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Optimizing the Effectiveness of Students' Health Communication Through Information Sources and Learning Factors

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ABSTRACT

The integration of communication processes occurs when conventional and digital communication patterns are used simultaneously, allowing communication activities to take place both face-to-face and through mediated channels. This condition has become increasingly relevant as the need for health information grows more dynamic and is obtained from diverse sources. This study aims to analyze the direct effect of information sources on learning factors and the effectiveness of health communication, the direct effect of learning factors on the effectiveness of health communication, and the indirect effect of information sources on the effectiveness of health communication through learning factors. The main concepts examined in this study include information sources, learning factors, and health communication effectiveness. This research employed an explanatory quantitative approach involving 97 students from Grade X and XI at SMA Sejahtera 1 Depok City. Data were collected through a survey using a Google Form questionnaire and analyzed using multivariate analysis. The results indicate that information sources have a direct and significant effect on both learning factors and the effectiveness of health communication. Learning factors also have a direct and significant effect on the effectiveness of health communication. However, learning factors do not mediate the relationship between information sources and health communication effectiveness. Future studies are recommended to involve a larger sample size and adopt a mixed-methods approach to allow for comparative analysis, such as multi-group analysis.

Keywords: Learning Factors; Communication Integration; Health Communication; Social Media; Information Sources

INTRODUCTION

The integration of communication processes occurs when conventional and digital communication patterns are used together, allowing communication activities to take place both face to face and through mediated channels. This condition has become increasingly common as information needs grow more dynamic and are fulfilled through multiple sources rather than a single channel. In contemporary society, individuals actively combine interpersonal communication, digital media, and online platforms to access information, particularly in the context of health (Fernández et al., 2025; Johansson & Johansson, 2023).

Information sources are not merely understood as tools or repositories of information, but as part of a broader information ecosystem that shapes how individuals search for, interpret, and use information. Chatterjee (2017) defines information sources as entities that provide information in both printed and digital forms, including experts, institutions, documents, and electronic media. This perspective is expanded by Söderlund and Lundin (2017), who emphasize the interactive dimension of information sources, positioning them as spaces where individuals engage in evaluating and interpreting information. Previous studies indicate that health information can be obtained through various channels, such as mass media, digital media, social media, health applications, family members, and peers (Chen et al., 2025; Cohen et al., 2025; Montagni et al., 2018).

Health communication has emerged as an important field of study in response to these developments. Health communication refers to the process of designing, delivering, and exchanging health-related messages with the aim of influencing knowledge, attitudes, decision-making, and health behaviors (Harrington, 2015; Zhao & Zhang, 2017). Effective health communication is not limited to message transmission but involves audience understanding, engagement, and the ability to apply information in real-life contexts. In this sense, the effectiveness of health communication is closely related to how individuals process and learn from the information they receive (Stauch et al., 2025).

Students represent a critical group in health communication research. As adolescents, students are in a developmental phase characterized by curiosity, identity exploration, and increased exposure to risk-taking behaviors. At the same time, they often face challenges related to limited health literacy and restricted access to reliable health information. Studies show that students actively seek health information related to healthy eating, reproductive health, mental health, and healthy lifestyles, particularly when direct communication within families is limited or considered sensitive (Harianti et al., 2021; Kim et al., 2019).

The increasing use of social media and digital health applications has significantly transformed students' health information-seeking behavior. Social media provides fast access, interactivity, and peer support, making it a popular source of health information among adolescents (Cohen et al., 2025; Mustofa & Sani, 2024). Health applications are also designed to support health monitoring, information access, and behavior change, offering flexibility in terms of time and place (Montagni et al., 2018; Peng et al., 2016). However, despite these advantages, digital health information also raises concerns related to misinformation, credibility, and users' ability to evaluate content quality (Afful-Dadzie et al., 2021; McKinnon et al., 2020).

Learning factors play an important role in determining whether exposure to health information leads to effective health communication. Learning factors such as motivation to learn, intensity of information use, and perceived information sufficiency influence how individuals engage with and process health messages. According to Zhou and Roberto (2022), perceived information insufficiency can motivate individuals to seek additional information and engage more deeply in learning processes. In the context of adolescents, family support, peer interaction, and digital media exposure contribute to learning motivation and information engagement, which in turn affect health-related understanding and decision-making (Cohen et al., 2025; Wang et al., 2024).

Although previous studies have examined health information sources, learning processes, and health communication outcomes, limited research has focused on how these elements interact among students. Specifically, the role of learning factors as a potential mechanism linking information sources and health communication effectiveness remains underexplored. Understanding these relationships is essential for developing health communication strategies that are appropriate for students' information-seeking behavior and learning characteristics. Therefore, this study aims to examine the direct effects of information sources on learning factors and health communication effectiveness, the direct effect of learning factors on health communication effectiveness, and the indirect effect of information sources on health communication effectiveness through learning factors among senior high school students.

LITERATURE REVIEW

Information Sources in Health Communication

Information sources play a central role in shaping how individuals access, interpret, and use health information. Information sources are commonly defined as entities that provide information in printed, digital, or interpersonal forms, including experts, institutions, media, and social networks (Chatterjee, 2017). Rather than functioning only as channels, information sources form part of an interactive ecosystem where individuals actively engage in searching, evaluating, and interpreting information (Söderlund & Lundin, 2017).

Previous studies show that health information is obtained through a wide range of sources, such as mass media, digital media, social media platforms, health applications, family members, and peers (Chen et al., 2025; Cohen et al., 2025; Montagni et al., 2018). Among adolescents and students, interpersonal sources such as parents and peers remain important due to trust, emotional closeness, and shared experiences. At the same time, digital sources offer speed, convenience, and anonymity, which are particularly appealing when accessing sensitive health topics (Harianti et al., 2021).

Social media has become one of the most dominant health information sources among young people. Platforms such as Instagram, TikTok, and YouTube allow users to access health-related content, interact with others, and share personal experiences. Studies indicate that adolescents frequently use social media to obtain information related to diet, fitness, mental health, and reproductive health (Cohen et al., 2025; Koya et al., 2024). However, the credibility of information on social media remains a major concern, as content is often produced by non-experts and may contain misinformation or misleading claims (Afful-Dadzie et al., 2021).
Health applications represent another growing source of health information. These applications are designed to support health monitoring, information access, and behavior change by allowing users to track activities, symptoms, or goals (Peng et al., 2016). Research shows that students perceive health applications as useful because they are accessible anytime and anywhere, although concerns about privacy, effectiveness, and trust may limit their consistent use (Montagni et al., 2018; Bautista & Schueller, 2023).

Learning Factors in Health Information Processing

Learning factors refer to internal processes that influence how individuals engage with, process, and apply information. In the context of health communication, learning factors commonly include motivation to learn, intensity of information use, and perceived information sufficiency. These factors determine whether exposure to information leads to meaningful understanding and informed decision-making.
Motivation to learn plays a crucial role in health information seeking. Individuals who perceive health issues as relevant or risky are more motivated to search for information and engage with health messages (Zhou & Roberto, 2022). Among students, motivation is influenced by personal experiences, peer discussions, family communication, and exposure to digital media (Cohen et al., 2025). A supportive social environment can strengthen students' confidence and willingness to learn about health-related topics (Wang et al., 2024).

Intensity of information use refers to how frequently and actively individuals search for, consume, and apply information. Studies suggest that repeated exposure and active engagement with health information increase familiarity, comprehension, and retention (Schäfer et al., 2021). In digital contexts, social media and health applications encourage frequent interaction, which can enhance learning intensity but also increase exposure to unverified information (Freeman et al., 2023).
Perceived information sufficiency describes an individual's perception of having enough information to make informed decisions. According to the Risk Information Seeking and Processing Model, individuals are motivated to seek information when they feel their current knowledge is insufficient (Zhou & Roberto, 2022). When students perceive information as sufficient, they are more confident in evaluating health messages and deciding whether to act on them.

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Effectiveness of Health Communication

Health communication effectiveness refers to the extent to which health messages achieve their intended outcomes, such as increasing attention, improving understanding, enhancing engagement, shaping perspectives, and encouraging healthy behaviors. Effective health communication goes beyond message delivery and involves audience comprehension, trust, and the ability to translate information into action (Harrington, 2015; Stauch et al., 2025). Research indicates that health communication is more effective when audiences actively engage with information and perceive it as relevant and credible. Among adolescents, effective health communication has been linked to improved dietary behaviors, increased physical activity, and better reproductive health awareness (Cushing et al., 2021; Schaafsma et al., 2024). Digital platforms can enhance effectiveness by offering interactive features, peer support, and personalized content, although their impact depends heavily on users' ability to evaluate information quality (Zimmermann & Tomczyk, 2025).

METHOD

Design and Sample

This study employed a quantitative explanatory research design. Explanatory research aims to examine causal relationships among variables and explain why a particular phenomenon occurs by testing the relationships between independent, mediating, and dependent variables. This design was considered appropriate because the study sought to analyze the effects of information sources on learning factors and health communication effectiveness among students. The population of this study consisted of students at SMA Sejahtera 1, located in Depok City, West Java, Indonesia. The sample was selected using purposive sampling, a non-probability sampling technique in which participants are deliberately chosen based on specific criteria relevant to the research objectives. The criteria for sample selection included students who had accessed or received health-related information through social media, health applications, family discussions, or peer interactions, particularly regarding healthy eating, reproductive health, and healthy lifestyle behaviors. Based on these criteria, a total of 97 students from Grade X and Grade XI participated in the study. This sample size was considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM), which is suitable for exploratory and explanatory models with relatively small samples.

Instrument and Procedures

Data were collected using a structured questionnaire designed to measure the three main variables: information sources, learning factors, and health communication effectiveness. The questionnaire consisted of closed-ended statements developed based on relevant literature and previous empirical studies. Information sources were measured through indicators related to family, peers, social media, and health applications. Learning factors were measured using indicators of learning motivation, intensity of information use, and perceived information sufficiency. Health communication effectiveness was measured through indicators such as attention, clarity of understanding, engagement, perceived importance, perspective formation, and overall effectiveness. All questionnaire items were measured using a four-point Likert scale ranging from 1 (never/disagree) to 4 (always/agree). The use of a four-point scale was intended to reduce neutral responses and encourage clearer participant choices. The questionnaire was distributed online using Google Forms to facilitate data collection and ensure accessibility for respondents. Prior to distribution, students were informed about the purpose of the study and assured that their responses would remain confidential and used solely for research purposes. Participation was voluntary, and respondents completed the questionnaire independently within the designated time period.

Data Analysis

The collected data were analyzed using descriptive and inferential statistical techniques. Descriptive analysis was conducted to summarize respondents' demographic characteristics, including age and gender. Inferential analysis was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships among variables. PLS-SEM analysis was conducted in two main stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model). The measurement model was assessed by examining convergent validity, discriminant validity, and reliability. Convergent validity was evaluated using outer loading values and average variance extracted (AVE), while discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT). Reliability was examined through composite reliability values. The structural model was evaluated by analyzing path coefficients, t-statistics, and p-values to determine the significance of direct and indirect effects. Additional assessments included the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and model fit indices. Bootstrapping procedures were applied to test the significance of the relationships among information sources, learning factors, and health communication effectiveness.

RESULT AND DICSUSSION

This results and discussion section presents research findings regarding the relationship between information sources (independent), learning factors (mediation), and the effectiveness of student health communication (dependent) among students at SMA 1 Sejahtera Depok. The focus of the study is directed at how students obtain and interpret health information including issues of healthy eating patterns, reproductive health, and healthy lifestyle behaviors. As well as how health information is discussed and processed in everyday life experiences. The discussion is adjusted to the research objectives, namely (1) information sources directly influence learning factors by students; (2) information sources directly influence the effectiveness of student health communication; (3) learning factors directly influence the effectiveness of student health communication; (4) information sources indirectly influence the effectiveness of student health communication through learning factors. The research results will be discussed descriptively to describe the characteristics of respondents, and inferential analysis to evaluate the relationship between variables in accordance with the research objectives on 97 respondents who emphasize direct and indirect influences within a mediation framework. Inferential analysis is carried out through SEM-PLS-based procedures, namely evaluation of measurement models and evaluation of structural models.

Demographic Characteristics

The demographic characteristics of the respondents are described to illustrate the basic profile of the students involved in the study. Data include the age and gender distribution of the 97 respondents.

Table 1. Respondents' Age Characteristics

No.	Category	Amount	Percentage
1.	15 years	30	31.0
2.	16 years	50	51.5
3.	17 years	17	17.5
	Total	**97**	**100**

Based on Table 1, it shows that respondents were dominated by 16-year-old students with 50 respondents (51.5%), followed by 15-year-old respondents with 30 people (31%), and 17-year-old students with 17 respondents (17.5%). This finding can be interpreted that the description of behavior and responses to health issues are more reflected in the 16-year-old group, especially regarding involvement in discussing health issues such as healthy eating patterns, reproductive health, and healthy living behaviors. This means that the behavioral patterns and responses of this age group are the most dominant representation compared to respondents aged 15 and 17 years.

Meanwhile, the data in Table 2 shows a relatively balanced gender composition of respondents, although male respondents predominated at 53 (54.6%). Female respondents also represented 44 (45.5%). This finding suggests that the experiences and responses described were slightly more representative of male respondents, particularly regarding their involvement in discussing health issues such as healthy eating, reproductive health, and healthy lifestyles.

Table 2. Respondent Gender Characteristics

No.	Category	Amount	Percentage
1.	Man	53	54.6
2.	Woman	44	45.4
	Total	**97**	**100**

Evaluation of Measurement Model

The evaluation of the measurement model aims to ensure the quality of the measuring instrument, that the indicators used have met the validity and reliability criteria, making it suitable for use in the model. In other words, the evaluation of the measurement model is carried out to ensure that convergent validity and discriminant validity are truly valid. Convergent validity is defined as an outer loading ≥0.60 and an average variance extracted or AVE ≥0.50. Discriminant validity is measured through the Heterotrait-Monotrait Ratio or HTMT which is <0.90. The reliability value is measured through the Composite Reliability result >0.70. Other tests related to model fit are carried out through goodness of fit to see the model's ability to explain and predict.(Hair et al., 2022). The evaluation was conducted in two stages because in stage 1 there were several invalid indicators that had to be removed from the model as seen in Figure 1.

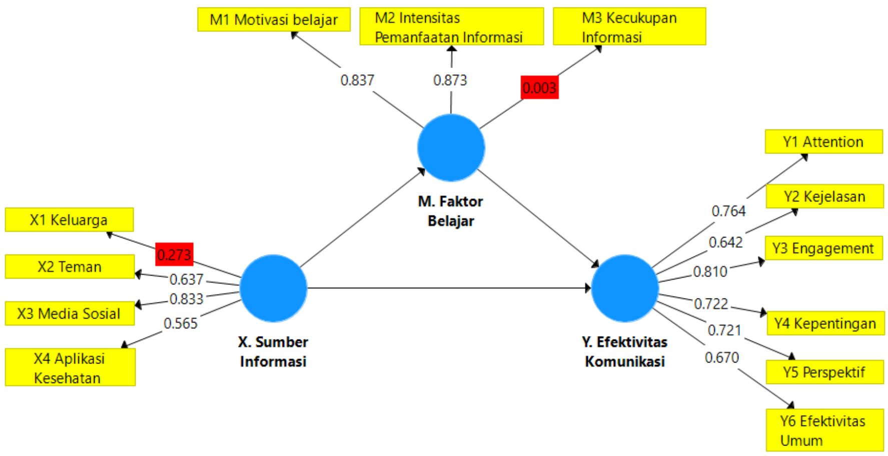

Figure 1. Stage 1 of Measurement Model Testing
(Before Indicator Deletion)

The measurement model shown in Figure 1 displays testing when all indicators are still complete. Based on the figure, indicator X1 (family) in the information source construct and M3 (information sufficiency) in the learning factor construct have outer loading values of 0.273 <0.60 and 0.003 <0.60, respectively, so it can be said that both indicators are considered invalid. Thus, both indicators, namely family and information sufficiency, must be removed or deleted from the model. Also, it is necessary to conduct a second stage of measurement evaluation testing. The evaluation test of the measurement model stage 2 can be seen in Figure 2 and Table 3. As seen, the data shows that all indicators have an outer loading value ≥0.60. This can be interpreted as all indicators for each construct are considered valid. The data also shows the reliability values of the three constructs: information sources (0.845), learning factors (0.733), and health communication effectiveness (0.868) have a composite reliability value greater than 0.70, so it is said to be reliable or consistent.

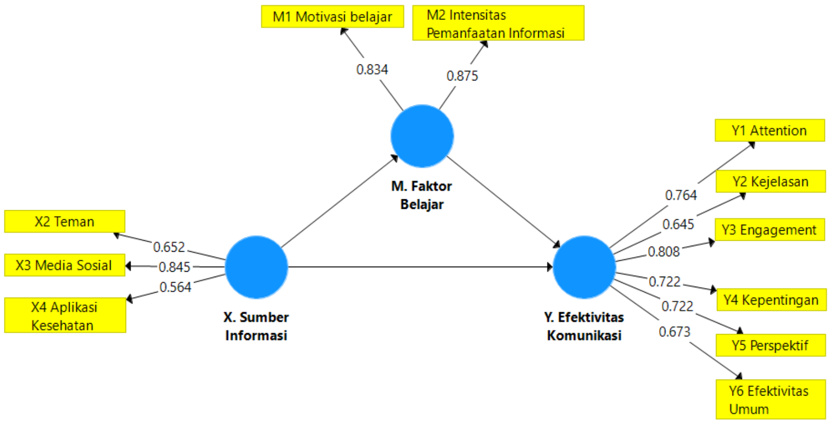

Figure 2. Stage 2 of Measurement Model Testing

Other data in Table 3 shows that the AVE values for the information source construct (0.731), learning factor (0.506), and health communication effectiveness (0.524) are greater than 0.50. Thus, convergent validity is met because the constructs explain more than 50% of the variables in their indicators. In other words, the indicators in this study adequately represent or align with their constructs.

Table 3. Composite Reliability Test Results and Averaged Variance Extracted(AVE)

Variables and Indicators	*Outer Loading*	*Composite Reliability*	AVE
X. Information Sources		0.845	0.731
X2 Friends	0.652		
X3 Social Media	0.845		
X4 Health App	0.564		
M. Learning Factors		0.733	0.506
M1 Learning Motivation	0.834		
M2 Intensity of Information Utilization	0.875		
Y. Communication Effectiveness		0.868	0.524
Y1 Attention	0.764		
Y2 Clarity	0.645		
Y3 Engagement	0.808		
Y4 Interests	0.722		
Y5 Perspective	0.722		
Y6 General Effectiveness	0.673		

Table 4 displays the results of the discriminant validity test using the Heterotrait-Monotrait Ratio (HTMT). Based on the data in the table, it is known that the constructs, namely the information source factor, learning factor, and communication effectiveness, have met the discriminant validity criteria because they have an HTMT value <0.90. This means that all constructs do not have overlapping symptoms or are considered different from each other. However, the value of 0.836 for the information source construct and the learning factor needs to be underlined, because it indicates that the two are almost similar, but are still considered different because the HTMT value is still below the threshold value.

Table 4. Results of Discriminant Validity Test (HTMT)

	M. Learning Factors	X. Information Sources
X. Information Sources	0.836	
Y. Communication Effectiveness	0.405	0.580

Based on the description of the measurement model evaluation, which shows that all tests have met the criteria for convergent validity (outer loading and average variance extracted or AVE), discriminant validity (Heterotrait-Monotrait Ratio or HTMT), and reliability, the structural model evaluation can now be conducted.

Structural Model Evaluation

Structural model evaluation was conducted to examine the relationships between constructs through path coefficients, including assessing model capability through determination coefficients using r-square, f-square, predictive relevance, and model fit. Decision-making criteria for path coefficient influence were based on p-values <0.05 and t-values >1.96.(Hair et al., 2022).The results of the structural model evaluation test for the relationship between variables can be seen in Figure 2 and Table 5. As seen in the Figure and Table below, there is a significant influence of information sources on learning factors (p=0.000<0.05; t=6.207>1.96). The data also shows a positive path coefficient because the original sample value (O) is 0.469. This means that when information sources increase, the learning factor will also increase by 0.469. The sample mean (M) value is 0.476 and the standard deviation (STDEV) is 0.076. At the indicator level, social media (t=15.732) is the most dominant indicator of the information source construct that influences the intensity of information utilization indicator (t=24.436) in the learning factor construct.

These findings indicate that exposure to health information obtained through discussions about healthy eating, reproductive health, and healthy lifestyles with parents/friends, social media, and health apps can improve students' learning factors, such as motivation, intensity of information utilization, and adequacy of health information. However, this study found that social media was the most dominant source of information in shaping learning factors, particularly in terms of intensity of information utilization. This encourages students to be more active in seeking, sorting, and utilizing the health information they obtain. Consistent with this, previous studies have shown that adolescents tend to obtain health information from a combination of digital sources (social media) and interpersonal sources such as parents. Meanwhile, adolescents' online health information-seeking behavior is largely influenced by their skills in searching and evaluating information, as well as parental support.(Gulec et al., 2022; Saraipour et al., 2025; Stauch et al., 2025).

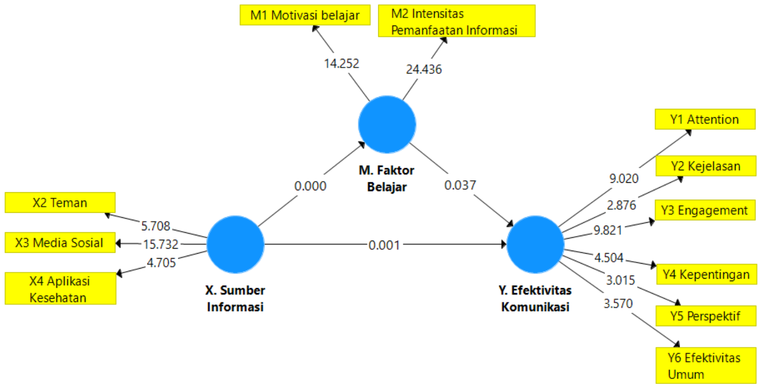

Figure 3. Structural Model Testing (Relationships Between Variables)

Other findings also showed the same results, namely the influence of information sources on the effectiveness of student health communication ($p = 0.001 < 0.05$; $t = 3.291 > 1.96$). The nature of the path coefficient influence is also positive because it has a positive original sample (O) value of 0.292. This means that when information sources increase, the effectiveness of student health communication also increases by 0.292. The sample mean (M) value is 0.310 and the standard deviation (STDEV) is 0.089. This study also found that information sources are able to influence the effectiveness of student health communication. The ability of information sources to influence learning factors shows interesting results, because if we look at the t value for each indicator, it can be seen that social media ($t = 15.732$) is an indicator that influences the construct of health communication effectiveness, especially the attention indicator ($t = 9.020$) and engagement ($t = 9.821$).

The findings indicate that overall information exposure can come from discussions about healthy eating patterns, reproductive health, and healthy lifestyle behaviors with parents/friends, social media, and health applications, increasing the effectiveness of health communication such as attention, clarity of understanding, involvement, interest, the formation of new insights, and assessment of general effectiveness. This is in line with previous studies that adolescents' online health information-seeking behavior is related to health literacy, and parental factors that contribute to shaping how adolescents access and process health information. (Tercova et al., 2025)However, this study found something interesting because social media is the most powerful source of health information that increases the effectiveness of students' health communication, specifically making students pay more attention to the content of discussions or health messages and more actively engage in discussions and seek further information related to these issues. Previous studies emphasized that student engagement with health information on social media is strongly influenced by trust in the platform, other users/peers, and content. Furthermore, social media interaction features such as Instagram (polls, quizzes, question stickers) are designed to encourage student participation and processing of message information.(Freeman et al., 2023).

Another direct influence finding comes from the significant influence of learning factors on the effectiveness of student health communication (p=0.037<0.05; t=2.093>1.96). The path coefficient of the learning factor construct on communication effectiveness is also positive because the original sample value (O) is 0.225. The sample mean (M) value is 0.250 and the standard deviation (STDEV) is 0.108. An interesting finding also shows the indicators of the learning factor construct that most strongly influence the effectiveness of student health communication. The data in Figure 3 shows the t value for the intensity of information utilization (t=24.436) as the indicator that most influences the effectiveness of student health communication, especially for the indicators of attention (t=9.020) and engagement (t=9.821). In other words, the more intensely students utilize health information, for example, actively seeking, filtering, and applying information, the more likely they are to pay attention to health messages or discussions and be more involved in communication processes such as healthy eating patterns, reproductive health, and healthy lifestyle behaviors. This finding is in line with the finding that orientation towards seeking health information and health literacy in students is related to more active health behavior.(You & Ahn, 2025). In the context of social media, student engagement with health information is related to platform-based beliefs.(Freeman et al., 2023), and the design of health dissemination through social media is aimed at increasing student engagement.(Zimmermann & Tomczyk, 2025).

Table 5. Direct Influence Path Coefficients

Path Coefficient	***Original Sample*(O)**	***Sample Mean*(M)**	***Standard Deviation* (STDEV)**	***T Statistics*(|O/STDEV|)**	***P Values***
X. Information Sources -> M. Learning Factors	0.469	0.476	0.076	6,207	**0.000**
X. Information Sources -> Y. Communication Effectiveness	0.292	0.310	0.089	3,291	**0.001**
M. Learning Factors -> Y. Communication Effectiveness	0.225	0.250	0.108	2,093	**0.037**

Table 6 presents the results of the data processing for the indirect influence path coefficient. Based on the table, this study found that learning factors were unable to mediate the influence of information sources on the effectiveness of students' health communication (p=0.072>0.05; 1.804<1.96). Although there was no mediation, the data processing results showed that this path coefficient was unidirectional because the original sample value (O) was positive at 0.106. The sample mean (M) value was 0.120 and the standard deviation (STDEV) was 0.059. These findings indicate that the influence of information sources on the effectiveness of students' health communication did not occur through learning factors as an intermediary. Therefore, it can be said that increased exposure to information from discussions with parents, friends, social media, and health applications is more accurately understood as directly driving the effectiveness of health communication. However, the direction of the coefficient remained positive indicating a tendency for a unidirectional relationship, although the magnitude of the indirect effect was not yet strong enough to be declared significant. This finding is consistent with previous studies that illustrate that information sources directly drive the effectiveness of health communication. Communication between parents and adolescents (students) is correlated with increasing adolescent self-efficacy in seeking health information and health services.(Javidi et al., 2025). In addition, other studies show that when parents become a source of information, it encourages higher levels of health-promoting behavior in adolescents.(You & Ahn, 2025)In the digital realm, exposure to social media and health apps is associated with adolescents' belief in action and attitude change, thus confirming that exposure to digital channels can be a direct pathway to student health communication.(Kirkpatrick & Lawrie, 2024; Martínez-García et al., 2023).

Table 6. Indirect Effect Coefficient (Specific Indirect Effect)

Path Coefficient	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
X. Information Sources -> M. Learning Factors -> Y. Communication Effectiveness	0.106	0.120	0.059	1,804	**0.072**

Table 7 displays the results of the coefficient of determination (r-square) data processing. Based on the data in the table, an r-square value of 0.220 indicates that the information source contributes 22% to the learning factor, with the remaining 78% being contributed by variables not examined in this study. Meanwhile, the data also shows an r-square value of 0.198, indicating that the information source and learning factor together contribute 19.8% to the effectiveness of health communication. The remaining 80.2% is contributed by other constructs not examined in this study. As with previous studies, the credibility of the information source is(Jenkins et al., 2020; L. Wang et al., 2024), trust in health institutions(Niederdeppe et al., 2025), health literacy(Ban et al., 2024; Taba et al.,

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2022)It determines whether messages are received, supported by the public, and whether communication is effective. It plays a major role in students' ability to understand, evaluate, and use health information.

Table 7. Results Of Rsquare Data Processing

Variables	***R Square***	***R Square Adjusted***
M. Learning Factors	0.220	0.212
Y. Communication Effectiveness	0.198	0.181

The following description provides information about Table 8 for the results of the model fit test using SRMR and NFI values. Based on the data in the table, the SRMR (0.100) and NFI (0.577) values indicate that the measurement model is considered appropriate or fit. This is in line with what is described bySchermelleh-Engel & Moosbrugger (2003)The SRMR value range of 0.08-0.10 indicates that the model is acceptable. Likewise, the NFI value indicates a good fit, but it is relatively low, because the closer the NFI value is to 1, the better the fit.(Hair et al., 2022).

Table 8 Model Fit

	Saturated Model	***Estimated Model***
SRMR	0.100	0.100
NFI	0.577	0.577

Table 9 displays the results of data processing on predictive relevance through blindfolding testing. Predictive relevance (Q2) is used to determine whether the model truly has the ability to predict the value of the endogenous variable. In other words, this test is conducted to determine the ability of information sources to predict learning factors. It also examines the ability of information sources and learning factors together to predict the effectiveness of students' health communication. If Q2 is greater than 0, then the model has predictive relevance. Based on Table 10, the Q2 values for the learning factor (0.152) and health communication effectiveness (0.076) are greater than 0, thus the model is considered to have predictive relevance for both endogenous variables. Furthermore, the large Q2 value for the learning factor indicates the information source's predictive ability for that construct is relatively stronger, compared to the model's predictive ability for the information source and learning factors on health communication effectiveness.

Table 9 Predictive relevance test (blindfolding)

Variables	**Q^2 (=1-SSE/SSO)**
M. Learning Factors	0.152
Y. Communication Effectiveness	0.076

CONCLUSION

The research conclusion summarizes the research results described previously. The research findings indicate that information sources have a direct and significant influence on student learning factors and the effectiveness of health communication. In the information source construct, social media is the strongest indicator, especially in encouraging the intensity of health information utilization in the learning factor, and increasing the indicators of attention and engagement in the effectiveness of student health communication. Furthermore, learning factors are also proven to have a significant influence on the effectiveness of health communication, especially with the intensity of information utilization as the most dominant indicator in strengthening students' attention and engagement in effective health communication. However, this study also found that learning factors were unable to mediate the influence of information sources on the effectiveness of student health communication, so the main influence pathway occurs more through the direct influence of information sources on health effectiveness, and not through the intermediary mechanism of learning factors. Future research needs to expand the scope of the design to provide a broader explanation of the relationships between variables. This is because this study used only a quantitative approach and involved a relatively small sample. Therefore, further studies are recommended using a larger sample to allow for comparative analysis, such as multi-group analysis (MGA) to examine differences in influence patterns based on student characteristics, level of media use intensity, and dominant information source category. Future research could also combine a mixed methods approach with interviews or focus group discussions (FGDs) to further explore why learning factors do not act as mediators.

REFERENCES

Afful-Dadzie, E., Afful-Dadzie, A., & Egala, S. B. (2021). Social Media in Health Communication: A Literature Review of Information Quality. Health Information Management Journal. https://doi.org/https://doi.org/10.1177/1833358321992683

Arigo, D., Jake-Schoffman, D.E., Wolin, K., Beckjord, E., Hekler, E.B., & Pagoto, S.L. (2019). The History and Future of Digital Health in the Field of Behavioral Medicine. Journal of Behavioral Medicine, 42(1), 67–83. https://doi.org/10.1007/s10865-018-9966-z

Ban, S., Kim, Y., & Seomun, G. (2024). Digital Health Literacy: A Concept Analysis. Digital Health, 10. https://doi.org/10.1177/20552076241287894

Bautista, J., & Schueller, S. M. (2023). Understanding the Adoption and Use of Digital Mental Health Apps Among College Students: Secondary Analysis of a National Survey. JMIR Mental Health, 10, e43942. https://doi.org/10.2196/43942

Chatterjee, A. (2017). Elements of Information Organization and Dissemination. Chandos Publishing.

Chen, N.-TN, Kee, K., Villalobos, B.T., Ortiz, M., & Lee, H. (2025). An in-Depth Exploration Into College Students' Information Acquisition and Evaluation Behaviors During the COVID-19 Infodemic. Frontiers in Communication, 10. https://doi.org/10.3389/fcomm.2025.1529161

Cohen, K.S., Fallik, D., & Cappola, A.R. (2025). The Role of Family as a Source of Health Information Among College Students. Journal of Community Health, 50, 613–622. https://doi.org/https://doi.org/10.1007/s10900-025-01448-8

Cushing, C.C., Bejarano, C.M., Ortega, A., Sayre, N., Fedele, D.A., & Smyth, J.M. (2021). Adaptive mHealth Intervention for Adolescent Physical Activity Promotion. Journal of Pediatric Psychology, 46(5), 536–546. https://doi.org/10.1093/jpepsy/jsaa125

Djurkalem, M., Tamaela, J., Soplanit, C., Souhaly, F., & Nifmaskossu, E. (2021). Health Communication on Digital Platforms: A Systematic Analysis of the Effectiveness of Medical Information Dissemination Through Social Media. BADATI Journal: Social Sciences and Humanities, 5(2), 160–180.

Fernández, A., Elmer, T., Sádaba, C., García-Manglano, J., & Vanden Abeele, M. (2025). The Quality of Face-to-Face and Digitally Mediated Social Interactions: Two Experience Sampling Studies Exploring the Moderating Role of Physical Location, Interaction Partner Familiarity, and Interaction Purpose. Journal of Computer-Mediated Communication, 30(2). https://doi.org/10.1093/jcmc/zmaf004

Freeman, J. L., Caldwell, P. H. Y., & Scott, K. M. (2023). How Adolescents Trust Health Information on Social Media: A Systematic Review. Academic Pediatrics, 23(4), 703–719. https://doi.org/10.1016/j.acap.2022.12.011

Gold, R.S., Auld, M.E., Abroms, L.C., Smyser, J., Yom-Tov, E., & Allegrante, J.P. (2019). Digital Health Communication Common Agenda 2.0: An Updated Consensus for the Public and Private Sectors to Advance Public Health. Health Education & Behavior, 46(2). https://doi.org/https://doi.org/10.1177/1090198119874086

Grønmo, S. (2020). Social Research Methods: Qualitative, Quantitative and Mixed Methods Approaches. SAGE Publications Ltd.

Gulec, H., Kvardova, N., & Smahel, D. (2022). Adolescents' Disease- and Fitness-Related Online Health Information Seeking Behaviors: The Roles of Perceived Trust in Online Health Information, eHealth Literacy, and Parental Factors. Computers in Human Behavior, 134, 107318. https://doi.org/10.1016/j.chb.2022.107318

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage Publications Inc.

Hanif, DR Al, Mahdalena, V., & Handayani, L. (2023). The Effectiveness of Health Communication through Short Videos for Health Behavior Change. Expression and Perception: Journal of Communication Science, 6(2). https://doi.org/http://dx.doi.org/10.33822/jep.v6i1.5725

Harianti, R., Nurjanah, T., & Hasrianto, N. (2021). Peer Education as a Method in Sexual, Reproductive Health Promotion and Risk Communication for

Adolescents. Journal of Communication Studies, 9(2), 213–223.
Harrington, N. G. (2015). Introduction to the Special Issue: Message Design in Health Communication Research. Health Communication, 30(2), 103–105. https://doi.org/http://dx.doi.org/10.1080/10410236.2014.974133
Hendekci, A., & Koç, F. (2025). Evaluation of the Peer-Supported E-Health Module Implemented for University Students to Develop Healthy Lifestyle Behaviors. Public Health Nursing, 42, 1525 of 1533. https://doi.org/https://doi.org/10.1111/phn.13563
Javidi, H., Verlenden, J. V., Chen, X., & Walsh-Buhi, E. R. (2025). Parent-Teen Sexual Health Communication and Teens' Health Information and Service Seeking. JAMA Network Open, 8(11), e2541712. https://doi.org/10.1001/jamanetworkopen.2025.41712
Jenkins, E.L., Ilicic, J., Barklamb, A.M., & McCaffrey, T.A. (2020). Assessing the Credibility and Authenticity of Social Media Content for Applications in Health Communication: Scoping Review. Journal of Medical Internet Research, 22(7), e17296. https://doi.org/10.2196/17296
Johansson, S., & Johansson, B. (2023). The Dynamics of Information-Seeking Repertoires: A Cross-Sectional Latent Class Analysis of Information-Seeking During the COVID-19 Pandemic. Mass Communication and Society, 27(2). https://doi.org/10.1080/15205436.2023.2258863
Kim, S.U., Martinović, I., & Katavić, S.S. (2019). The Use of Mobile Devices and Applications for Health Information: A Survey of Croatian Students. Journal of Librarianship and Information Science, 1–19. https://doi.org/DOI: 10.1177/0961000619880937
Kirkpatrick, C.E., & Lawrie, L.L. (2024). TikTok as a Source of Health Information and Misinformation for Young Women in the United States: Survey Study. JMIR Infodemiology, 4, e54663. https://doi.org/10.2196/54663
Koya, K., Chowdhury, G., & Green, E. (2024). Young Informal Carers' Information Needs Communicated Online: Professional and Personal Growth, Finance, Health and Relationships. Journal of Information Science, 50(3), 738–750. https://doi.org/10.1177/01655515221136829
Kucharczuk, A. J., Oliver, T. L., & Dowdell, E. B. (2022). Social Media's Influence on Adolescents′ Food Choices: A Mixed Studies Systematic Literature Review. Appetite, 168, 105765. https://doi.org/10.1016/j.appet.2021.105765
Kumalasari, EP, Imawati, Nursanti, DP, Rohmah, M., & Villasari, A. (2025). The Influence Of Peer Group Support On Knowledge And Personal Hygiene Attitudes During Menstruation In Adolescent Girls At Smp Negeri 2 Tumpang, Malang District. Journal for Quality in Women's Health, 8(1), 63–73. https://doi.org/DOI : https://doi.org/10.30994/jqwh.v8i1.280
Lim, MSC, Molenaar, A., Brennan, L., Reid, M., & McCaffrey, T. (2022). Young Adults' Use of Different Social Media Platforms for Health Information: Insights From Web-Based Conversations. Journal of Medical Internet Research, 24(1). https://doi.org/10.2196/23656
Martínez-García, G., Ewing, A.C., Olugbade, Y., DiClemente, R.J., & Kourtis, A.P. (2023). Crush: A Randomized Trial to Evaluate the Impact of a Mobile Health App on Adolescent Sexual Health. Journal of Adolescent Health, 72(2), 287–

294. https://doi.org/10.1016/j.jadohealth.2022.09.019
McGrew, S., Breakstone, J., Ortega, T., Smith, M., & Wineburg, S. (2018). Can Students Evaluate Online Sources? Learning From Assessments of Civic Online Reasoning. Theory & Research in Social Education, 46(2), 165–193. https://doi.org/10.1080/00933104.2017.1416320
McKinnon, K.A., Caldwell, P.H., & Scott, K.M. (2020). How Adolescent Patients Search for and Appraise Online Health Information: A Pilot Study. Journal of Pediatrics and Child Health. https://doi.org/doi:10.1111/jpc.14918
Montagni, I., Cariou, T., Feuillet, T., Langlois, E., & Tzourio, C. (2018). Exploring Digital Health Use and Opinions of University Students: Field Survey Study. JMIR MHealth and UHealth, 6(3), e65. https://doi.org/10.2196/mhealth.9131
Mustofa, RAB, & Sani, M. (2024). The Effectiveness of Health Promotion Through Social Media in Encouraging Healthy Lifestyle Behaviors in Adolescents. Social Symbiosis: Journal of Social and Political Science Integration, 1(3), 212–223. https://doi.org/https://doi.org/10.62383/sosial.v1i3.484
Niederdeppe, J., Boyd, A.D., King, A.J., & Rimal, R.N. (2025). Strategies for Effective Public Health Communication in a Complex Information Environment. Annual Review of Public Health, 46(1), 411–431. https://doi.org/10.1146/annurev-publhealth-071723-120721
Peng, Q. (2024). Research on the Information Consumption Behavior and Influencing Factors of Asian Youth in the Digital Age. Asia Youth Perspectives, 1(1), 1–10. https://doi.org/10.70433/ayp202401.1
Peng, W., Kanthawala, S., Yuan, S., & Hussain, S. A. (2016). A Qualitative Study of User Perceptions of Mobile Health Apps. BMC Public Health, 16, 1–11. https://doi.org/DOI 10.1186/s12889-016-3808-0
Peterson, E. B., Gaysynsky, A., Chou, W.-YS, & Rising, C. (2019). The Role and Impact of Health Literacy on Peer-to-Peer Health Communication. Information Services and Use, 39(1–2), 37–49. https://doi.org/10.3233/ISU-180039
Riyanto, S., & Putera, AR (2022). Research Methods for Health and Science Research. Deepublish.
Rusgis, M.M., Bays, J.E., Abt, R.M., & Sperry, M.L. (2022). Impact of COVID-19 Health Information Sources on Student Vaccine Hesitancy. Currents in Pharmacy Teaching and Learning, 14(4), 468–475. https://doi.org/10.1016/j.cptl.2022.02.004
Saraipour, F., Panahi, S., Nemati-Anaraki, L., & Shahraki-Mohammadi, A. (2025). Adolescents' Health Information–Seeking Behavior: A Scoping Review. Journal of Adolescent Health, 77(4), 592–601. https://doi.org/10.1016/j.jadohealth.2025.05.030
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial Least Squares Structural Equation Modeling. In Handbook of Market Research (pp. 587–632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15
Schaafsma, H.N., Jantzi, H.A., Seabrook, JA, McEachern, L.W., Burke, S.M., Irwin, J.D., & Gilliland, J.A. (2024). The Impact of Smartphone App–Based Interventions on Adolescents' Dietary Intake: A Systematic Review and Evaluation of Equity Factor Reporting in Intervention Studies. Nutrition

Reviews, 82(4), 467–486. https://doi.org/10.1093/nutrit/nuad058
Schäfer, M., Stark, B., Werner, A.M., Tibubos, A.N., Reichel, J.L., Pfirrmann, D., Edelmann, D., Heller, S., Mülder, L.M., Rigotti, T., Letzel, S., & Dietz, P. (2021). Health Information Seeking Among University Students Before and During the Corona Crisis—Findings From Germany. Frontiers in Public Health, 8. https://doi.org/10.3389/fpubh.2020.616603
Scharrer, E., & Ramasubramanian, S. (2021). Quantitative Research Methods in Communication: The Power of Numbers for Social Justice. Routledge.
Schermelleh-Engel, K., & Moosbrugger, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. Methods of Psychological Research Online, 8(2).
Söderlund, C., & Lundin, J. (2017). What is An Information Source? Communication Design Quarterly, 4(3), 12–19. https://doi.org/10.1145/3071078.3071081
Stauch, L., Renninger, D., Rangnow, P., Hartmann, A., Fischer, L., Dadaczynski, K., & Okan, O. (2025). Digital Health Literacy of Children and Adolescents and Its Association With Sociodemographic Factors: Representative Study Findings From Germany. Journal of Medical Internet Research, 27, e69170. https://doi.org/10.2196/69170
Sugiarto. (2022). Business Research Methods. Andi.
Taba, M., Allen, T.B., Caldwell, PHY, Skinner, S.R., Kang, M., McCaffery, K., & Scott, K.M. (2022). Adolescents' Self-Efficacy and Digital Health Literacy: a Cross-Sectional Mixed Methods Study. BMC Public Health, 22(1), 1223. https://doi.org/10.1186/s12889-022-13599-7
Tercova, N., Muzik, M., Dedkova, L., & Smahel, D. (2025). The Reciprocal Relationship Between Parental eHealth Literacy Mediation and Adolescents' eHealth Literacy: Three-Wave Longitudinal Study. Journal of Medical Internet Research, 27, e67034. https://doi.org/10.2196/67034
Thon, F. M., & Jucks, R. (2017). Believing in Expertise: How Authors' Credentials and Language Use Influence the Credibility of Online Health Information. Health Communication, 32(7), 828–836. https://doi.org/10.1080/10410236.2016.1172296
Wang, L., Li, X., Wang, D., & Zhu, J. (2024). Influence of Social Media Fitness Influencers' Credibility on Users' Physical Activity Intentions. DIGITAL HEALTH, 10. https://doi.org/10.1177/20552076241302016
Wang, Y., Zhang, J., & Huang, K. (2024). A Study on the Effect of School and Family Environments and Self-Efficacy on Health Literacy of College Students. Frontiers in Public Health, 12. https://doi.org/10.3389/fpubh.2024.1449819
Xu, Q., Hou, X., Xiao, T., & Zhao, W. (2022). Factors Affecting Medical Students' Continuance Intention to Use Mobile Health Applications. Journal of Multidisciplinary Healthcare, Volume 15, 471–484. https://doi.org/10.2147/JMDH.S327347
You, M.-A., & Ahn, J.-A. (2025). Health Information Orientation and Health Literacy as Determinants of Health Promotion Behaviors in Adolescents: a Cross-Sectional Study. Frontiers in Public Health, 12.

https://doi.org/10.3389/fpubh.2024.1522838
Zhao, Y., & Zhang, J. (2017). Consumer Health Information Seeking in Social Media: a Literature Review. Health Information and Libraries Journal. https://doi.org/DOI: 10.1111/hir.12192
Zhou, X., & Roberto, A. J. (2022). An Application of the Risk Information Seeking and Processing Model in Understanding College Students' COVID-19 Vaccination Information Seeking and Behavior. Science Communication, 44(4), 446–474. https://doi.org/10.1177/10755470221120415
Zimmermann, E., & Tomczyk, S. (2025). The Ways of Using Social Media for Health Promotion Among Adolescents: Qualitative Interview and Focus Group Study. Journal of Medical Internet Research, 27, e71510. https://doi.org/10.2196/71510