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The Power of Algorithms: How Algorithmic Trust Shapes the “News Finds Me” Perception Among Gen Z

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Article

Keywords: social media use, algorithmic influence, algorithmic trust, news finds me perception, Generation Z

Posted Date: August 4th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10313893/v1

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Additional Declarations: No competing interests reported.

Abstract

Social media platforms increasingly influence how young people encounter news, leading to the perception that they can stay informed without actively seeking news—the “News Finds Me” (NFM) perception. While previous research has linked NFM perceptions to incidental exposure and social connectivity, the psychological process connecting platform engagement to passive news attitudes remains underexplored. This study proposes that algorithmic trust serves as that process. Using a survey of Gen Z college students in Türkiye (N = 592), we test a structural model where habitual social media use and perceived algorithmic influence are associated with algorithmic trust, which in turn is associated with the three components of the NFM perception. Data were analyzed using structural equation modeling in R: construct validity was established through exploratory and confirmatory factor analyses on split samples, measurement invariance across gender was confirmed, and indirect effects were tested with bias-corrected bootstrapped confidence intervals (5,000 resamples). Results show that both factors are positively related to algorithmic trust, which strongly correlates with feeling informed without actively seeking news, decreased motivation for intentional news consumption, and reliance on peers for news exposure. Indirect effects from both factors to all three NFM dimensions through algorithmic trust were confirmed, and the findings held when modeling NFM as a higher-order construct. These results underscore algorithmic trust as a key psychological factor supporting passive news consumption in algorithm-driven environments and expand NFM research beyond Anglo-American contexts.

Introduction

Digital media environments have fundamentally changed how people encounter, interpret, and assess news. Unlike the era of mass communication, when news consumption mainly relied on intentional exposure through institutional media channels, modern information flow is increasingly driven by platform-based systems that integrate news into everyday social interactions (Van Dijck et al., 2018). In algorithmically curated settings, news is no longer mainly sought out; instead, it often appears unintentionally through regular social media use, blurring the lines between social interaction, entertainment, and public information (Hermida, 2010; Fletcher & Nielsen, 2018).

This change has led to increased research on incidental news exposure, the process where people encounter news unintentionally while engaging in non-news activities on social media platforms (Tewksbury et al., 2001; Boczkowski et al., 2018). Although incidental exposure can broaden the range of viewpoints people see, it also raises important questions about users’ dependence on platform systems to manage their information. As news becomes more ambient and ever-present, the responsibility for choosing information gradually shifts from the user to algorithmic systems that select, filter, and rank content (Thorson & Wells, 2016; Diakopoulos, 2019).

One influential concept capturing this shift is the News Finds Me (NFM) perception, which refers to individuals’ belief that they can stay adequately informed about public affairs without actively seeking

news, as relevant information will reach them through their social networks and digital platforms. Research has consistently linked NFM perceptions with lower levels of traditional news consumption, reduced political knowledge, and increased susceptibility to misinformation (Shehata & Strömbäck, 2021). However, existing NFM research has mainly concentrated on patterns of incidental exposure and social connectivity as causes of passive news habits, while paying comparatively less attention to the role of algorithmic systems as an independent explanatory mechanism. This gap matters: as platform algorithms more and more control not only what content users see but also how trustworthy and relevant that content seems, users' trust in these systems could be a more immediate psychological factor influencing NFM perceptions than how often they are exposed to news.

Recent developments in communication and platform studies indicate that algorithms should not be viewed simply as neutral technical tools, but as socio-technical actors that actively influence users' informational environments (Gillespie, 2014; Bucher, 2018). Social media algorithms depend on machine learning techniques to determine user preferences, increase engagement, and personalize content streams on a large scale (Ashuri et al., 2026). Through repeated interactions with these systems, users form expectations about how platforms "work," often internalizing algorithmic logic as a dependable mechanism for distinguishing relevant from irrelevant information (Eslami et al., 2015; Shin, 2020). This process fosters algorithmic trust, a type of trust based not on personal relationships but on perceived system competence, consistency, and functional reliability (Lee & See, 2004; Shin & Park, 2019).

A key conceptual difference underpins this study: algorithmic influence and algorithmic trust, although related, are conceptually distinct ideas. Algorithmic influence refers to users' perception of how much algorithms shape the visibility and ranking of content in their feeds, and an externally focused awareness of platform operations. Algorithmic trust, on the other hand, reflects an internally focused psychological attitude: how much users believe platform algorithms are dependable, capable, and act in their informational interests. While algorithmic influence describes what users think algorithms do, algorithmic trust pertains to how users feel about those algorithms. This difference matters because trust, not just awareness, motivates users to delegate editorial control to automated systems. When users trust platform algorithms to deliver timely and relevant content, they are more likely to reduce active monitoring and accept algorithmic curation as a substitute for intentional news seeking. Emerging research shows that higher algorithmic trust is linked to greater acceptance of automated decision-making and less critical scrutiny of curated content (Shin et al., 2024; Logg et al., 2019). Still, despite its increasing importance, algorithmic trust has rarely been placed at the center of explanations within the NFM framework.

Furthermore, users' perceptions of algorithmic influence—which is, their awareness of how much algorithms determine content visibility and prioritization—add more complexity to this relationship. While early normative debates often assumed that awareness of algorithmic intervention would lead to skepticism or resistance, recent empirical research suggests a more mixed pattern. In some cases, perceived algorithmic influence might increase trust by indicating efficiency, personalization, and less cognitive effort, rather than manipulation (Shin, 2020; De Haan et al., 2022). This tension underscores

the importance of studying how social media use and perceived algorithmic influence together shape algorithmic trust, and how that trust, in turn, influences users' news preferences.

Against this backdrop, the present study offers two related contributions. First, it expands NFM scholarship by introducing algorithmic trust as a key psychological mechanism that mediates the relationship between platform engagement and passive news orientations — a pathway that has received little systematic attention in existing research. Second, it provides empirical evidence from Türkiye, a non-Western context underrepresented in NFM and algorithmic trust studies, thus testing the cross-cultural applicability of these concepts. The study focuses on Generation Z, a group for whom social media platforms are a primary way to access news and public information (Mitchell et al., 2016), and explores two research questions: (1) How do social media use and perceived algorithmic influence together shape algorithmic trust? and (2) How does algorithmic trust influence the three dimensions of the News Finds Me perception? By highlighting algorithmic trust as a psychological orientation that legitimizes passive news consumption, this study provides a clear account of how platform systems shift the responsibility for staying informed in today's digital media landscape. What sets this study apart from previous NFM research is not just the existence of passive news orientations, but the identification of the psychological mechanism, algorithmic trust, through which engagement with platforms translates into a mental disposition to disengage from active news seeking. Earlier NFM studies have mainly modeled incidental exposure and social network ties as direct causes of passive orientations (Gil de Zúñiga et al., 2017; Shehata and Strömbäck 2021), without examining the trust-based psychological pathway that supports them. This study addresses that gap by considering algorithmic trust not merely as a background factor but as the main explanatory mechanism, and by empirically testing this model in a non-Western setting where platform usage among Gen Z is particularly high.

1. Social Media Use as an Everyday Information Environment

Social media platforms have become primary sources of information that fundamentally change how people encounter news (Van Dijck et al., 2018). Instead of just being communication tools, these platforms now function as algorithm-driven systems that control which content is visible, prioritized, and accessible. In this context, the frequency and habitual use of social media are important: the more often people use these platforms regularly, the more they interact with algorithmically selected content, increasing the chances for platform logic to influence their informational expectations and attitudes.

Three conceptually distinct but interconnected phenomena shape this information environment, and it is crucial to distinguish them clearly. Social media use refers to the habitual practice of engaging with platforms—scrolling, liking, sharing—on a daily basis. Incidental news exposure is a specific result of this behavior: the unintentional encounter with news content while involved in non-news activities (Tewksbury et al., 2001). Ambient journalism, on the other hand, is a broader structural condition in which news exists as a constant, low-level presence across digital environments, accessible for awareness without sustained focus (Hermida, 2010). Though these phenomena often happen together, they are analytically separate: social media use is the behavioral input, incidental exposure is the

perceptual outcome, and ambient journalism describes the larger media-ecological setting that enables such exposure. This study primarily examines the behavioral aspect of social media use as a predictor, rather than treating incidental exposure as a separate construct, to keep the analysis straightforward. Central to this process is the mechanism of incidental news exposure, where users encounter news not through intentional searching but as a byproduct of platform engagement. As social media becomes an unavoidable part of daily life, incidental exposure shifts news from being actively sought to a passive resource absorbed through social interaction and algorithmically curated feeds (Tewksbury et al., 2001; Fletcher & Nielsen, 2018). Importantly, this exposure is not random: it is governed by algorithmic systems that decide which stories appear, how often, and to whom (Bandy & Diakopoulos, 2021, 2023). The habitual, often automatic nature of social media use creates a context where repeated encounters with algorithmically selected content are experienced as a natural informational environment rather than conscious editorial choices.

This constant and extensive use fosters a sense of reliance and familiarity between the user and the platform, beyond merely a technical connection (Plantin et al., 2018). Users are increasingly delegating the task of determining which information is “relevant” or “accurate” to the platform’s algorithmic systems (Thorson & Wells, 2016; Martens et al., 2023). At this point, the central role of social media as an information environment establishes the foundation of the user’s reliance on the systems known as algorithms, which manage this environment. Therefore, as social media use increases, trust in the validity of information and in the system’s logic is expected to evolve accordingly.

Numerous studies in the literature have shown how social media has transformed traditional news consumption behaviors. For example, Mitchell et al. (2016) found that a large portion of users now prefer social media feeds over television or newspapers for news. This shift has changed not only how information is consumed but also its reliability and perception. The study by Westerman et al. (2014) indicates that users see the timeliness of social media information as a sign of trust. As a result, using social media as a daily source of information promotes a mental familiarity with the data provided by these platforms.

Beyond simple frequency of use, this mental familiarity often manifests as routine behavior driven by automatic responses. Tracking evidence supports this view, showing that online news engagement is largely organized around habitual, routinized modes of use, including news use triggered by social media (Möller et al., 2020). Two psychological mechanisms explain how habitual social media use fosters trust in algorithmic systems. First, based on dual-process theories of cognition (Kahneman, 2011), habitual platform engagement triggers System 1 processing, quick, associative, and with minimal deliberate analysis. In this state, algorithmically curated content is perceived as a default part of the environment rather than an actively curated editorial decision, reducing the likelihood that users will question the logic behind their feeds. Second, cognitive load theory (Sweller, 1988) suggests that the information-rich nature of social media environments encourages users to delegate informational decision-making to automated systems. As content selection increasingly depends on algorithms, users develop a functional dependence on these systems that, through repeated positive experiences, evolves into trust.

In this lowered cognitive effort state, users are more prone to accept incidental news without critical thinking, thereby increasing their reliance on algorithmic curation. To test this idea's validity, a hypothesis is proposed below.

H1

Social media use positively predicts algorithmic trust

2. Experiencing Algorithmic Influence on Social Media

The rapid transformation of social media has fundamentally changed how users access and interpret information, engage, and make decisions on platforms driven by algorithms that significantly influence public opinion and shape perceptions of the news (Moravec et al., 2025). Algorithmic influence alters news production by shifting editorial gatekeeping toward "share-worthiness" instead of traditional newsworthiness. Social media algorithms favor content that generates shares, likes, and comments, so stories with high emotional or viral potential gain greater visibility (Van Dijck et al., 2018). One of the most important developments in research on social media's effects on news perception is the growing recognition of algorithmic curation. The idea of algorithmic news perception highlights the combined role of social media algorithms in shaping how users engage with news content and the resulting impact on news formation. Social media algorithms use machine learning techniques to identify patterns from large datasets, actively influencing what users see and which voices are made visible or hidden (Bucher, 2018; Gillespie, 2014). Instead of neutral channels, these systems function as socio-technical actors with significant power over the informational environment.

Recent studies in the field show that algorithmic influence not only changes how users consume news but also fosters a specific sense of "algorithmic trust" in these systems. Research on the "News Finds Me" (NFM) perception, in particular, highlights that the belief that news will passively reach the user promotes more positive attitudes toward the algorithmic editorial process (Gil de Zúñiga et al., 2022; Shin, 2020; Lee, 2018; Tuomi et al., 2024). In this context, algorithmic influence is not just a content-filtering tool; it also acts to improve "algorithmic efficiency" by reducing the user's cognitive effort, which increases reliance on the system (Lu, 2020). Additionally, recent research (Diakopoulos & Koliska, 2017; Shin et al., 2020) suggests that as users become more aware of algorithmic logic and perceive a strong match between content and their interests, their trust in and compliance with the system's decision-making increases. As a result, the central role an algorithm plays in an individual's digital environment directly influences the system's ability to build trust through perceived transparency and usefulness. To explore the limited literature on algorithmic influence and trust, a hypothesis is proposed below.

H2

Algorithmic influence positively predicts algorithmic trust

3. The Formation of Algorithmic Trust

The development of algorithmic trust is a multi-faceted process rooted in the interaction between human thinking and machine logic (Kizilcec, 2016). Unlike trust between people, algorithmic trust comes from how reliable and accurate the system's personalization seems. As users interact with social media platforms, they create mental models to understand the underlying logic of their feeds (Lee, 2018). The trade-off between accuracy and transparency greatly affects this process; when an algorithm consistently provides content that matches a user's preferences, a sense of functional closeness is formed (Lim & Kim, 2024). Experimental evidence likewise shows that the transparency and explainability of algorithmic systems shape how far people rely on—and how well they can scrutinize—algorithmic suggestions (Janssen et al., 2022).

Furthermore, the shift from algorithmic awareness to algorithmic trust happens when users see the system not as a manipulative "black box" but as a personalized curator that enhances their information environment (Reviglio & Agosti, 2020). This process shows that trust is not fixed; it is constantly renegotiated with every like, share, and scroll, eventually leading the user to delegate their editorial control to the algorithm.

In this context, strengthening algorithmic trust can play a key role in reinforcing the News Finds Me perception. As people increasingly trust platforms to provide relevant and timely information, they are less likely to actively search for news content (Reisdorf & Blank, 2021). Instead, reliance on algorithmically filtered feeds encourages the belief that important news will reach them accidentally rather than through deliberate effort. This transfer of editorial control to algorithmic systems aligns closely with the main ideas of NFM, where perceived informational sufficiency replaces intentional news seeking (Snijders et al., 2023). As a result, algorithmic trust not only supports passive news exposure but also helps establish a news engagement style where users feel informed, even if they don't actively seek out news.

4. "News Finds Me" Perception

In today's media environment, people are increasingly exposed to multimedia platforms that raise the chance of encountering news content unintentionally. Gil de Zúñiga et al. (2017) described this phenomenon as the "News Finds Me" perception. This idea refers to the belief that individuals can stay informed about current events through online connections and social networks without actively seeking news. The existing research highlights three main aspects of the News Finds Me perception. These include an epistemic component, staying informed (Song et al., 2021; Goyanes et al., 2023), where people see themselves as informed without actively looking for news; an instrumental component, depending on peers for information, which indicates reliance on social ties; and a motivational component, not actively seeking news, characterized by depending on incidental news exposure via friends rather than purposeful news consumption.

Understanding these perceptions is important because they can lead users away from critical news topics, like politics, and instead expose them to less important but more entertaining information (Park &

Lee, 2023; Shi & Li, 2025). Previous research has mainly focused on the NFM perception in political news consumption. Gil de Zúñiga et al. (2017) showed that individuals who strongly endorse the NFM perception are less likely to intentionally seek out political news and are more reliant on incidental exposure through social media feeds, which weakens systematic political learning. Song et al. (2021) found that NFM-oriented users tend to feel politically informed despite engaging less frequently in intentional news consumption, revealing a gap between perceived and actual political knowledge. Similarly, Shehata and Strömbäck (2021) discovered that stronger NFM perceptions are linked to lower levels of political knowledge and less political participation, especially among Gen Z.

However, the scale used in the literature to measure NFM encompasses a broader range of related concepts and information that go beyond political news consumption. For example, Strauß et al. (2021) have shown that NFM orientations are also present in everyday news areas, where users rely on social media feeds to stay informed about a wide variety of issues without intentionally engaging.

Our study fills this gap by examining NFM perceptions across a wider range of news topics, including entertainment, sports, politics, sustainability, and climate change, using a sample from Türkiye. Research on NFM perception has mostly been done in the United States, and although emerging evidence shows that NFM perceptions are spreading across different societies (Gil de Zúñiga et al., 2020), the question of how NFM functions outside Anglo-American contexts remains open (Strauß et al., 2021). Additionally, this study is among the first to highlight algorithmic trust as a key mediating factor in shaping NFM perceptions, shedding light on how platform systems influence passive news attitudes among Gen Z users.

H3

Algorithmic trust positively predicts NFM-informed.

H4

Algorithmic trust positively predicts NFM not seeking.

H5

Algorithmic trust positively predicts NFM peers.

5. Proposed Conceptual Model

To illustrate the connections between the theoretical constructs and the research hypotheses, a conceptual model is shown below (Fig. 1).

6. Method

We conducted a cross-sectional online survey with Generation Z college students enrolled at private universities in Istanbul, Türkiye. Participants were recruited through a convenience sampling method, with survey invitations sent via university communication channels and student social media groups across multiple private universities in Istanbul. The sample is best described as urban, private-university-educated Generation Z students; therefore, the findings should be viewed within this context and may not apply to students at public or regional universities in Türkiye. Because recruitment was conducted exclusively through undergraduate and associate-degree student channels, the sample consists of university students, the large majority of whom fall within the age band corresponding to Generation Z. Cohort membership was therefore inferred from the recruitment frame rather than verified through individual-level age data. Data collection was carried out entirely online using Google Forms. Recruitment and data collection started after ethical approval had been granted (see Ethics approval). Before participating, all respondents were informed about the study's goals and told that their participation was voluntary, with the option to withdraw at any time without penalty. Digital informed consent was formally obtained from each participant through the survey interface.

The survey tool was conducted in Turkish. All scales were adapted from validated English-language instruments using a translation and back-translation process (Brislin, 1970): items were first translated into Turkish, then independently back-translated into English, and any discrepancies were resolved by consensus to ensure conceptual consistency.

After screening the data and removing incomplete or invalid responses, the study resulted in 592 valid cases. Two respondents selected the "other" gender option; because this group was too small to support meaningful comparison, these cases were treated as missing for that variable. The gender distribution in the sample was 69.8% female (n = 413) and 29.9% male (n = 177). Although this gender imbalance reflects broader participation trends in social science surveys in Türkiye, it is addressed empirically through measurement invariance testing (see Results) and is recognized as a sampling limitation. Unless otherwise noted, all variables were measured on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*).

6.1. Measures

Social media use was assessed with three items adapted from Campbell and Hawkins (2025), capturing habitual, low-deliberation engagement with social media where usage occurs despite, or beyond, users' conscious intentions. Sample items include "I find myself using social media even when I do not intend to" and "I am usually directed by social media." The scale originally included five items; however, exploratory factor analysis showed that two items reflecting perceived control over social media use loaded on a separate factor, with near-zero correlations with the other items, and were therefore removed. The final three-item measure demonstrated good internal consistency (α = .82).

Algorithmic influence was evaluated using four items adapted from Campbell and Hawkins (2025), which measure users' perception of how much algorithms affect news visibility and prioritization. Example

items include “Algorithms are used to recommend news to me while online” and “Algorithms are used to prioritize certain news stories above others” (α = .89).

Algorithmic trust was evaluated using two items adapted from Jian et al. (2000) and contextualized for algorithmic news curation: “I trust social media algorithms to decide what is important in the news” and “I trust social media algorithms to provide me with important news and public affairs.” Since Cronbach’s alpha underestimates the reliability of two-item scales, the Spearman–Brown coefficient is reported as recommended by Eisinga et al. (2013) (Spearman–Brown = .78; inter-item r = .64). The short length of this measure was a conscious choice to lessen respondent burden, and its limitations are discussed in the Limitations section.

The three dimensions of the News Finds Me perception were measured with items adapted from Gil de Zúñiga et al. (2017). *NFM-informed* was assessed with three items, including “I can be well-informed even when I do not actively follow the news” (α = .79). NFM not seeking was assessed with three items, including “I do not have to actively seek news because when important public affairs happen, other people will notify me” (α = .76). *NFM peers* was measured with three items, including “I rely on other people to tell me what’s important when news happens” (α = .84).

Data were analyzed using the two-step approach of Anderson and Gerbing (1988). To maintain the independence of exploratory and confirmatory procedures, the sample was randomly split into two halves: exploratory factor analysis (EFA) was performed on the first half (n = 296) and confirmatory factor analysis (CFA) on the second half (n = 296). The measurement model was then re-estimated on the full sample, followed by measurement invariance testing across gender and the estimation of the complete latent structural model. All latent-variable analyses were carried out with maximum likelihood estimation in the R package lavaan (Rosseel, 2012). Indirect effects were tested using bootstrapped confidence intervals (5,000 resamples, bias-corrected and accelerated). Model fit was evaluated using the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), with CFI/TLI ≥ .90, RMSEA ≤ .08, and SRMR ≤ .08 indicating acceptable fit (Hu & Bentler, 1999).

7. Results

In the EFA subsample, sampling adequacy was strong (KMO = .82; Bartlett’s test of sphericity: χ^2 = 3,106.9, p < .001). Principal axis factoring with oblimin rotation and the eigenvalue-greater-than-one criterion produced the expected six-factor solution, explaining 70.3% of the total variance, with all retained items loading ≥ .60 on their intended factors.

The six-factor measurement model was then estimated with CFA in the holdout subsample and showed acceptable fit, $\chi^2(120) = 257.3$, CFI = .948, TLI = .934, RMSEA = .062, 90% CI [.052, .073], SRMR = .050. Re-estimated on the full sample, the model also fit the data well, $\chi^2(120) = 386.3$, CFI = .950, TLI = .936, RMSEA = .061, SRMR = .050. As shown in Table 1, all standardized factor loadings were significant

(range = .65–.89), all average variance extracted (AVE) values exceeded .50 (range = .53–.68), and all composite reliability (CR) values exceeded .70 (range = .77–.89), supporting convergent validity.

Discriminant validity was evaluated using the Fornell–Larcker criterion. The square root of each construct's AVE was higher than its correlations with all other constructs, except for one case: the latent correlation between NFM-informed and NFM not seeking (r = .84) surpassed the square root of their AVEs. This overlap aligns with previous NFM research showing strong empirical connections between the epistemic and motivational aspects of the construct. To address this, a second-order robustness model is presented below in which the three dimensions load onto a higher-order NFM factor; the main conclusions remain unchanged.

To address potential common method bias, Harman's single-factor test was performed; the first unrotated factor explained 32.0% of the total variance, which is well below the 50% threshold, indicating that common method bias is unlikely to significantly affect the results.

Table 1
Measurement model results

Construct	Item	Std. loading	AVE	CR	Reliability
Social media use	SMU1	.80	.62	.83	α = .82
	SMU2	.89			
	SMU3	.65			
Algorithmic influence	AI1	.88	.68	.89	α = .89
	AI2	.88			
	AI3	.84			
	AI4	.68			
Algorithmic trust	AT1	.74	.64	.78	SB = .78
	AT2	.86			
NFM-informed	INF1	.67	.56	.79	α = .79
	INF2	.78			
	INF3	.80			
NFM not seeking	NS1	.65	.53	.77	α = .76
	NS2	.69			
	NS3	.83			
NFM peers	PEER1	.80	.65	.85	α = .84
	PEER2	.78			
	PEER3	.83			

Note. AVE = average variance extracted; CR = composite reliability; SB = Spearman–Brown coefficient (reported for the two-item scale following Eisinga et al., 2013). *All loadings significant at p < .001.*

Given the gender imbalance in the sample, measurement invariance across gender was tested with multi-group CFA. The configural model fit acceptably: $\chi^2(240) = 608.9$, CFI = .932, RMSEA = .072, SRMR = .056. Constraining factor loadings to equality (metric invariance) did not significantly worsen fit: $\Delta\chi^2(12) = 15.88$, p = .197, ΔCFI = .001; nor did additionally constraining intercepts (scalar invariance): $\Delta\chi^2(12) = 6.20$, *p* = .906, ΔCFI = .001. Both ΔCFI values fall well below the .01 criterion (Cheung & Rensvold, 2002), supporting full scalar invariance. The constructs were therefore measured equivalently across gender, indicating that the structural relationships reported below are not artifacts of the sample's demographic composition.

Table 2 shows descriptive statistics and Pearson correlations among the composite variables. NFM-informed had the highest mean (M = 3.58), followed by NFM not seeking (M = 3.35), while algorithmic trust (M = 2.92) and NFM peers (M = 2.75) showed moderate means. All variables were significantly and positively correlated, except for one case: the relationship between algorithmic influence and NFM peers was negligible and not significant (r = .04, p = .29). Algorithmic trust had moderate to strong correlations with all three NFM dimensions: NFM-informed (r = .46), NFM peers (r = .44), and NFM not seeking (r = .38), all p < .001. NFM-informed and NFM not seeking were strongly correlated (r = .65, p < .001), consistent with previous NFM research.

Table 2
Descriptive statistics and correlations

Variable	***M***	***SD***	**1**	**2**	**3**	**4**	**5**	**6**
1. Social media use	3.07	1.15	—					
2. Algorithmic influence	3.07	1.14	.17***	—				
3. Algorithmic trust	2.92	1.06	.35***	.18***	—			
4. NFM-informed	3.58	0.98	.35***	.19***	.46***	—		
5. NFM not seeking	3.35	1.00	.32***	.12**	.38***	.65***	—	
6. NFM peers	2.75	1.04	.36***	.04	.44***	.37***	.51***	—
Note. **p < .01.** ***p* < .001. Two-tailed.*								

The hypothesized structural model was estimated as a full latent-variable model, accounting for measurement error in all constructs. The model demonstrated acceptable fit, $\chi^2(126) = 431.8$, CFI = .942, TLI = .930, RMSEA = .064, SRMR = .065. As shown in Table 3, all five hypotheses were supported. Social media use was positively related to algorithmic trust (β = .43, p < .001), supporting H1, and algorithmic influence also showed a positive, though weaker, relationship with algorithmic trust (β = .13, p = .003), supporting H2. Collectively, social media use and algorithmic influence explained 21.9% of the variance in algorithmic trust. In turn, algorithmic trust was positively associated with all three NFM dimensions: NFM-informed (β = .64, $p < .001$; $R^2 = .40$), NFM not seeking (β = .51, $p < .001$; $R^2 = .26$), and NFM peers (β = .56, $p < .001$; $R^2 = .31$), supporting H3, H4, and H5.

Table 3
Structural path estimates

Hypothesis	Structural path	β	*SE*	*p*	R^2 (outcome)	Result
H1	Social media use → Algorithmic trust	.43	.04	< .001	.22	Supported
H2	Algorithmic influence → Algorithmic trust	.13	.04	.003	(.22)	Supported
H3	Algorithmic trust → NFM-informed	.64	.04	< .001	.40	Supported
H4	Algorithmic trust → NFM not seeking	.51	.04	< .001	.26	Supported
H5	Algorithmic trust → NFM peers	.56	.04	< .001	.31	Supported

Note. β = standardized coefficient. R^2 for algorithmic trust reflects the joint contribution of both antecedents.

To examine whether algorithmic trust mediates the relationship between the two antecedents and NFM perceptions, indirect effects were estimated using bootstrapped bias-corrected and accelerated 95% confidence intervals (5,000 resamples). All six indirect pathways were significant, as none of the confidence intervals included zero. Algorithmic trust mediated the link between social media use and NFM-informed (.27, 95% CI [.22, .53], standardized effect; unstandardized = .35), NFM not seeking (.22, unstandardized = .25, 95% CI [.16, .38]), and NFM peers (.24, unstandardized = .29, 95% CI [.18, .43]). Similarly, algorithmic trust mediated the relationship between algorithmic influence and NFM-informed (.08, unstandardized = .11, 95% CI [.03, .20]), NFM not seeking (.07, unstandardized = .08, 95% CI [.02, .14]), and NFM peers (.07, unstandardized = .09, 95% CI [.02, .16]). These findings support the conceptualization of algorithmic trust as a psychological pathway through which habitual platform engagement and perceived algorithmic influence relate to passive news orientations, although the cross-sectional design limits causal conclusions about these indirect effects.

Table 4
Bootstrapped indirect effects

Indirect path	*b*	95% CI	β
Social media use → AT → NFM-informed	0.35	[0.22, 0.53]	.27
Social media use → AT → NFM not seeking	0.25	[0.16, 0.38]	.22
Social media use → AT → NFM peers	0.29	[0.18, 0.43]	.24
Algorithmic influence → AT → NFM-informed	0.11	[0.03, 0.20]	.08
Algorithmic influence → AT → NFM not seeking	0.08	[0.02, 0.14]	.07
Algorithmic influence → AT → NFM peers	0.09	[0.02, 0.16]	.07

Note. AT = algorithmic trust. b = unstandardized estimate; CI = bias-corrected and accelerated bootstrap confidence interval (5,000 resamples); β = standardized estimate. All intervals exclude zero.

Given the strong empirical overlap between NFM-informed and NFM not seeking, an alternative model was estimated where the three NFM dimensions loaded onto a second-order NFM factor predicted by algorithmic trust. The model fit reasonably well: $\chi^2(128) = 496.7$, CFI = .930, TLI = .917, RMSEA = .070, SRMR = .073. All three dimensions significantly loaded onto the higher-order factor (NFM-informed = .89; NFM not seeking = .92; NFM peers = .64), and the structural relationships aligned with the primary model: social media use (β = .41, $p < .001$) and algorithmic influence (β = .14, p = .002) linked to algorithmic trust, which was strongly connected to the second-order NFM factor (β = .66, $p < .001$; $R^2 = .44$). The main conclusions remain consistent whether NFM is modeled as three correlated dimensions or as a single higher-order construct.

8. Discussion

This study explored the relationships among social media use, algorithmic influence, and algorithmic trust, and further examined how such trust influences the News Finds Me (NFM) perception among Gen Z users. Based on a cross-sectional survey of 592 Gen Z college students in Türkiye, the results consistently support all five hypotheses, emphasizing algorithmic trust as a key psychological factor shaping passive news consumption in algorithmically driven environments.

First, the results show that social media use is positively linked to algorithmic trust (β = .43, $p < .001$), indicating that regular, habitual engagement with social media platforms builds confidence in their systems. This agrees with extensive research showing that repeated exposure and daily reliance on digital platforms help normalize algorithmic decision-making within the information environment (Hutchinson, 2020). As social media becomes more deeply integrated into daily routines, users seem more likely to delegate their informational agency to platform algorithms, adopting a less critical attitude toward content selection and prioritization. Second, algorithmic influence has a significant positive relationship with algorithmic trust (β = .13, p = .003), as expected. This pattern supports the idea that

awareness of algorithmic intervention doesn't necessarily lead to skepticism or distrust; rather, perceived algorithmic influence may boost trust by signaling personalization and reducing cognitive effort, and is increasingly viewed as a normal and functional part of platform-mediated environments (Shin, 2020; Tuomi et al., 2024). This finding helps inform ongoing debates in the literature about the relationship between algorithmic awareness and trust, providing empirical support for a positive connection in the context of Gen Z news consumption.

Most notably, the findings show that algorithmic trust is strongly linked with all three aspects of the News Finds Me perception. It was the strongest predictor of NFM-informed ($\beta = .64$, $p < .001$), followed by NFM peers ($\beta = .56$, $p < .001$), and NFM not seeking ($\beta = .51$, $p < .001$). Users who trust platform algorithms more are significantly more likely to see themselves as well-informed without actively seeking news, feel less need for deliberate news consumption, and rely on news encountered through social connections. This supports existing NFM research, suggesting that passive news behaviors are maintained not just by incidental exposure but also by users' underlying confidence in automated information systems (Paik, 2025). The close relationship between algorithmic trust and the NFM-informed dimension is especially important. It aligns with previous research showing that feeling well-informed increasingly depends on trust in information intermediaries rather than direct, intentional engagement with news (Dörr & Hollnbuchner, 2017). In this context, algorithmic trust acts as a psychological mechanism that legitimizes passive news consumption, giving users a sense of mental security despite not actively monitoring news content. Importantly, bootstrapped mediation analyses confirmed that algorithmic trust significantly mediates the relationship between social media use and algorithmic influence on all three NFM dimensions (all 95% CIs exclude zero). This pattern is consistent with conceptualizing algorithmic trust as a psychological pathway linking habitual platform use and perceived algorithmic influence to passive news habits, although the cross-sectional design means these indirect effects cannot be interpreted causally. The mediation effect of social media use on NFM through algorithmic trust (standardized indirect effects from .22 to .27) suggests that NFM perceptions are more closely tied to trust in algorithmic systems than to social media use itself. Additionally, the finding of full scalar measurement invariance across gender indicates these mechanisms work similarly for female and male users, reinforcing confidence that the pattern observed isn't just due to demographic differences.

The broader implications of these findings go beyond news consumption patterns to include questions of democratic engagement, journalism, and the quality of information. When citizens trust platform algorithms to keep them informed and rely less on actively seeking news, the responsibility for keeping the public well-informed shifts from individuals and journalistic institutions to proprietary algorithmic systems whose priorities are focused on engagement rather than informational quality or democratic importance (Diakopoulos, 2019; Dörr & Hollnbuchner, 2017). This transfer of informational authority raises particular concerns for political knowledge and civic participation: prior research shows that NFM-oriented individuals often report feeling informed despite having lower levels of actual political knowledge (Song et al., 2021), a discrepancy that may grow when algorithmic trust further decreases the motivation to verify, seek out, or critically evaluate news. Additionally, high trust in algorithms without

adequate digital literacy may increase vulnerability to misinformation, as users who believe their algorithms consistently surface relevant and accurate content are less likely to critically evaluate algorithmically recommended information (Shin et al., 2024; Snijders et al., 2023). These dynamics suggest that while algorithmic trust reflects a psychological adaptation to information-saturated environments, it may also have significant costs for the quality of democratic participation and the long-term viability of public interest journalism.

A note on the link between NFM dimensions and news types is needed. The theoretical framework introduced NFM as relevant across various content areas — including politics, entertainment, climate change, and sports — aligning with the expanded NFM concept in recent research (Strauß et al., 2021). However, the empirical model measures NFM through its three main structural dimensions (informed, not seeking, peers) rather than testing effects specific to each domain separately. This choice reflects a preference for simplicity: the three-dimensional structure captures the essential attitudes and behaviors of NFM believed to be influenced by algorithmic trust, regardless of the news category. Future studies should explore whether algorithmic trust predicts NFM orientations differently across topics — for example, whether trust has a stronger effect on political versus entertainment news — as domain-specific differences may have unique implications for civic knowledge and democratic engagement. Overall, these findings expand NFM research in two key ways. Theoretically, this study goes beyond exposure-focused accounts of passive news consumption by identifying algorithmic trust as a distinct psychological mechanism linking platform engagement to NFM perceptions, a pathway often overlooked in earlier research. Empirically, it provides evidence from Türkiye, broadening the geographic scope of NFM studies and demonstrating that the concept applies beyond Western contexts. By highlighting algorithmic trust as the primary mediating factor, this research contributes to the growing exploration of how algorithmic designs shift the burden of staying informed in today's media environment (Diakopoulos, 2019; Paik, 2025).

8.1. Limitations and Future Work

This research has several limitations to consider when interpreting the findings. First, while the Gen Z college student sample is suitable for studying algorithmically mediated news consumption, it limits how broadly the findings can be applied. Future research should expand the model to include wider Gen Z populations and diverse demographic groups, such as non-student samples and cross-national contexts. Second, the gender makeup of the sample (69.8% female) is unbalanced; however, multi-group analyses showed full scalar measurement invariance across gender, meaning the constructs were measured equally for male and female participants. Still, future studies should aim for more balanced sampling. Third, the cross-sectional survey design captures perceptions at only one point in time, which prevents causal conclusions. The proposed directional relationships are grounded in theory, but reverse causality or omitted variables cannot be ruled out. Longitudinal studies would provide stronger causal evidence and help examine how algorithmic trust and NFM perceptions develop over time. Fourth, relying solely on self-reported measures may introduce social desirability or recall bias. Although Harman's single-factor test suggests common method bias is unlikely to be a major issue, future

research could benefit from including objective behavioral data or platform-level information. Fifth, although bootstrapped mediation analyses were conducted to test the indirect effects of social media use and algorithmic influence on NFM perceptions through algorithmic trust, the cross-sectional design limits the strength of causal claims from these effects. Longitudinal or experimental studies would yield more definitive evidence for the mediating role of algorithmic trust. Sixth, the model focused on social media use and perceived algorithmic influence as predictors of algorithmic trust, reflecting a deliberate choice to examine behavioral and platform-level factors. However, individual differences such as digital literacy, platform experience, privacy concerns, and transparency perceptions may also influence algorithmic trust but were not included. This omission is a limitation; future research should explore how these personal characteristics interact with behavioral factors in shaping trust, leading to a more complete understanding of its determinants. Seventh, the structural model was not tested against alternative models. The proposed path—social media use and algorithmic influence as predictors of algorithmic trust, which then affects NFM perceptions—is grounded in theory, but other configurations (like direct effects of social media use on NFM perceptions, or reciprocal paths between algorithmic trust and NFM dimensions) were not examined. Future research should compare different models to determine which best explains the data, increasing confidence in the findings. Eighth, algorithmic trust was measured with only two items. While the scale had acceptable reliability (Spearman–Brown = .78) and convergent validity (AVE = .64), two items cannot fully capture the multidimensional nature of trust, which includes perceived competence, benevolence, and integrity of algorithmic systems. Because the items were reworded for the news context rather than used in their original form, their psychometric properties have not been established beyond this sample. Future studies should develop and validate multi-item, multidimensional measures of algorithmic trust in independent samples. Ninth, generational membership was inferred from the student recruitment frame rather than measured directly at the individual level; future research should verify cohort membership using individual age data. Tenth, the study did not distinguish between different social media platforms, whose recommendation systems work through various mechanisms. Platform-specific replications could clarify whether the results apply across different algorithmic environments. Finally, as algorithmic systems evolve, future research should include more detailed indicators of algorithmic functionality, transparency, and user awareness to better understand the multifaceted nature of algorithmic trust.

Conclusion

This study identifies algorithmic trust as a key psychological factor linking habitual social media use and perceived algorithmic influence to passive news consumption among Gen Z users. Using a thoroughly validated measurement model, a full latent structural model, bootstrapped indirect-effect tests, and a higher-order robustness check, the results consistently point to users' trust in platform algorithms, rather than platform engagement alone, as the factor most closely associated with the belief that news will reach them. By presenting evidence from Türkiye, the study also broadens the geographic scope of NFM research beyond Anglo-American contexts. As algorithmic systems progressively take on editorial roles

once held by journalists and users, understanding when and why people trust these systems remains a crucial area for communication research.

Declarations

Data availability

The dataset supporting the findings of this study is openly available in the Zenodo repository at https://doi.org/10.5281/zenodo.19163266. The deposit contains the complete participant-level survey dataset in CSV format and a variable-level codebook giving the construct, the original Turkish wording, the English translation and the coding of every item, together with the sample composition and scale details. No directly or indirectly identifying information was collected from participants, and the deposited file therefore requires no further de-identification. The data are released under a Creative Commons Attribution 4.0 International license.

Code availability

All analyses were conducted in R with the lavaan package (Rosseel, 2012) using standard estimation procedures; no bespoke software or algorithms were developed for this study. The model specifications, estimator, resampling settings and fit criteria are reported in full in the Methods section, and the deposited dataset permits re-estimation of every model reported in this article.

Ethics approval

Ethical approval for this study was granted by the Social and Human Sciences Ethics Committee of the author's institution (Meeting No. 2025/12) on 13 November 2025, prior to the commencement of data collection. Data collection began on 14 November 2025 and was completed within one month. All procedures involving human participants were carried out in accordance with the relevant ethical guidelines and regulations, including the principles of the 1964 Declaration of Helsinki and its later amendments.

Informed consent

Informed consent was obtained from all participants through a digital consent form presented at the beginning of the online survey. Participants were required to read the consent information and actively indicate their agreement before proceeding to the questionnaire. Participation was voluntary, and respondents were informed of the purpose of the study, the confidentiality of their responses, and their right to withdraw at any time without penalty. All participants were 18 years of age or older.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing interests

The author declares no competing interests.

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Figures

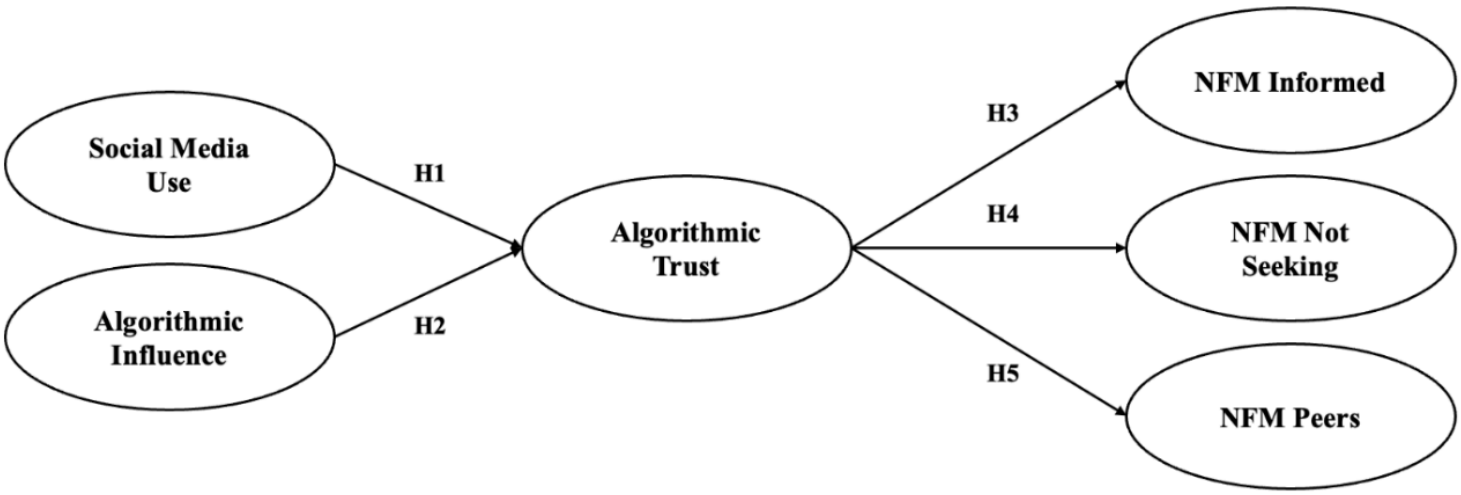


Figure 1

Proposed model