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Navigating Health Information: An Analysis of Social Media's Influence on University Students' Health Literacy

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Abstract

This study examines the impact of social media on health literacy among the university students in the city of Multan, Pakistan, using a cross-sectional survey design. For this purpose, we collected data from 200 students aged 18 - 30 years old across multiple departments of public and private universities. The study used a survey instrument with validated questions that have been tested and proven reliable. It asked how participants used social media platforms such as Instagram and Facebook, and measured their health literacy, encompassing knowledge, attitudes, behaviors and critical evaluation skills. statistical analysis using ANOVA and correlation tests revealed significant differences in health literacy across various social media platforms and highlighted the complex, multi-factorial nature of health information processing. Furthermore, the study findings demonstrate that social media apps such as YouTube, Facebook and WhatsApp have a positive relationship with certain aspects of health literacy, while also emphasizing that better health results ultimately depend on critical evaluation and fact-checking. Moreover, this research emphasizes the importance of tailored health communication strategies and digital literacy education to empower students in navigating health information online. This study has several limitations, including its cross-sectional design and self-reported data. To confirm causal relationships, longitudinal research is needed.

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Despite these limitations, this study provides valuable guidance for policy makers, educators and communicators aiming to leverage social media as a tool for enhancing health literacy in the university population.

Keywords

Social Media Usage, Health Literacy, Health Information Awareness, Digital Health Assessment

1. Introduction

Social media has significantly impacted social systems worldwide, becoming a popular tool for social interaction due to its freedom, anonymity, and network interactions. The young generation particularly enjoys these diverse spaces for online communication. Health-related information is easily accessible online, with social media playing a pivotal role in the health sector by helping individuals choose healthcare providers and promoting health behaviors. However, digital influencers can also spread health information, potentially leading to adverse health risks (de Oliveira Collet et al., 2024). The accessibility and interactive nature of these platforms allow students to actively seek, share, and discuss health-related content, which can enhance their electronic health literacy (eHealth literacy)—defined as the ability to locate, evaluate, and apply health information from electronic sources. Yet, the potential benefits may be limited by barriers including gaps in digital health literacy and worries about the authenticity and dependability of information shared on these platforms (Abrha et al., 2024).

Social media is a primary source of information for university students, especially for health literacy and knowledge. However, its popularity has also led to significant lifestyle changes and negative physical, psychological, and social problems. In recent years, students have become more reliant on social media for health information, as demonstrated by the extensive use of platforms like Facebook, WhatsApp, YouTube, Instagram, and Twitter (Moorhead et al., 2013). Although these platforms are convenient for accessing a multitude of information, there is a significant risk due to the prevalence of misleading information, unvetted content, and the lack of professional moderation (Waszak et al., 2018). Consequently, misinformation or poorly substantiated claims can negatively impact students' health literacy and decision-making process, seriously hampering their capacity to exhibit critical health competences if they are unable to identify false information and use critical thinking techniques (Vraga & Bode, 2017). It is therefore critical to comprehend how college students engage with online health information and how this engagement affects their health literacy-the capacity to get, comprehend, evaluate, and use health information to improve health (Sørensen et al., 2012).

Despite a growing body of literature, a notable gap remains in understanding how social media usage specifically shapes health literacy among university students in developing countries such as Pakistan. Existing studies have mostly focused on Western or high-income contexts, where internet infrastructure, digital literacy, and healthcare access differ significantly from the South Asian region (Moorhead et al., 2013; Levin-Zamir & Bertschi, 2018). Furthermore, while prior research acknowledges the dual role of social media as both an enabler and barrier, there is limited empirical evidence exploring the critical evaluation abilities of university students in these contexts-specifically, how well they can assess, verify, and apply health-related information gathered online. Most available studies tend to either generalize social media's impact or lack contextual depth regarding specific platforms (e.g., WhatsApp, YouTube, Facebook) and their unique patterns of influence. Another critical gap lies in the absence of a multidimensional analysis that treats health literacy as a composite of knowledge, comprehension, critical thinking, and behavioral response, rather than a single construct (Sørensen et al., 2012). This oversimplification ignores the complex interplay between content type, platform use, and user characteristics. In Pakistan, very few studies have examined how students from diverse faculties interpret health content via social media, and no substantial research has used stratified sampling across multiple institutions to ensure representation of different academic backgrounds-a key methodological gap this study addresses.

This study aims to fill these gaps by focusing on a developing country context (Pakistan) using localized data from Multan, analyzing social media's influence on distinct dimensions of health literacy, assessing students' ability to critically evaluate information across platforms, and utilizing stratified random sampling to capture demographic and academic diversity. It seeks to answer the following research questions:

- How does social media affect health literacy levels among university students?
- What types of health information do university students commonly evaluate on social media?
- To what extent does social media use influence university students' ability to critically assess health information?

The main objectives of this research are:

- To investigate the impact of social media on university students' health literacy, focusing on its influence on health knowledge, attitudes and behaviors.
- To evaluate whether exposure to health-related content on social media improves health literacy among university students.

This study holds considerable significance as it contributes to academic literature by providing a localized, nuanced understanding from a developing country context, which may guide regional education and health initiatives. It emphasizes the critical dimension of health literacy, which goes beyond simple knowledge acquisition to include evaluation and application, which is essential in an era of rapid misinformation spread. From a practical perspective, the findings can support healthcare professionals and policymakers in designing targeted, evidence-based health communication strategies tailored to youth, particularly for campaigns related to mental health, nutrition, and disease prevention. By ensuring representation from diverse academic and demographic groups, this study enables the development of customized health literacy programs and sets the stage for future comparative studies.

2. Literature Review

2.1. Media Usage and Health Literacy Levels

Health literacy refers to cognitive-social skills and motivation to understand, and use information for health improvement. It impacts health-related environments and critical health decisions. HL benefits home, work, society, and culture, but can lead to negative health outcomes. Individuals engage in various healthcare situations, including referring to healthcare centers, understanding health information, analyzing risks, making treatment decisions, and addressing health hazards in the workplace, with increased HL promoting increased participation in health-related activities (Yildiz et al., 2023). Health literacy is a significant issue in healthcare, with almost half of adults lacking reading or computation skills. Up to 48% of English-speaking patients lack functional health literacy, leading to poorer health status, knowledge of medical conditions, decreased understanding of preventive services, poor self-reported health, increased hospitalizations, and higher healthcare costs Adolescent's face challenges when using the internet for health information, including spelling medical terms and assessing site trustworthiness. Recommendations include using colloquial language, creating frequently asked question repositories, and training for improved search skills (Gray et al., 2005).

Health literacy refers to the ability to understand and process basic health information for appropriate health decisions. Low health literacy can lead to delayed diagnoses, poor treatment adherence, increased morbidity and mortality, and higher hospitalization rates. A systematic review aims to examine the relationship between health literacy and the use of online health resources, such as mobile and web-based applications (Kim & Xie, 2015). The World Wide Web provides extensive mental health information, including Mental Health Info source, to the public. With increasing internet access, it can inform patients about mental health disorders and their treatment options. However, issues like information overload and quality need to be addressed. Portal websites dedicated to mental health are being developed to address these issues (Christensen & Griffiths, 2000). Additionally, health literacy is related to screen time, as screen time is a requirement for internet addiction diagnosis. In response to reward impulsivity theory, individuals with Internet Addiction (IA) tend to have high trait impulsivity, leading to poor decision-making skills (Liu et al., 2023).

A study involving 418 Brazilians found that those with higher eHealth literacy use social media to seek dentists and learn about symptoms, diagnoses, and treatments. They avoid digital influencer-promoted products and conduct health status research, suggesting they are less influenced by these influencers (de Oliveira

Collet et al., 2024).

H1: Social media usage has a significant effect on the health literacy levels of university students.

2.2. Health Information on Social Media Platforms

A study explores the role of the Worldwide Web in mental health, focusing on its advantages, disadvantages, and potential dangers. It examines the clinician's perspective and the public's mental health literacy. The results show that the Web offers access to information, online therapy, and adjunctive therapy, but also presents issues like information overload, poor quality, potential harm, and lack of scientific evaluation. The paper concludes that the Internet should be evaluated for its effectiveness (Christensen & Griffiths, 2000). A study on health literacy among American and European adults found that motivation for health-related Internet use is mediated by health-related Internet use and perceived health information overload, suggesting the Cognitive Mediation Model's extension to health literacy (Jiang & Beaudoin, 2016). A study in Ireland found that 78% and 93% of respondents correctly identified depression and psychosis/schizophrenia, respectively. However, half referred to schizophrenia as a'split personality disorder'. Age and urbanicity did not affect diagnosis accuracy, but females and university students were more likely to identify the diagnosis (Lawlor et al., 2008).

A study in Ankara, Turkey, involving 756 adolescents aged 15 - 18, found that 56.1% had inadequate health literacy, 30.1% had sufficient literacy, and 13.8% had excellent literacy. The study also found a significant correlation between health literacy and self-efficacy levels, with participants with poor self-efficacy levels more likely to have inadequate health literacy. The importance of internet use and self-efficacy in health literacy was also highlighted (Ceylan et al., 2022). A study of literature review found a positive association between eHealth literacy and health-related behaviors among 29 studies out of 1922. A moderate correlation was found, with a positive correlation observed for older adults, individuals with diseases, and health-promoting behavior. The study suggests that eHealth literacy can act as a mediator in the process of health-related information leading to changes in health-related behaviors. However, larger-scale studies with stronger validity are needed for future health promotion (Kim et al., 2023).

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H2: University students commonly evaluate specific types of health information (e.g., diet, mental health, fitness) on social media platforms.

2.3. Health Information Is Influenced by Social Media Usage Patterns

Adolescents face challenges when using the internet for health information, including spelling medical terms and assessing site trustworthiness. Recommendations include using colloquial language, creating frequently asked question repositories, and training for improved search skills (Gray et al., 2005). Health literacy is related to screen time, as screen time is a requirement for internet addiction diagnosis. In response to reward impulsivity theory, individuals with Internet Addiction (IA) tend to have high trait impulsivity, leading to poor decision-making skills (Liu et al., 2023). A study of literature review found a positive association between eHealth literacy and health-related behaviors among 29 studies out of 1922. A moderate correlation was found, with a positive correlation observed for older adults, individuals with diseases, and health-promoting behavior. The study suggests that e-Health literacy can act as a mediator in the process of health-related information leading to changes in health-related behaviors. However, larger-scale studies with stronger validity are needed for future health promotion (Kim et al., 2023).

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H3: The ability of university students to critically assess health information is significantly influenced by their social media usage patterns.

2.4. Theory Integration

Theory adoption, also known as theory integration or theoretical framework development, refers to the process of selecting and applying existing theories to guide the design, interpretation, and analysis of a study. It helps researchers explain relationships between variables, contextualize findings, and connect their work to broader scholarly discourse. Adopting relevant theories strengthens the academic foundation of a study, enhances its analytical depth, and provides a systematic lens for interpreting complex phenomena (Creswell, 2014; Eisenhardt, 1989). When theories are integrated thoughtfully, they offer a more holistic understanding of the research problem and contribute to theory development or refinement in the field. In this study, the integration of Media Ecology Theory and health literacy models provides a comprehensive framework for examining how media environments—particularly social media—affect individuals' ability to access, interpret, evaluate, and apply health information in daily life. Media Ecology Theory, introduced by McLuhan (1994) and later expanded by Eurich, A. C. (1970), posits that media are not merely tools for communication but environments that shape human perception, understanding, and social behavior. In the realm of health communication, this theory explains how different digital platforms (e.g., Instagram, TikTok, Facebook) construct unique informational ecosystems that influence how users engage with and internalize health messages.

For instance, the theory's view of media as distinct "environments" directly informs the investigation of how a platform's specific affordances (e.g., the ephemeral nature of stories, the algorithm-driven feed of TikTok) shapes the critical health literacy skill of evaluating the credibility and applicability of platform-specific content.

When integrated with health literacy models such as those proposed by

Nutbeam (2000) and Sørensen et al. (2012)—which conceptualize health literacy in terms of functional, interactive, and critical components, this theoretical framework allows for a nuanced investigation into how young adults understand and act upon health information sourced from social media. This is particularly relevant for university students, who are active social media users and frequently engage with digital health content. The adoption of these theories enhances the study's explanatory power and provides a solid foundation for analyzing how media exposure and usage patterns relate to students' health literacy levels. Additionally, this integration supports meaningful contributions to the academic fields of digital health communication, media studies, and public health education. The integration of Media Ecology Theory and health literacy models provides a comprehensive framework for understanding how media environments influence individuals' ability to access, interpret, and apply health information. In the context of health literacy, this theory highlights how digital and social media platforms act not merely as channels but as environments that reshape how people engage with health-related content.

For instance, individuals with higher levels of critical health literacy are more capable of evaluating the credibility of online health information, especially within media-rich environments that often contain misinformation. Norman and Skinner (2006) further introduced the concept of eHealth literacy, emphasizing the need for digital competence in navigating complex online health ecosystems. By integrating Media Ecology Theory with health literacy models, researchers and practitioners can better understand how the medium (e.g., social media, mobile apps, websites) influences the message and the user's interpretation, ultimately affecting health behavior and decision-making. This approach underscores the importance of designing health communication strategies that consider not just the content but also the media environment in which it is delivered (Chinn, 2011), fostering more effective health education and behavior change in a digitally connected world.

Aligning Media Ecology Theory offers a valuable lens through which to examine how digital environments shape young adults' understanding and engagement with health information. Media Ecology Theory, proposed by McLuhan (1994) and further developed by Eurich, A. C. (1970), suggests that media are not just passive channels of communication but active environments that influence how individuals think, perceive, and interact with information. In the context of university students, who are frequent users of social media platforms, this theory helps explain how their constant interaction with digital media affects the way they access and evaluate health-related content.

University students are immersed in a digital ecosystem where platforms like Instagram, TikTok, Twitter, and YouTube serve as primary sources of health information. According to Norman and Skinner (2006), navigating this complex online environment requires a high level of eHealth literacy, which involves not only understanding health content but also evaluating its credibility and applying it effectively. Social media, therefore, becomes both a tool and a challenge—

providing immediate access to health content but also exposing students to misinformation and varying levels of source reliability.

By integrating Media Ecology Theory with the concept of health literacy, researchers can better understand the mechanisms through which social media influences students' health knowledge, attitudes, and behaviors. This alignment underscores the need to equip students with critical media and health literacy skills to help them navigate digital health information responsibly and effectively. Thus, Media Ecology Theory not only supports the investigation of social media's impact on health literacy but also provides a theoretical foundation for developing interventions that promote informed health behaviors among university students.

3. Methodology

3.1. Research Design and Approach

Study's undergraduate participants were enrolled full-time in Multan, Pakistan's public and private institutions and universities. In addition to focusing on university students' health literacy, this study aimed to determine how much social media affects students' health-related behaviors and knowledge. In order to gather data at a particular point in time, the researchers used a cross-sectional survey as part of their quantitative technique. According to Creswell (2014) and Bryman (2016), cross-sectional surveys provide a thorough picture of a population, its characteristics, and their relationships, making them ideal for descriptive and exploratory research. The approach eliminates the need for lengthy observation periods by concurrently gathering and analyzing data on the relationships between social media usage and health literacy (Levin, 2006).

3.2. Study Setting and Population

Because structured questionnaires allow for more consistent responses and make quantitative analysis easier, they are a suggested method in social science and health communication research (DeVellis & Thorpe, 2021). To verify construct validity and reliability, the questionnaire items were adapted from previously examined measures (Nutbeam, 2008; Sørensen et al., 2012). Before the instrument was fully deployed, pilot testing was done to ensure that it was suitable for the target culture and easily understood. Students between the ages of 18 and 30 made up the target population, which is representative of the normal student body with an active social media presence (Lenhart et al., 2015). Since young people' reading skills are crucial for making informed health decisions, this emphasis is in line with earlier studies that have highlighted the importance of young adults as major consumers of digital health information (Paakkari & Okan, 2020).

3.3. Sampling Strategy

Stratified random sampling was used to provide a sample that was representative of the population. To reduce sample bias and maximize generalizability, this sampling approach is suggested for populations that are heterogeneous. It entails splitting the population into different strata and then randomly selecting individuals proportionally from each category (Kish, 1965; Creswell, 2014). The study was able to capture diversity within the student body and conduct complex subgroup analysis because of the stratification by faculties and demographic characteristics.

3.4. Data Collection Instruments

In this work, structured questionnaires were used as the main tool for gathering data. The purpose of the study was to learn more about college students' health literacy and how they typically use and access health-related content on social media. By using items from validated scales and previous research, the questionnaire's content validity and reliability were ensured (e.g., Nutbeam, 2008; Paakkari & Okan, 2020). The questionnaire's sections on demographics, social media use, health information provided or requested, and self-assessed health literacy (including the ability to comprehend, assess, and use health information) were all categorised. Rapid data collection from a large sample and quantitative analysis, including statistical testing for correlations and differences, are made easier by the use of a structured questionnaire. A pilot study was conducted to evaluate the instrument and find any ambiguities or contradictions. This improved the data's integrity by allowing the required adjustments to be made before the full-scale administration.

Data was collected using a three-part self-administered questionnaire:

1) Personal Information (e.g., gender, age, educational background).

2) Health Literacy Measurement: The HLQ, a dependable and widely used instrument for assessing health literacy, was developed by Osborne et al. (2013). These enquiries were derived from the HLQ.

3) Health Content Engagement and Social Media Use: This section was updated based on previous research on online health practices and disinformation (e.g., Kühn et al., 2022; Rehman et al., 2023a). Engagement with health-related content, knowledge of health-related misinformation, preferable platforms, and utilisation of social media were all evaluated.

3.5. Measurement of Variables

The investigation's goal was to measure a number of important factors in order to gauge college students' health literacy and social media use. One of these measures was a student's health literacy, which indicated how well they could find, evaluate, and apply health-related information. We evaluated the platforms and students' interaction with the content to have a more thorough grasp of the quantity and type of social media use. The study also looked at how well students were able to recognise and assess false health information on social media, which revealed how well they understood the problem. In order to comprehend the impact of online content on students' attitudes and behaviors surrounding personal health, the perceived influence of social media on health behavior was finally explored. Before data was gathered on a broader scale, the questionnaire was pilot tested with a group of college students to make sure the items were clear, pertinent, and consistent.

3.6. Pilot Study and Instrument Validation

Of the 25 individuals who participated in this preliminary testing, 25 met the study's inclusion criteria. In an effort to enhance clarity and eliminate any potential for interpretational error, a number of queries were rephrased in accordance with the feedback of the pilot group. The reliability study, which employed Cronbach's alpha, resulted in satisfactory internal consistency across the primary constructs, with alpha values ranging from 0.72 to 0.84. The questionnaire was suitable for the primary study, as it assessed health literacy, social media use, knowledge of inaccurate information, and perceived influence on health behavior, as indicated by these results.

3.7. Conceptual Framework

The study's conceptual framework (**Figure 1**), which was developed by combining media ecology theory with health literacy frameworks, states that social media platforms serve as unique informational ecosystems that impact how people learn and use health-related information. In the area of media theory, this conceptual paradigm expands on the work of McLuhan (1994) and Nutbeam (2000). It argues that the functional, interactive, and critical literacy aspects of users' ability to process health information are all affected differently by platform-specific affordances, such as TikTok's algorithmic curation and WhatsApp's privacy settings. By combining Bandura's (2001) social cognitive theory with Metzger's (2007) digital literacy principles, the framework clarifies how people's practices of seeking health information are supported by their consistent use of platforms. It also takes into account how people check the information they find.

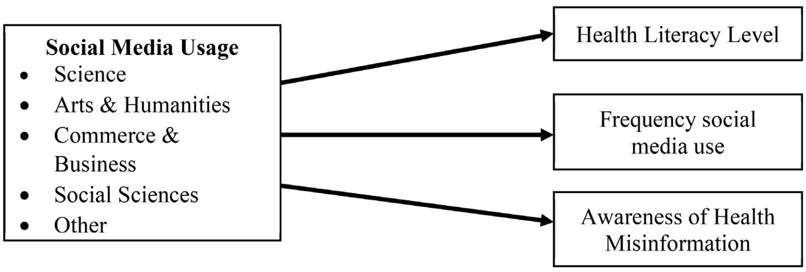

Figure 1. Research model.

This synthesized model builds on the health literacy framework developed by Sørensen et al. (2012) by incorporating platform-mediated variables as modifiers between information exposure and health decision-making. It particularly discusses how echo chamber effects (Dubois & Blank, 2018) and algorithmic personalization (Pariser, 2011) can either raise or lower the hazards of health misinformation. This conceptual model bridges the gap between public health and communication studies by offering a media-sensitive framework for understanding the development of health literacy in today's information-rich cultures.

4. Results

The results of the statistical analysis carried out for the study using IBM SPSS Version 20.0 are shown in this section. Following a demographic analysis of the respondents, the results are arranged to correspond with the goals of the study. We then look into social media usage, health literacy, knowledge of false information, and the perceived influence of social media on conduct related to health. To understand the trends and relationships between important variables, statisticians use descriptive and inferential statistics. IBM SPSS Version 20.0, a well-known application for statistical analysis in the social sciences, was systematically analyzed to produce the study's findings. After data classification, the data was loaded into SPSS for statistical analysis. There, both descriptive and inferential approaches were used. To describe the demographic traits and broad trends among the variables, descriptive statistics were used, including frequencies, percentages, means, and standard deviations. To look at the relationships between students' social media use and their health literacy levels, inferential statistics such as correlation analysis, independent samples t-tests, and analysis of variance were used. This section begins with the respondent's demographic profile in order to lay the groundwork for understanding the analytical findings that will follow.

4.1. Demographic Analysis

By elucidating the features of the population under investigation, demographic analysis forms the basis of social science research. To better understand their backgrounds, the demographic traits of the college students who took part in the study were examined. A more thorough understanding of social media usage trends and patterns as well as health literacy is made possible by this contextual knowledge. Descriptive statistics were applied to the coded demographic data collected from the questionnaire using IBM SPSS Version 20.0. Critical demographic factors included age, gender, academic major, graduation year, and family income. These factors are crucial for determining if student groups differ in their use of social media and health literacy. Gender, academic year, economic level, and faculty were considered categorical factors, while age was considered a continuous variable. For categorical data, descriptive statistics like percentages and frequencies were used. Age was one of the continuous variables for which we computed the mean and standard deviation. The sample's demographics are thoroughly reviewed in this section; the results and their interpretation will be covered in more detail in the sections that follow. A more thorough understanding of the knowledge- and behavior-based outcomes of the study can be facilitated by the demographic profile.

Demographic analysis refers to the process of looking at and analyzing statistical information about a community or a subset of it. Demographic data, including age, gender, income, education, race/ethnicity, and occupation, are gathered and analyzed. This analysis gives researchers a more thorough understanding of a population's makeup, distribution, and trends. To make sure that the samples are representative of the community of interest and to compare different subgroups in order to fully comprehend the findings, demographic analysis is a crucial part of research. Researchers might more successfully focus treatments or policies to particular demographic subsets by looking for trends and correlations in demographic data that might have an impact on the phenomenon being studied (Babbie, 2013).

According to the demographic analysis, the 200-person sample is gender-balanced, with 48.0% of the participants being men (n = 96) and 52.0% being women (n = 104). The fact that the age distribution is biassed towards younger respondents—the largest group was 22 - 25 years old (48.0%, n = 96), followed by 18 - 21 years old (32.5%, n = 65), and 26 - 30 years old (19.5%, n = 39)—indicates that the results primarily represent the opinions of younger adults. Science (28.0%, n = 56), Arts & Humanities (23.5%, n = 47), Commerce & Business (21.0%, n = 42), Social Sciences (15.5%, n = 31), and other faculties (12.0%, n = 24) are the most popular academic fields. Given that STEM areas are more prevalent, this distribution may affect health literacy and awareness of false information. The findings may not be as applicable to older populations or non-STEM areas due to the demographic profile's concentration on youth and science-oriented respondents. Nonetheless, greater generalisability across sexes is made possible by the gender balance. Additional demographic details, such as socioeconomic status or geographic location, would further enhance the contextual understanding of the sample (**Table 1**).

Table 1. Demographic variables.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	96	48.0
	Female	104	52.0
Age Group	18 - 21	65	32.5
	22 - 25	96	48.0
	26 - 30	39	19.5
Faculty	Science	56	28.0
	Arts & Humanities	47	23.5
	Commerce & Business	42	21.0
	Social Sciences	31	15.5
	Other	24	12.0

4.2. Reliability Test

A reliability test evaluates the stability and repeatability of a research scale or measuring instrument. It assesses the consistency and dependability of the tool's output across a range of samples and time periods. If the data collected by the instrument is accurate and consistent with the construct being measured, then the instrument must be considered dependable. A commonly used reliability metric that measures how closely a group of objects are related to one another is Cronbach's Alpha (Cronbach, 1951). This measure evaluates the set's internal consistency. The components of the instrument consistently quantify the same basic notion when the reliability coefficient is high, usually greater than 0.70. For the purpose of removing measurement errors, boosting confidence in the results, and validating research tools, reliability tests are crucial (Nunnally & Bernstein, 1994).

The reliability statistics **Table 2** presents Cronbach's alpha coefficients for an 18-item scale, demonstrating strong internal consistency. The scale items appear to be extremely dependable based on the reported Cronbach's alpha of 0.844, which is higher than the generally accepted threshold of 0.70 (Nunnally, 1978). Consistent performance across standardised items is suggested by the slightly decreased standardised alpha coefficient of 0.773, which is still within the acceptable range. These findings, based on an analysis of 18 items, show that the scale regularly yields reliable results. Researchers can be sure that the scale assesses the intended construct accurately because of its strong reliability coefficients. These findings, along with the theoretical underpinnings of the scale and validity assessments, must be taken into account in order to perform a thorough interpretation (Field, 2018). Future studies could look at test-retest reliability to further demonstrate how measurements hold up over time.

Table 2. Reliability statistics.

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.844	0.773	18

4.3. Standard Deviation Test

One statistical metric for assessing the volatility or dispersion in a collection of data values is the standard deviation. This computation is known as the standard deviation test. When compared to the dataset mean, it displays the average degree of dispersion of the data elements. The standard deviation can be used to better comprehend the data's distribution and regularity. The data points are more evenly distributed and show less fluctuation when the standard deviation is low. A high standard deviation indicates greater dispersion since the data points are spread across a wider range of values.

In research, calculating standard deviation helps understand the reliability and variability of responses, assess data distribution, and compare differences within and between groups. It is a fundamental descriptive statistic used before conducting more complex analyses.

Table 3 presents descriptive statistics related to the use of social media for health-related purposes, health literacy, and awareness among a sample of 200 respondents. The construct of "App usage" indicates relatively low mean scores across all platforms, suggesting that participants seldom use social media platforms such as WhatsApp (M = 1.09, SD = 0.287), YouTube (M = 1.11, SD = 0.314), Facebook (M = 1.34, SD = 0.473), Instagram (M = 1.36, SD = 0.480), TikTok (M = 1.49, SD = 0.501), and Twitter (M = 1.70, SD = 0.462) for obtaining health-related information. This implies limited reliance on these platforms for health purposes, aligning with findings by Vosoughi, Roy, and Aral (2018), who noted that although social media is widely used, its credibility in health communication is often questioned.

Table 3. Standard deviation.

Constructs	Item Statistics			
	Description	Mean	Std. Deviation	N
App usage	Do you use WhatsApp for health-related information?	1.09	0.287	200
	Do you use YouTube for health-related information?	1.11	0.314	200
	Do you use Facebook for health-related information?	1.34	0.473	200
	Do you use Instagram for health-related information?	1.36	0.480	200
	Do you use TikTok for health-related information?	1.49	0.501	200
	Do you use twitter for health-related information?	1.70	0.462	200
Health literacy	I feel confident in understanding health information.	3.47	1.111	200
	I can judge when health information is right or wrong.	3.90	1.143	200
	I know how to find helpful health information.	3.75	1.190	200
	I can follow instructions from healthcare providers.	3.80	1.152	200
	I understand how to take care of my health.	3.67	1.095	200
	I know when and where to seek health care.	3.55	1.106	200
	I can manage my health conditions using information available to me.	3.47	1.276	200
Usage of social media for Health	How often do you use social media per day?	1.52	0.820	200
	Do you follow health-related pages/accounts on social media?	1.70	0.462	200
Awareness	How often do you engage (like/share/comment) on health posts?	3.80	1.152	200
	Have you ever encountered misleading or false health information on social media?	3.67	1.095	200
	Do your fact-check health information seen on social media before acting on it?	3.55	1.106	200

In contrast, the "Health literacy" construct demonstrates higher mean values, showing that respondents exhibit a relatively strong ability to understand and engage with health information. For instance, participants reported confidence in judging the credibility of health information (M = 3.90, SD = 1.143) and following instructions from healthcare providers (M = 3.80, SD = 1.152). They also indicated awareness of where to seek healthcare (M = 3.55, SD = 1.106) and how to take care of their health (M = 3.67, SD = 1.095). This reflects a well-developed sense of health literacy among the sample, supporting Nutbeam's (2000) conceptualization of health literacy as not just the ability to read health information but to critically evaluate and apply it effectively. The construct "Usage of social media for health" also reveals low levels of engagement, with participants reporting infrequent daily use of social media for health purposes (M = 1.52, SD = 0.820) and limited following of health-related pages (M = 1.70, SD = 0.462). However, when it comes to "Awareness", the results are more encouraging. Participants indicated relatively frequent engagement with health-related posts (M = 3.80, SD = 1.152), recognition of misleading health content (M = 3.67, SD = 1.095), and a tendency to fact-check information before acting on it (M = 3.55, SD = 1.106). This research is consistent with the findings of Chou et al. (2009), who emphasized the growing significance of social media in the promotion of public health awareness and the development of well-informed decision-making mechanisms. In general, the statistics suggest that users are relatively knowledgeable about health concerns and are cautious and discerning about the content they encounter online, despite the fact that social media is not frequently used as a primary source of health information among the respondents. Social media has the ability to function as a supportive instrument in the promotion of public health by utilising strategies that enhance the trustworthiness and credibility of digital health material (Korda & Itani, 2013).

4.4. ANOVA Test Friedman's Test and Tukey's Test for Non-Additivity

The statistical technique known as analysis of variance, or ANOVA, compares the means of several groups to find statistically significant differences. When group mean deviations beyond the expected range, it helps researchers determine whether the variables being studied show considerable variations (Field, 2024). Friedman's Test is a parameter-independent substitute for the one-way repeated-measures ANOVA. When the normality and other assumptions of parametric ANOVA are not met, this process is used. Both ordinally and non-normally distributed interval data can be used with this test. It evaluates differences across a range of related groups or conditions by ranking data within subjects and analysing those ranks.

Tukey's Test for Non-additivity is a diagnostic procedure designed to detect non-additive interactions in a two-way ANOVA model (Friedman, 1937). Non-additivity occurs when the combined effect of factors is not simply the sum of their individual effects, suggesting interactions or nonlinear relationships between variables. Tukey's test helps determine whether transforming the data (e.g., applying a power transformation) is necessary to meet the additive model assumptions, thus improving the accuracy and interpretability of the ANOVA results (Tukey, 1949).

The ANOVA **Table 4** presented above includes Friedman's Test and Tukey's Test for Non-additivity, which are used to assess the variation within and between items and individuals in a dataset. The total sum of squares is 7618.556, with 3599 degrees of freedom, indicating the overall variability in the dataset. The "Between People" sum of squares is 819.889 with a mean square of 4.120 across 199 degrees of freedom, reflecting variability among the individuals in the sample. The "Within People" section shows that the sum of squares between items is 4619.836 with 17 degrees of freedom, resulting in a mean square of 271.755. Friedman's chi-square value for this portion is 421.945 with a significance level of 0.000, indicating a statistically significant difference in responses across the items, as supported by findings from Friedman (1937). Furthermore, the residual within people is broken down into non-additivity and balance components. The non-additivity component has a sum of squares of 541.086 and a mean square of the same value with 1 degree of freedom. The corresponding Friedman's chi-square is 1117.360 and the *p*-value is 0.000, suggesting a significant level of non-additivity, meaning that the data may not perfectly follow the assumptions of additivity in the ANOVA model.

Table 4. ANOVA.

			Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People			819.889	199	4.120		
Within People	Between Items		4619.836	17	271.755	421.945	0.000
	Residual	Non-additivity	541.086[a]	1	541.086	1117.360	0.000
		Balance	1637.745	3382	0.484		
		Total	2178.831	3383	0.644		
	Total		6798.667	3400	2.000		
Total			7618.556	3599	2.117		
Grand Mean = 2.66							

a: Tukey's estimate of power to which observations must be raised to achieve additivity = −0.908.

Tukey's estimate indicates that observations must be raised to the power of −0.908 to achieve additivity, confirming the presence of non-linear interactions among variables (Tukey, 1949). The remaining variation, labeled as "Balance", accounts for a sum of squares of 1637.745 across 3382 degrees of freedom, with a mean square of 0.484. This part represents the residual or unexplained variation after accounting for the effects of items and non-additivity. The total residual within people is 2178.831 with 3383 degrees of freedom, giving a mean square of 0.644. Overall, the table supports the presence of statistically significant differences across items and suggests the need to consider potential interaction effects in the model due to the detected non-additivity, which is consistent with the recommendations made by Tabachnick and Fidell (2013) regarding the assessment of model assumptions in complex ANOVA designs.

4.5. Correlation Test

A correlation test is a statistical procedure used to measure and analyze the strength and direction of the relationship between two continuous variables. It helps determine whether, and how strongly, pairs of variables are related. The result of a correlation test is usually expressed as a correlation coefficient (commonly Pearson's r), which ranges from −1 to +1. A coefficient close to +1 indicates a strong positive relationship, meaning that as one variable increases, the other tends to increase as well. A coefficient near −1 indicates a strong negative relationship, where one variable increases as the other decreases. A value around 0 suggests no linear relationship between the variables. Correlation tests are important in research because they help identify associations between variables without implying causation. They provide insights into patterns and trends that may guide further analysis or hypothesis testing (Field, 2024).

The correlation matrix reveals several significant relationships among social media usage patterns and health literacy dimensions. Notably, WhatsApp usage for health information shows weak but statistically significant positive correlations with YouTube ($r = 0.224$, $p = 0.001$) and Facebook ($r = 0.221$, $p = 0.002$) usage, suggesting overlapping platform engagement behaviors. This pattern of inter-correlation suggests that students who seek health information on one platform are likely to use other platforms concurrently, indicating a behavior of cross-referencing or diversifying their information sources rather than relying on a single app. This could imply a strategic approach to information gathering, where users compare content across different digital environments to form a more comprehensive understanding of health topics.

Health literacy items demonstrate strong intercorrelations, particularly between confidence in understanding health information and ability to judge information accuracy ($r = 0.524$, $p < 0.001$), consistent with established health literacy frameworks (Nutbeam, 2008). The strongest negative correlation emerges between TikTok and Twitter usage ($r = −0.357$, $p < 0.001$), indicating distinct user preferences across these platforms. Health literacy dimensions show moderate-to-strong positive correlations with fact-checking behaviors ($r = 0.308$ to 0.521, $p < 0.001$), supporting contemporary findings about critical health literacy's role in information verification (Paakkari & Okan, 2020). Interestingly, frequency of social media use per day correlates negatively with YouTube usage ($r = −0.145$, $p = 0.040$), aligning with recent observations about platform-specific engagement patterns (Sundar et al., 2021). The robust correlations among health literacy items (ranging from 0.308 to 0.629) confirm the multidimensional yet interrelated nature of health literacy constructs, as theorized in Sørensen et al.'s (2012) integrated model. Platform usage variables generally show weaker correlations with health literacy outcomes (most $r < 0.150$), except for Facebook's marginal association with health information understanding (r = 0.082), reflecting the complex interplay between media consumption and health competence noted by Levin-Zamir et al. (2017). The pattern of correlations underscores the need for platform-specific health communication strategies while affirming core health literacy principles. The table is presented in annexture.

4.6. Discussion

This analysis delves deeper into the findings of Experiment 1, which explored the relationship between social media engagement and health literacy among university students in Pakistan, specifically within the context of universities in Multan. The study was designed with two primary objectives: first, to investigate how social media influences students' health knowledge, attitudes, and behaviors; and second, to evaluate whether exposure to health-related content on social media platforms correlates with improved health literacy. 200 college students participated in this cross-sectional study to answer questions about their general social media usage, health literacy, and social media behaviours (such as how often, for how long, and what kinds of health-related content they viewed). The findings showed that those with higher health literacy were more likely to actively interact with trustworthy health information on social media. Regular access to validated health content improved students' understanding and perception of illness prevention and health maintenance.

Our results are consistent with earlier studies and highlight social media's potential as a cutting-edge medium for health education among millennials. According to studies by Moorhead et al. (2013) and Chou et al. (2013), for example, social media platforms are great places to share health information, ask for peer support, and get ideas for health-promoting activities. Similarly, our findings corroborate the claim by Basch et al. (2017) that college students who used social media to look for health information were more cognisant of public health concerns.

However, this study also highlights challenges noted in earlier research, such as the risk of misinformation and the variable quality of health content on social media platforms. Unlike some prior studies which emphasized negative impacts due to misinformation (e.g., Tang et al., 2018), the current study suggests that when students engage with credible and verified sources—often promoted through university campaigns or official health organizations—social media can be an effective tool for enhancing health literacy. When examining social media usage patterns, the current study's results differ significantly from global trends. While Rehman et al. (2023b) found nursing students actively engaged with health content on social media, the Pakistani sample showed limited interaction, with only 1.52 (SD = 0.82) indicating frequent daily use for health purposes. This discrepancy may reflect cultural differences in digital health adoption or varying levels of trust in online health information. The strong awareness of misinformation (mean = 3.67) coupled with fact-checking behaviors (mean = 3.55) mirrors findings from China, where digital health literacy was positively associated with misinformation detection (Ahmed et al., 2021).

However, the weak correlations between platform usage and health literacy (most $r < 0.15$) suggest social media engagement alone does not strongly predict health knowledge acquisition, a finding that contrasts with some Western studies showing stronger media effects (Berkman et al., 2011). Furthermore, the study of Pakistani university students offers a cultural viewpoint that is absent from most research conducted in Western nations. According to the study, social media can significantly affect health literacy in developing countries, especially in cases where there are notable deficiencies in infrastructure and educational resources. Research from the area indicates that using digital platforms can assist in overcoming the typical barriers to health education (Tariq et al., 2020). There might be a connection between the low reliance on social media for health information and the widespread scepticism of online health content. According to Vosoughi et al. (2018), the abundance of misinformation on social media platforms means that only about 40% of consumers trust health advice from these sources. It follows that despite having internet access, Pakistani students are cautious about disclosing private health information on social media.

While the Dunning-Kruger effect offers one plausible explanation for the paradox of high self-perceived health literacy alongside low social media engagement for health purposes, an alternative explanation lies in the role of formal university education. The sampled students, deriving from diverse academic faculties, likely receive foundational health knowledge through their formal curricula, general science education, and on-campus wellness initiatives. This established baseline of knowledge may foster a sense of confidence in understanding health information (as reflected in the high mean scores for health literacy items) while simultaneously reducing the perceived necessity to actively seek out health content on social media platforms. Consequently, their engagement with social media for health information may be limited to passive, occasional consumption rather than active seeking, as their primary knowledge needs are being met through traditional, and perhaps more trusted, academic channels. This perspective suggests that high self-assessed literacy is not necessarily a cognitive bias but may be a reflection of knowledge acquired through formal education, which then shapes their specific patterns of social media use.

This contrasts sharply with findings from China, where Wu et al. (2023) found 76.3% of internet users regularly sought health information online. Despite low social media engagement for health purposes, students demonstrated relatively high self-perceived health literacy. Participants expressed confidence in understanding health information (mean = 3.47), judging its accuracy (mean = 3.90), and applying it practically (mean = 3.80). These findings partially align with research in Ethiopia by Kühn et al. (2022), where university students showed moderate eHealth literacy but struggled with misinformation identification.

General Discussion

This research aims to explore the impact of social media on health literacy among university students, focusing on how social media influences their health knowledge, attitudes, and behaviors. Given the widespread use of social media as a fast and accessible source of information, particularly among the younger generation, it is crucial to understand both its benefits and potential risks in the context of health communication. Social media platforms offer opportunities for social interaction, information exchange, and health promotion; however, they also pose challenges such as the spread of misinformation and the risk of negative physical, psychological, and social consequences (Nazari et al., 2023). By informing people about their alternatives for healthcare providers and promoting healthy lifestyle choices, social media is quickly becoming a crucial part of the healthcare industry. However, uncontrolled access to online health information and the influence of digital health influencers could have negative health effects (de Oliveira Collet et al., 2024).

By investigating how social media use affects college students' health literacy, this study aims to close a knowledge gap and aid in the creation of more potent health communication strategies and interventions. Determining the degree to which social media affects college students' health literacy was the aim of researchers in Multan, Pakistan. The goal of the study was to find out how different social media platforms affected students' health knowledge, attitudes, and behaviours, given the growing dependence on these platforms as sources of health information. This study aims to fill in a knowledge gap about the influence of platform-specific factors on health literacy in Pakistani higher education.

A cross-sectional survey design was employed, collecting data from 200 university students aged 18 to 30 across multiple faculties using a stratified random sampling technique. A structured questionnaire assessed both social media usage patterns and multiple dimensions of health literacy, enabling a detailed examination of their relationships. Key findings revealed significant variation in health literacy levels related to social media engagement, with notable differences across health literacy items. Statistical analysis showed significant non-additivity, highlighting complex, nonlinear interactions between social media use and health literacy. Correlation analyses indicated that students tend to use platforms like WhatsApp, YouTube, and Facebook concurrently for health information, with critical health literacy skills such as fact-checking strongly linked to better health literacy outcomes. However, the relationships between specific platform usage and health literacy were generally weak, suggesting that mere exposure to health content does not directly translate into improved literacy.

The study concludes that social media plays a multifaceted role in shaping health literacy among university students, emphasizing the importance of critical digital skills in maximizing the benefits of online health information. It recommends that universities, health educators, and policymakers develop targeted, multi-platform health communication strategies that incorporate digital literacy training to empower students in navigating health information effectively. Limitations of the study include its reliance on self-reported data and a cross-sectional design, which limit causal inferences and may introduce response biases. Future research should adopt longitudinal approaches and consider additional moderating factors such as socioeconomic background, digital competence, and motivational aspects to deepen understanding of the dynamics involved. Overall, this research contributes valuable insights into the interplay between social media and health literacy in a developing country context and provides actionable recommendations for enhancing health communication strategies in higher education settings.

5. Conclusion

An extensive examination of the impact of social media on health literacy was conducted among university students in Multan, Pakistan. Results indicate that social media, a popular source of health information for this age group (18 - 30), has a complicated influence on students' health-related knowledge, attitudes, and actions. The study reveals that while social media platforms like Facebook, WhatsApp, and YouTube are favourably linked to certain aspects of health literacy, the methods in which these sites impact students' ability to understand, assess, and apply health information vary widely. The high correlations between health literacy components, such as the ability to evaluate the accuracy of information and the confidence in understanding health material, demonstrate the complexity of health literacy and the importance of critical digital literacy skills. Additionally, the data demonstrates interaction effects and non-additivity, suggesting that the relationship between social media use and health literacy is complex and may involve nonlinear dynamics. In order to completely comprehend this link, future research should make use of advanced analytical tools.

The results can be more broadly applied to institutions in Multan because a stratified random sampling technique was used to ensure that the sample was representative of the diverse student population across faculties and demographic groupings. Recommendations can be made specifically for distinct student groupings thanks to the methodological rigour that backs up the findings. Most importantly, the study highlights how focused actions, beyond just disseminating knowledge, are necessary. Health communication strategies should focus on enhancing students' critical evaluation and fact-checking skills to empower them as active, discerning consumers of digital health information. Such efforts will help mitigate the risks posed by misinformation and promote healthier behaviors and decision-making among university students.

In conclusion, social media holds significant potential as a tool for improving health literacy, but this potential can only be fully realized through deliberate educational and policy initiatives that address the complexities of digital engagement and health information processing. Future research should explore longitudinal designs and intervention studies to further elucidate causal pathways and effective strategies for leveraging social media in health promotion.

6. Limitations and Future Research

The study suggests several important implications for health education and digital literacy programs. First, while social media remains underutilized for health information among Pakistani students, targeted interventions featuring verified health channels could improve engagement. Second, universities should implement critical health literacy training programs, as awareness of misinformation alone does not guarantee proper information evaluation. Platform-specific strategies may prove most effective, given the varying patterns of use across different social media applications. The weak overall correlation between social media use and health literacy suggests that generic approaches will likely fail, while content tailored to specific platforms (e.g., tutorial videos on YouTube, reminder systems on WhatsApp) might yield better results. Future research should employ longitudinal designs to assess whether increased social media health engagement actually improves literacy over time. Additionally, comparative studies across different cultural contexts could help disentangle the effects of digital infrastructure, educational systems, and cultural attitudes toward online health information.

In conclusion, this study reveals that Pakistani university students exhibit strong self-perceived health literacy but remain cautious about using social media for health information. These findings highlight the need for more sophisticated approaches to digital health literacy that go beyond simple access to information and address issues of trust, verification, and practical application.

6.1. Implication for Future Research and Practice

The results suggest that universities and public health authorities should consider strategic collaborations to curate and promote reliable health content on social media channels frequently accessed by students. Interventions could include integrating social media campaigns with formal health education curricula to amplify their impact on students' health literacy. Future research might explore longitudinal designs to assess the long-term effects of sustained social media exposure on health outcomes and investigate the moderating roles of demographic factors such as gender, socioeconomic status, and digital literacy levels.

6.2. Future Directions

This study highlights a number of possible research topics. Since the relationship between social media use and health literacy has been found to be complicated and nonlinear, future research should use longitudinal and mixed-method designs to provide a more thorough knowledge of causal pathways and temporal dynamics.

Examining mediating and moderating factors, such as digital literacy abilities, socioeconomic status, motivation, and cultural influences, will lead to a more thorough understanding of the connection between social media exposure and health literacy outcomes. Research on age-related differences in social media health involvement should also cover other demographic groups, such as younger adolescents and older people. Comparative research between nations or in different parts of Pakistan may highlight contextual factors and increase the conclusions' generalisability. Examining the reliability and quality of health information on various social media platforms is also crucial, particularly given the rise in false information.

7. Recommendations

The results highlight the need for legislators, administrators, and health educators to create tailored health communication plans that make the most of various social media channels. Disseminating accurate health information should be a top priority for programs, as should improving students' digital literacy and critical thinking abilities so they can check claims and recognize trustworthy sources. Students can learn to be more critical consumers of health information and less receptive to false information by integrating digital health literacy training into their coursework and extracurricular activities. Social media firms, public health agencies, and universities may work together to improve the accessibility and legitimacy of health messaging.

For college students to completely benefit from social media's ability to encourage better behaviours and raise health awareness, a multi-platform, context-sensitive approach is required. Finally, the comparison study demonstrates that interacting with credible health-related content on social media can have a good impact on Pakistani university students' health literacy. Digital health communication therefore has a lot of promise as an adjunct to conventional university health teaching.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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