The Influence of Social Media Recommendation Algorithms on Information-Seeking Behavior and Filter Bubble among Generation Z Users in Indonesia

Megawati, Syaifullah*., Afif Alfarisi Hernas., Muhammad Habib Rafi., M. Farel, Al Fitto Rizki

Department of Information Systems, Faculty of Science and Technology, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia

***Corresponding Author**

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ABSTRACT

Social media platforms increasingly function as algorithmic information systems that shape how young users access, select, and interpret information. Recommendation algorithms on TikTok, Instagram, YouTube, Facebook, and X personalize feeds based on interaction patterns, interests, and digital activity histories. Although personalization can improve relevance, it may also narrow information exposure and encourage filter bubbles. This study examines the relationships among perceived social media recommendation algorithms, algorithmic awareness, filter bubble formation, and information-seeking behavior among Generation Z users in Indonesia. An explanatory quantitative design was employed using an online questionnaire distributed to active social media users aged 18-27 years. The data were analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) using a reflective measurement model and 5,000 bootstrap subsamples. From 257 recorded data rows, 137 valid responses were analyzed after 120 spreadsheet rows with no questionnaire answers were removed. The results indicate that perceived recommendation algorithms are positively and significantly associated with filter bubbles ($\beta = 0.544$; $p < 0.001$), while filter bubbles are positively and significantly associated with information-seeking behavior ($\beta = 0.401$; $p = 0.001$). Perceived recommendation algorithms also show a significant negative association with information-seeking behavior ($\beta = -0.426$; $p < 0.001$), indicating that the proposed positive-direction hypothesis is not supported. Algorithmic awareness is not significantly associated with either filter bubbles or information-seeking behavior. These findings suggest that algorithmic personalization is associated with homogeneous information exposure and lower active information seeking when users rely heavily on recommended feeds. However, because the study uses cross-sectional self-reported survey data, the results should be interpreted as statistical associations rather than causal effects. The study highlights the need for algorithmic literacy that encourages users to verify sources, compare perspectives, and manage recommendation preferences critically.

Keywords: recommendation algorithm, social media, information-seeking behavior, filter bubble, Generation Z

INTRODUCTION

Social media is no longer only a communication space; it has become a digital information system that mediates the searching, presentation, and consumption of information. Users do not always receive content chronologically. Instead, they encounter automatically curated feeds shaped by recommendation algorithms. These algorithms learn from user interactions, including watched content, likes, comments, shares, searches, followed accounts, and other digital traces, and then present content predicted to match the user's preferences.

From an information systems perspective, recommendation algorithms can be understood as technological components that are associated with how users access, evaluate, and act upon information. Prior studies on echo chambers and polarization indicate that platform structures, user behavior, and information curation mechanisms may contribute to increasingly homogeneous information spaces [1], [10]. This condition is important because information received through social media may shape how users interpret social, educational, health, political, lifestyle, and everyday decision-making issues.

Generation Z is a relevant population for this study because this group has grown up with internet access, smartphones, and recommendation-based social media platforms. Social media is widely used by Generation Z for learning, entertainment, communication, and identity expression [3]. Research on TikTok also suggests that algorithmic personalization may influence user experience, self-perceived identity, personal values, and perceived social connectedness [7], [14]. However, empirical research that connects recommendation algorithms, filter bubbles, algorithmic awareness, and information-seeking behavior in the Indonesian Generation Z context remains limited.

This study addresses that gap by testing a structural model that places perceived recommendation algorithms and algorithmic awareness as antecedents of filter bubbles and information-seeking behavior. The study contributes to information systems literature by showing how algorithmic personalization is statistically associated not only with perceived information homogeneity but also with users' active information-searching patterns. Practically, the findings provide insight for digital literacy education, especially for young users who rely heavily on algorithmic feeds to obtain information.

LITERATURE REVIEW

Recommendation algorithms and algorithmic awareness

Recommendation algorithms are computational mechanisms used by digital platforms to select, rank, and deliver content based on user data. In social media environments, recommendations may be influenced by viewing history, engagement patterns, search activities, social networks, location, attention duration, and other recorded behavior. A personalization engine can make users receive content that feels relevant to their interests, but it can also limit exposure diversity when the presented content becomes too uniform.

Algorithmic awareness refers to the extent to which users understand that digital content is selected, ranked, and personalized by algorithms. Users with higher algorithmic awareness tend to recognize that content appearing on their feeds is not a neutral representation of all available information but the result of system-level selection [4]. In theory, this awareness may help users become more critical when consuming recommended content.

Information-seeking behavior and filter bubble

Information-seeking behavior describes users' actions in identifying information needs, searching for sources, evaluating information, comparing alternatives, and using information for decision-making. In social media settings, this behavior may change because users frequently encounter information incidentally through recommended content. Online information-seeking models are useful for understanding how users search, evaluate, and use information in digital environments [9].

A filter bubble occurs when users are repeatedly exposed to information that matches their prior interests, preferences, or beliefs due to content personalization. The concept is closely related to echo chambers, where users interact more often with similar viewpoints and become less exposed to alternative perspectives. AI-based recommendation systems can intensify information homogeneity and polarization when users are mainly shown content that aligns with their preferences [12]. Social media news overload may also lead users to avoid or filter news, while media literacy can moderate this process [15].

Theoretical framework

This study is grounded in information behavior research and Uses and Gratifications Theory. Information-seeking behavior models view users as active actors who recognize information needs, select information channels, search for relevant sources, evaluate retrieved information, and use information to reduce uncertainty or support decisions [16]. In social media environments, this process is partly mediated by algorithmic curation because users encounter not only deliberately searched information but also automatically recommended content.

Uses and Gratifications Theory explains that media users select media and platforms to satisfy needs such as information, entertainment, social interaction, and self-expression [17]. In recommendation-based platforms, these gratifications may be shaped by perceived relevance and convenience. When recommended feeds satisfy users' immediate information needs, users may rely more on algorithmically curated content and engage less in independent searching or source comparison. At the same time, repeated personalization may strengthen filter bubble perception by reinforcing similar content, viewpoints, and topics.

Based on this theoretical foundation, the proposed relationships are interpreted as statistical associations between perceived algorithmic curation, algorithmic awareness, homogeneous exposure, and information-seeking behavior. The hypothesized relationships refer to path relationships in the PLS-SEM model and should not be interpreted as evidence of causal influence because the research design is cross-sectional.

Conceptual model and hypotheses

The conceptual model positions perceived recommendation algorithms as the main exogenous variable, algorithmic awareness as an additional predictor, filter bubble as an intervening endogenous variable, and information-seeking behavior as the main endogenous outcome. The hypotheses are formulated as follows:

H1: Perceived social media recommendation algorithms have a positive relationship with information-seeking behavior among Generation Z users.

H2: Perceived social media recommendation algorithms have a positive relationship with filter bubble formation among Generation Z users.

H3: Filter bubbles have a positive relationship with information-seeking behavior among Generation Z users.

H4: Algorithmic awareness has a negative relationship with filter bubbles among Generation Z users.

H5: Algorithmic awareness has a positive relationship with critical information-seeking behavior among Generation Z users.

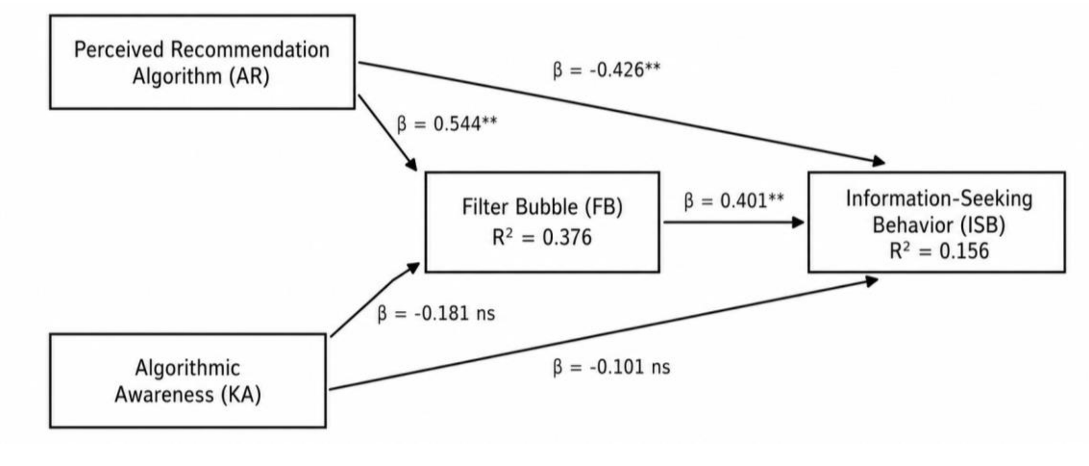

Figure 1: Final PLS-SEM model

METHODOLOGY

This study used a quantitative explanatory approach. The quantitative approach was selected because the research aimed to test statistical relationships among variables using numerical data collected from respondents. The explanatory design was applied to examine how perceived recommendation algorithms, algorithmic awareness, and filter bubbles are associated with information-seeking behavior among Generation Z users. Because the study uses cross-sectional survey data, the results are interpreted as associations within the tested model rather than causal relationships.

The population consisted of Generation Z social media users in Indonesia. The respondent criteria were: aged 18-27 years, domiciled in Indonesia, actively using social media, and having received recommended content on platforms such as TikTok, Instagram, YouTube, Facebook, or X. Purposive sampling was used because respondents were selected based on predetermined eligibility criteria that were relevant to the research objectives [13].

Instrument development

The questionnaire items were developed based on the operational definitions of the four constructs and prior literature on algorithmic awareness, online information seeking, filter bubbles, media literacy, and social media personalization [4], [9], [12], [15]. The items were written in clear language suitable for Indonesian Generation Z respondents and measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The research team reviewed the items for clarity, relevance to the constructs, and suitability for the respondent criteria before distribution. A separate pilot test and external expert validation were not conducted; therefore, this issue is acknowledged as a methodological limitation. To improve measurement quality, the final instrument was evaluated empirically through outer loading, Cronbach's alpha, composite reliability, AVE, HTMT, VIF, and bootstrapping criteria.

The adequacy of the final sample was evaluated using several PLS-SEM sample-size recommendations. Following the 10-times rule described in PLS-SEM guidelines, the minimum sample size was estimated by multiplying 10 by the largest number of structural paths directed at an endogenous construct [6]. In the proposed model, the largest number of incoming paths is three, namely perceived recommendation algorithms, algorithmic awareness, and filter bubbles directed to information-seeking behavior; therefore, the minimum sample requirement is 30 respondents. A complementary power-analysis rationale was also applied based on Cohen's statistical power principles and the G*Power approach for regression-based analysis [2], [5]. Assuming a medium effect size (f-square = 0.15), alpha = 0.05, and statistical power = 0.80, the recommended minimum sample is 55 respondents. The final sample of 137 valid responses exceeds both thresholds and is therefore considered adequate for PLS-SEM estimation. This justification is further supported by PLS-SEM sample-size estimation literature, including the inverse square root and gamma-exponential methods, as well as guidance that PLS-SEM can be appropriate for small-to-medium samples when reliability, validity, and statistical power criteria are satisfied [8], [11].

Primary data were analyzed using PLS-SEM with a reflective measurement model. The analytical stages included data cleaning, outer loading assessment, Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), Heterotrait-Monotrait Ratio (HTMT), Variance Inflation Factor (VIF), path coefficients, t-statistics, p-values, R-square, f-square, Q-square, and bootstrapping with 5,000 subsamples following PLS-SEM guidelines [6].

During the measurement model assessment, indicators with low or inconsistent outer loadings were eliminated gradually to improve convergent and discriminant validity. The final model retained AR3, AR4, KA1, KA3, FB2, FB4, ISB1, and ISB3. Other initial indicators were removed because they did not meet the measurement model criteria in the empirical dataset.

Table 1: Operational definitions and final indicators

Variable	**Operational Definition**	**Final Indicators**
Perceived Recommendation Algorithm (AR)	Users' perception that feed content is selected and personalized based on their digital activities.	AR3, AR4

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Algorithmic Awareness (KA)	Users' understanding of the existence, operation, and impact of social media algorithms.	KA1, KA3
Filter Bubble (FB)	Users' perception that received information tends to be uniform and consistent with prior interests or viewpoints.	FB2, FB4
Information-Seeking Behavior (ISB)	Users' actions in searching, verifying, comparing, and using information from social media.	ISB1, ISB3

RESULTS

Data cleaning

The questionnaire dataset contained 257 rows in the exported spreadsheet. During screening, 120 rows contained no answers for the measurement indicators and were therefore classified as blank or incomplete entries. These blank rows were not used because they could not provide construct scores for perceived recommendation algorithms, algorithmic awareness, filter bubbles, or information-seeking behavior. The screening procedure removed rows with missing responses across the final indicators; only complete responses that met the respondent criteria were retained. After this process, 137 valid responses were analyzed.

Table 2: Data cleaning results

Description	**Total**
Rows in the questionnaire file	257
Blank rows removed	120
Valid data analyzed	137

Respondent profile and demographic data availability

All retained responses came from respondents who met the eligibility criteria: Generation Z users aged 18-27 years, domiciled in Indonesia, actively using social media, and having received recommended content on major platforms. However, the final dataset did not include complete demographic variables such as gender, education level, dominant platform, frequency or duration of social media use, and digital literacy background. Consequently, subgroup comparison could not be conducted in the current study, and the findings should be interpreted as an overall pattern among the valid Generation Z respondents rather than a demographic-specific conclusion.

Descriptive statistics

Table 3: Descriptive statistics of final constructs

Code	**Construct**	**Mean**	**Std. Deviation**
AR	Perceived Recommendation Algorithm	3.288	0.977
KA	Algorithmic Awareness	1.339	0.774
FB	Filter Bubble	4.511	0.567
ISB	Information-Seeking Behavior	4.109	0.484

The descriptive results show that perceived filter bubbles are high (mean = 4.511) and information-seeking behavior is also high (mean = 4.109). Perceived recommendation algorithms are at a moderate-to-high level (mean = 3.288), while algorithmic awareness is low (mean = 1.339). This indicates that respondents may not yet have strong understanding of how algorithms curate social media content. Because detailed demographic data were not available, these descriptive results focus on the main research constructs.

Measurement model assessment

Table 4: Outer loadings of the final model

Construct	**Indicator**	**Outer Loading**	**Decision**
AR	AR3	0.926	Valid
AR	AR4	0.822	Valid
KA	KA1	0.991	Valid
KA	KA3	0.994	Valid
FB	FB2	0.892	Valid
FB	FB4	0.821	Valid
ISB	ISB1	0.920	Valid
ISB	ISB3	0.781	Valid

All retained indicators have outer loading values above 0.70. Therefore, the retained indicators adequately reflect their respective constructs. The eliminated indicators were AR1, AR2, AR5, KA2, KA4, KA5, FB1, FB3, FB5, FB6, ISB2, ISB4, ISB5, and ISB6 because they did not meet the measurement model criteria in the empirical data.

Table 5: Reliability and convergent validity

Construct	**Cronbach's Alpha**	**Composite Reliability**	**AVE**	**Decision**
AR	0.706	0.868	0.767	Adequate
KA	0.985	0.992	0.985	Adequate
FB	0.643	0.847	0.734	Adequate
ISB	0.643	0.842	0.728	Adequate

Composite reliability values for all constructs are above 0.70, and AVE values are above 0.50. Thus, the model meets composite reliability and convergent validity criteria. Cronbach's alpha for FB and ISB is 0.643, which is still acceptable for exploratory research because composite reliability and AVE meet the required thresholds.

Table 6: Discriminant validity using HTMT

Construct Pair	**HTMT**	**Decision**
AR - KA	0.289	Adequate

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AR - FB	0.853	Adequate
AR - ISB	0.229	Adequate
KA - FB	0.381	Adequate
KA - ISB	0.172	Adequate
FB - ISB	0.386	Adequate

All HTMT values are below 0.90. Therefore, the final model meets discriminant validity criteria and each construct can be empirically distinguished from the others.

Structural model assessment

Table 7: Collinearity assessment

Endogenous Construct	**Predictor**	**VIF**	**Decision**
FB	AR	1.060	Adequate
FB	KA	1.060	Adequate
ISB	AR	1.535	Adequate
ISB	KA	1.113	Adequate
ISB	FB	1.602	Adequate

All VIF values are below 5, indicating that the structural model does not contain multicollinearity problems.

Table 8: R-square and Q-square values

Endogenous Construct	**R-square**	**Q-square**	**Interpretation**
FB	0.376	0.339	Moderate
ISB	0.156	0.076	Weak to moderate

The R-square value for FB is 0.376, indicating that perceived recommendation algorithms and algorithmic awareness explain 37.6% of the variation in filter bubbles. The R-square value for ISB is 0.156, meaning that perceived recommendation algorithms, algorithmic awareness, and filter bubbles explain 15.6% of the variation in information-seeking behavior. This relatively low explanatory value suggests that important determinants of information-seeking behavior remain outside the current model, such as digital literacy, information needs, trust in information sources, topic involvement, platform preference, peer influence, and social media use intensity. Therefore, the relationships involving ISB should be interpreted cautiously. The Q-square values for FB and ISB are greater than 0, indicating predictive relevance.

Table 9: Effect size f-square

Relationship	**f-square**	**Interpretation**
AR -> FB	0.448	Large

KA -> FB	0.049	Small
AR -> ISB	0.140	Small
KA -> ISB	0.011	Very small
FB -> ISB	0.119	Small

The largest effect size is found in the relationship between AR and FB, with an f-square value of 0.448. This indicates that perceived recommendation algorithms make a substantial contribution to explaining filter bubble formation. The effects of AR on ISB and FB on ISB are small, while the effects of KA on FB and ISB are relatively limited.

Hypothesis testing

Table 10: Hypothesis testing results

Hypothesis	Relationship	Coefficient	t-statistic	p-value	Decision
H1	AR -> ISB	-0.426	-3.591	<0.001	Rejected (significant, opposite direction)
H2	AR -> FB	0.544	7.888	<0.001	Supported
H3	FB -> ISB	0.401	3.180	0.001	Supported
H4	KA -> FB	-0.181	-1.617	0.106	Rejected
H5	KA -> ISB	-0.101	-0.928	0.354	Rejected

DISCUSSION

The hypothesis testing results show that H2 and H3 are supported. Perceived recommendation algorithms are positively and significantly associated with filter bubbles, and filter bubbles are positively and significantly associated with information-seeking behavior. These results indicate that users who perceive their feeds as more algorithmically personalized also tend to report more homogeneous information exposure. In the Generation Z context, repeated exposure to similar content may be related to what users consider relevant and what they search for next. Because the data are cross-sectional and self-reported, these findings indicate associations within the tested model rather than causal mechanisms.

H1 is rejected because the path from perceived recommendation algorithms to information-seeking behavior is significant but negative, which does not match the proposed positive direction. This result suggests that, after accounting for filter bubbles, stronger perceptions of algorithmic personalization are associated with lower levels of active information-seeking behavior. A possible interpretation is that users who believe that platforms already provide relevant content may rely more on feeds and conduct fewer additional searches or source comparisons. This interpretation should be viewed cautiously and not as proof that algorithms directly reduce information seeking.

H4 and H5 are not supported because algorithmic awareness does not show significant relationships with filter bubbles or information-seeking behavior. This finding indicates that simply knowing that algorithms curate content may not be sufficient to reduce information homogeneity or improve critical searching. Algorithmic literacy should therefore move beyond awareness and include practical skills, such as checking source credibility, diversifying followed accounts, resetting recommendation preferences, and intentionally seeking alternative viewpoints.

The weak-to-moderate explanatory power for information-seeking behavior (R-square = 0.156) further indicates that the model captures only a limited part of this behavior. Future models should include additional determinants, such as digital literacy, information needs, trust in information sources, topic involvement, platform preference, social influence, and media-use intensity. This is important because information seeking is a complex behavior shaped by individual, technological, and social factors.

CONCLUSION

Based on PLS-SEM analysis of 137 valid respondents, this study concludes that perceived social media recommendation algorithms are positively and significantly associated with filter bubbles among Generation Z users in Indonesia. Filter bubbles are also positively and significantly associated with information-seeking behavior. However, the direct relationship between perceived recommendation algorithms and information-seeking behavior is significant in a negative direction; therefore, the proposed positive-direction hypothesis is not supported. Algorithmic awareness is not significantly associated with either filter bubbles or information-seeking behavior.

The practical implication is that algorithmic literacy should not only inform users that social media platforms use algorithms. It should also encourage users to verify sources, compare perspectives, and actively manage recommendation preferences. Generation Z users should be encouraged not to depend solely on content appearing in their feeds because algorithmic personalization may be associated with more homogeneous exposure and less active searching. This implication should be understood as a recommendation for digital literacy practice rather than a causal claim derived from experimental evidence.

This study has several limitations. First, the cross-sectional self-report design does not allow causal inference; therefore, the findings should be interpreted as statistical associations. Second, the final dataset contained responses to the main indicators but did not contain complete demographic information, so subgroup analysis by gender, education level, platform preference, social media use intensity, or digital literacy background could not be performed. Third, the questionnaire did not undergo a separate pilot test or external expert validation, and several initial indicators had to be eliminated during measurement-model assessment. Fourth, the R-square for information-seeking behavior was relatively low, suggesting that important determinants outside the current model were not included. Future research should refine and validate the questionnaire instrument, increase the sample size, collect demographic and digital-literacy variables, and test the model on specific platforms such as TikTok, Instagram, or YouTube to obtain more platform-specific insights.

Ethical Considerations

This study used an anonymous online questionnaire and did not collect sensitive personal data that could directly identify respondents. Participation was voluntary, and responses were analyzed in aggregate for academic purposes.

Data Availability

The research data are available from the corresponding author upon reasonable request, subject to respondent confidentiality and ethical data-use considerations.

Conflict Of Interest

The authors declare that there is no conflict of interest related to this study.

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