular items should be interpreted on a scale of *1* = strongly disagree to *5* = strongly agree. Reverse-scored items should be interpreted on a scale of *1* = strongly agree to *5* = strongly disagree.

Next, we examined whether demonstrating algorithm awareness on specific questions was associated with media literacy knowledge. We did this through a series of 2x2 between-subjects ANOVAs with algorithm awareness (aware, unaware) and group (treatment, control) as between-subjects factors and media literacy knowledge as the dependent variable. For the question *After shopping online, you might see an ad for the product you bought somewhere else on the Internet, like on your social networking site or on YouTube. How does the Internet know what you have been shopping for?* algorithm-aware students (M 79.8%, SD 17.0) demonstrated more accurate media literacy knowledge than algorithm-unaware students (M 72.9%, SD 18.2), $F(1, 240) = 5.31$, $p = .022$. Likewise, for the question *How does the Internet limit what products you see online?* algorithm-aware students (M 81.1%, SD 15.4) demonstrated more accurate media literacy knowledge than algorithm-unaware students (M 76.3%, SD 18.8), $F(1, 240) = 4.71$, $p = .031$. No other effects were significant.

Discussion

Study 2 examined algorithm awareness for online shopping and searches. Students indicated awareness of how algorithms track their shopping behaviors and use their search histories to recommend new products, which aligns with reports that students are aware of targeted advertising (Head et al., 2020). Algorithm awareness was less evident in students' understanding of how the Internet limits online search results, suggesting they are less aware of how online content is filtered. In general, students who demonstrated algorithm awareness for online shopping often failed to do so for online searches. Even after watching a video about algorithms, many students still failed to grasp that algorithms personalize search results through filtering mechanisms. These findings suggest that algorithm awareness may be context-specific. While students are likely to have more overt experience with personalized advertising (Head et al., 2020), they are unlikely to see how search results differ across users and thus be less aware of personalization of content by search engines such as Google (Pariser, 2011).

We were also intrigued to observe a context-specific relationship between algorithm awareness and accuracy of media literacy knowledge, since media literacy instruction does not explicitly target understanding of algorithms. Media literacy knowledge was associated with algorithm awareness for online shopping, but not online search questions. This finding may be due to the explicit attention paid to analyzing advertisements as part of traditional media literacy interventions (Jeong et al., 2012).

GENERAL DISCUSSION

Two studies examined undergraduates' algorithm awareness across three online contexts: social media sites, shopping, and searches. Students' awareness appeared to be context-specific, with students showing greater algorithm awareness in the online shopping context (Study 2) than for social media sites (Study 1) or online searches (Study 2). Our findings align with less optimistic assessments of algorithm awareness among college students (Powers, 2017) and adults (Eslami et al., 2015; Hitlin & Rainie, 2019). These findings differ from Head et al. (2020), who found that college students were aware of how algorithms influence their online experiences, even if they could not explain how they worked. This difference may be due to the different methodologies employed across studies. Head et al. (2020) interviewed students in focus groups, where their views and algorithm awareness may have been enhanced through discussions with peers. In contrast, the other studies tested students individually.

The observed context-specific nature of algorithm awareness may be due in part to how students learn about algorithms. If students generate an informal understanding of algorithms based on their observations and experiences (Bucher, 2018; Devito et al., 2018; Eslami et al., 2016) it is not surprising that students may have greater awareness of algorithms in the context of online shopping, where they can observe targeted advertisements follow them across platforms. In contrast, it is more difficult to observe how content is filtered and organized in Facebook's News Feed or in Google results.

Students' lack of algorithm awareness for social media sites and online searches may also reflect poor technical understanding of the Internet. The Internet is challenging for children and adults to understand because its online interface does not reflect the Internet's underlying technical complexity (Yan, 2009). Even people with higher education degrees demonstrate limited understanding of how the Internet works (Vogels & Anderson, 2019): When U.S. adults completed a ten-question digital knowledge survey, including questions about online security, popular social media sites, and net neutrality, respondents with a college degree or higher had a median score of only six correct, while those with some college typically had a median score of only four correct.

Our findings indicate that students may come to college with high general media literacy knowledge, but this knowledge is inconsistently related to their algorithm awareness. As in previous studies (Brodsky et al., 2020) students in both studies demonstrated high media literacy knowledge. While this knowledge was associated with algorithm awareness for online shopping (Study 2), it was not associated with algorithm awareness in social networking (Study 1) or online search contexts (Study 2). The association with algorithm awareness in the online shopping context may reflect ongoing efforts from media literacy researchers, parents, and pediatricians to increase children's understanding and skepticism of advertising messages (Jeong et al., 2012) and targeted advertising (O'Keeffe et al., 2011).

Since today's undergraduates are unlikely to abandon algorithmically driven social media sites, shopping sites, and search engines (Head et al., 2020), algorithm literacy instruction, as well as self-report and performance-based assessments of algorithm literacy (Hobbs, 2017), must be integrated into media literacy curricula. Increasing awareness of algorithms may also help students grasp how personalized Internet content contributes to an increasingly polarized digital information landscape where fake news can proliferate. As such, media literacy interventions also need to teach students lateral reading strategies so they fact-check the information they encounter online. Lateral reading involves leaving the initial article, image, social media post, etc. to verify claims and learn more about the potential biases of its source (Wineburg & McGrew, 2017). Research suggests that students of all ages rarely read laterally (McGrew et al., 2018). It is critical for students to develop awareness that different users receive different information feeds (Pariser, 2011) and to use strategies, like lateral reading, that help them look beyond the information curated for them by algorithms.

In Study 2, direct instruction about algorithms improved students' algorithm awareness. This finding is in keeping with the previous research on the benefits of direct instruction over unassisted discovery-based learning across academic domains (Alfieri et al., 2011). However, many students did not transfer their algorithm awareness across the online shopping and search contexts, even with the aid of explicit instruction. Since media literacy interventions are more effective when they occur over multiple sessions (Jeong et al., 2012), more extensive interventions may be needed to help students develop understanding that generalizes across online contexts. Additionally, future research should investigate the characteristics of students who do not respond to algorithm literacy interventions as well as the extent to which new understanding translates into efforts to manipulate and thus engage with algorithms across different online contexts.

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