ISSN: XXX-XXXX
e ISSN: XXXX-XX

NCMT JOURNAL OF MULTIDISCIPLINARY STUDIES (NJMS)

(A peer-reviewed, open access journal)

Vol. 1 No. 1 September 2026

OPEN ACCESS

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NCMT Journal of Multidisciplinary Studies (NJMS)

(The double blind, peer-reviewed journal of NCMT College)

Vol. 1 No. 1 Sept. 2026

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Email**:** research@ncmt.edu.np

Published by

Research Management Cell
National College of Management and Technical Science,
Samakhusi, Ranibari Marg-03, Kathmandu, Nepal
Tel: +977-1-4952831, 4986217, 4958694, 9802075662
E-mail: research@ncmt.edu.np, info@ncmt.edu.np
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ABOUT THE JOURNAL

PURPOSE OF THE JOURNAL

NCMT Journal of Multidisciplinary Studies (NJMS) is a double-blind, peer-reviewed academic journal published by **NCMT College**, affiliated with Lincoln University College, Petaling Jaya, Malaysia, accredited by MQA and approved by Malaysia's Ministry of Higher Education. Its curriculum is recognized by Tribhuvan University/CDC, Nepal.

NJMS aims to promote and disseminate original, innovative, and high-quality research in management, business, technology, and social sciences. The journal provides a scholarly platform for academicians, researchers, policy makers, professionals, entrepreneurs, and students to exchange ideas and address contemporary academic and societal issues.

The journal particularly encourages interdisciplinary research, emerging perspectives, and contributions from budding researchers and students. Through rigorous peer review and academic collaboration, **NJMS** seeks to strengthen research culture and promote knowledge sharing nationally and internationally.

BEGINNING & FREQUENCY OF THE PUBLICATION

NCMT Journal of Multidisciplinary Studies (NJMS) was established in **2026** as annual scholarly publication of NCMT College. The journal is published single a year, in **September**, providing a regular platform for the dissemination of innovative research, academic insights, and multidisciplinary scholarship.

SCOPE (THEMATIC AREAS) OF THE JOURNAL

NCMT covers the disciplines of management, business, managerial economics, technology and social sciences.

Banking Management	Industrial Relations
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ISSN:

NCMT Journal of Multidisciplinary Studies (NJMS)

(The double blind, peer-reviewed journal of NCMT College)

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DOUBLE-BLIND PEER REVIEW STATEMENT

The NCMT Journal of Multidisciplinary Studies (NJMS) uses a rigorous double-blind peer-review process to protect the quality, integrity, and academic credibility of every article it publishes. Each submitted manuscript is first anonymized and coded. The editorial team then gives it an initial screening for fit with the journal's scope, relevance, originality, and ethical requirements. The Associate Editor sends suitable manuscripts to qualified subject experts for double-blind peer review. Authors revise their manuscripts in response to the reviewers' comments and recommendations. Where necessary, revised manuscripts go through further rounds of review to confirm that they meet the journal's standards of originality, methodological rigor, academic relevance, and scholarly quality.

Following the completion of the peer-review and revision process, the Associate Editor evaluates the revised manuscript and ensures that the reviewers' recommendations and required academic standards have been appropriately addressed. The manuscript is then submitted to the Editor-in-Chief, who provides the final editorial oversight and makes the final publication decision. This final stage ensures that all published articles maintain the academic standards, consistency, integrity, and quality expected of NJMS.

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NJMS is committed to originality, academic integrity, and ethical research. The editorial team first gives every submitted manuscript a desk review, checking its fit with the journal's scope, its relevance, originality, and academic quality, and whether it follows the submission guidelines. Manuscripts that meet these basic requirements move on to the next stage of review.

The journal also screens every manuscript for plagiarism using recognized detection software. If substantial similarity or improper use of existing material is found, the author must revise the manuscript in consultation with the editorial team. NJMS also checks that any AI-assisted tools used in preparing the manuscript were used appropriately and are properly disclosed. Acceptable limits for the Similarity Index and AI use follow university policy. NJMS considers for publication only manuscripts that meet its standards of originality, ethical scholarship, and academic integrity.

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NCMT Journal of Multidisciplinary Studies (NJMS)

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FOREWORD

It is my great pleasure to present the inaugural issue of the *NCMT Journal of Multidisciplinary Studies (NJMS)*, a scholarly platform dedicated to promoting research, critical inquiry, innovation, and the exchange of knowledge across diverse academic disciplines. The publication of this first volume and issue marks an important milestone in the academic journey of National College of Management and Technical Science (NCMT), reflecting our commitment to fostering a culture of research and continuous intellectual development. Through NJMS, we aspire to provide researchers, academicians, professionals, and students with a meaningful forum to share evidence-based ideas, explore emerging issues, and contribute to knowledge that has relevance both within academia and beyond. I sincerely appreciate the valuable contributions of the authors, reviewers, editorial team, faculty members, and everyone involved in bringing this journal to publication, and I look forward to NJMS growing into a respected platform for multidisciplinary scholarship and academic collaboration. I extend my best wishes for the success of this inaugural issue and encourage our academic community to continue engaging in research that advances knowledge and contributes positively to society.

Mr. Pramod Kumar Baniya
Chairman
National College of Management and Technical Science (NCMT)

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NCMT Journal of Multidisciplinary Studies (NJMS)

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The initiation for launching of the *NCMT Journal of Multidisciplinary Studies (NJMS)* marks a meaningful advancement in NCMT's continuing efforts to strengthen research, scholarship, and academic engagement. As higher education increasingly emphasizes inquiry, innovation, and evidence-based knowledge, the establishment of a multidisciplinary journal provides an important avenue for researchers, academicians, professionals, and students to share ideas and contribute to contemporary academic discourse. NJMS reflects our institutional commitment to nurturing a vibrant research environment in which diverse perspectives can interact, scholarly findings can be disseminated, and emerging issues can be examined through rigorous academic inquiry. We believe that the exchange of knowledge across disciplines not only enriches academic understanding but also contributes to addressing the complex challenges of society and professional practice. I acknowledge with appreciation the dedicated efforts of the editorial team, reviewers, authors, faculty members, and all contributors whose collective efforts have made this inaugural issue possible. I am confident that NJMS will continue to develop as a credible platform for scholarly communication and will encourage our academic community to pursue research, innovation, and knowledge creation with greater purpose and responsibility.

Assoc. Prof. Dr. Arun Kumar Thakur

Principal

National College of Management and Technical Science (NCMT)

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NCMT Journal of Multidisciplinary Studies (NJMS)

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A thriving academic institution is built not only through effective teaching and learning, but also through a sustained commitment to inquiry, reflection, and the creation of new knowledge. In this spirit, the *NCMT Journal of Multidisciplinary Studies (NJMS)* has been initiated as a platform for bringing together diverse scholarly perspectives and encouraging meaningful academic discourse. A journal of this nature provides an opportunity for faculty members, researchers, professionals, and students to engage with contemporary issues through systematic inquiry and scholarly discussion. At NCMT, we recognize that quality education extends beyond classroom learning and requires continuous engagement with research, innovation, critical thinking, and practical knowledge. NJMS is therefore envisioned as a platform that connects academic ideas with emerging challenges and opportunities across different disciplines. I appreciate the valuable efforts of the editorial team, contributors, reviewers, and members of the institution whose dedication has supported the realization of this initiative. I believe that this inaugural issue will encourage greater research participation and collaboration across our academic community and will lay a strong foundation for the continued development of scholarly activities at NCMT. I extend my sincere best wishes for the success and sustained growth of NJMS.

Mr. Bikash Bidari

Vice Principal

National College of Management and Technical Science (NCMT)

ISSN:

NCMT Journal of Multidisciplinary Studies (NJMS)

(The double blind, peer-reviewed journal of Nepal Open University)

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FROM THE DESK OF EDITORIAL COMMITTEE

The *NCMT Journal of Multidisciplinary Studies (NJMS)* emerges from a shared commitment to advancing a culture of research, scholarly dialogue, and knowledge dissemination at National College of Management and Technical Science (NCMT). As an academic journal, NJMS seeks to provide a constructive forum for researchers, academicians, professionals, and students to present original research, engage with contemporary issues, and exchange ideas across disciplinary boundaries. The inaugural issue brings together scholarly contributions that reflect diverse areas of inquiry and demonstrate the value of research in expanding academic understanding and addressing practical concerns. The Editorial Team has sought to maintain appropriate standards of academic rigor, originality, relevance, and ethical scholarship throughout the editorial and review process. We are grateful to all authors who entrusted their work to this inaugural volume, as well as to the reviewers, editorial members, and institutional leadership for their valuable support and contributions. We hope that NJMS will develop into a sustained platform for meaningful scholarly communication, encourage emerging researchers, and foster greater collaboration within and beyond the NCMT academic community. With this inaugural issue, we invite readers and researchers to engage with the ideas presented and contribute to the continuing development of multidisciplinary scholarship.

Editorial Team

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The NJMS Editorial Team makes every effort to uphold the quality, integrity, and academic standards of published research; however, it does not warrant the technical accuracy, completeness, or reliability of the data, analyses, or findings presented in individual articles. The views, interpretations, methodologies, and conclusions expressed in published papers remain the sole responsibility of the respective authors. Publication of an article does not constitute an endorsement by NJMS or the Research Management Cell of National College of Management and Technical Science, nor does it guarantee that the study, analytical methods, or findings are suitable for any particular purpose. While authors are expected to carefully consider and incorporate editorial and peer-review recommendations, the ultimate responsibility for the accuracy, originality, and content of each published article rests with the authors.

ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Trust in Social Media News: *The Role of Fake News Awareness, Detection Ability, and Credibility*

Manish Sharma
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
sh.manish23@ncmt.edu.np

Received: 17 Jul., 2026 | Revised: 5 Aug., 2026 | Accepted: 9 Sept., 2026

Abstract: *Social media has developed as a major source of news and information, but the rise of fake news has raised worries about the credibility of the information consumers receive. This study examines the factors that influence users' trust in social media as a news source. The independent variables in this study were fake news awareness, fake news detection ability, and social media credibility, while the dependent variable was users' trust in social media news, guided by Truth Default Theory. The study uses a quantitative research approach and descriptive statistics, correlation analysis, and causal research design. Primary data were collected through Google Forms based on a five-point Likert scale and SPSS software was used for analysis. The target population consisted of social media users in Lalitpur District, specifically Dhobighat, who used platforms like Facebook, X, Instagram, and TikTok. The precise population was unknown, so 391 respondents were chosen using convenience sampling methods. The regression study revealed that fake news awareness and fake news detection ability have no significant effect on users' trust in social media as a news source. However, social media credibility has a positive and significant effect on users' trust in social media as a news source. The study suggests that social media credibility is a better indicator of user trust than awareness or ability to identify fake news. According to the findings, social media platforms and news providers should prioritize increasing information accuracy, reliability, and credibility, as well as encouraging users to verify and critically assess news material.*

Keywords: Fake news awareness, fake news detection ability, social media credibility, users trust in social media news

JEL Classification: D83, L86, C83

Cite as: Sharma, M. (2026). Trust in social media news: The role of fake news awareness, detection ability, and credibility. *NCMT Journal of Multidisciplinary Studies, 1*(1), 1-16.

INTRODUCTION

Social media has become an integral component of our daily life, serving as a primary source of news and information (Krisnan et al., 2025). People use platforms such as Facebook, X, Instagram, and other social networking sites to communicate with one another and obtain information from all over the world (Cheng & Chen, 2021; Melchior et al., 2025). Unlike traditional media, news reports are vetted

before publication. However, social media uses algorithms to choose what to display to us, and it is more concerned with keeping us interested than with providing correct information, making it impossible to distinguish between real and fake news (Soumya & Babu, 2025).

Furthermore, social media has a significant impact on how individuals communicate, share information, and understand global concerns (Kuorsoh & Nkrumah, 2025). As a result, people who spend more time on social media are more likely to encounter disinformation, which leads to increasing mistrust of information (Park & Lee, 2023). In addition, many consumers fail to determine the accuracy of social media news. Therefore, fact-checking allows users to verify the validity and veracity of news stories shared on social media sites.

Further, as more individuals utilize social media, the propagation of fake news accelerates (Olan et al., 2022). This is a concern because it causes consumers to mistrust if the information, they find online is accurate. This phenomenon happens because users may generate, distribute, and access information in a matter of seconds, allowing incorrect information to spread swiftly (Orhan, 2023). In addition, many people lack the skills and knowledge to critically analyze the information they discover online, making them more likely to believe and disseminate misleading information (Guess et al., 2020). This has caused individuals to lose trust in the news they discover on social media, and it has made governments, organizations, and corporations concerned about the negative consequences of fake news (Park & Lee, 2023; Talwar et al., 2020).

Previous research has found that fake news awareness, fake news detection ability, and social media credibility are essential elements in assisting consumers to evaluate online information and limit the influence of disinformation (Guess et al., 2020; Majerczak & Strzelecki, 2022). Individuals with stronger fake news awareness and good detecting skills examine information before trusting or distributing it (Zoonen et al., 2023). Furthermore, effective fact-checking and increased social media credibility can diminish users' confidence in disinformation and improve trust in online news (Vu & Saling, 2026; Olan et al., 2022). Previous studies used mediating variables such as fake news, news engagement, social media usage, perception of sensationalism, fake news awareness, information verification, trust, and distrust (Olan et al., 2022; Kožuh & Cakš, 2021; Obadă & Dabija, 2022; Pelau et al., 2023; Majerczak & Strzelecki, 2022; Cheng & Chen, 2021). However, there are no mediating variables in this study. Furthermore, previous research employed moderating variables such as fake news knowledge (Negi & Bedi, 2024), but no moderating variable is included in this study. Nonetheless, no research has been conducted to analyze the synergistic factors impacting consumers' trust in social media as a news source in Nepal, making this the first study on the subject. As a result, the purpose of this study was to fill a research gap and solve concerns.

This study contributes to the existing literature by providing empirical evidence from Nepal and examining fake news awareness, fake news detection ability, and social media credibility in relation to users' trust in social media news. By applying Truth Default Theory (TDT), the study reveals the nature of social media news trust and offers practical value for social media platforms, news providers, policymakers, and users.

Research questions

- Is there a relationship between fake news awareness, fake news detection ability, social media credibility, and users' trust in social media as a news source?

- Do fake news awareness, fake news detection ability, and social media credibility affect users' trust in social media as a news source?

Objectives of the study

Due to the rapid growth of social media platforms as a source of news and the demand for research in this area, this study seeks to explore the factors influencing users' trust in social media as a news source. The fast expansion of social media has changed how individuals receive news and information. Increased spread of fake news has raised concern over the credibility of news shared on social media. Understanding the factors influencing users' trust is essential for increasing responsible news consumption and reducing the impact of misinformation. Therefore, this study aims to examine how fake news awareness, fake news detection ability, and social media credibility influence users' trust in social media as a news source. The objectives of this study are:

- To analyze the relationship between fake news awareness, fake news detection ability, and social media credibility on users' trusts in social media as a news source.

- To examine the effect of fake news awareness, fake news detection ability, and social media credibility on users' trust in social media as a news source.

LITERATURE REVIEWS

Theoretical review

Truth Default Theory: Levine (2014) introduced the Truth Default Theory (TDT), which states that people normally assume the information they receive from others is true unless there is clear proof of dishonesty. This tendency, known as the truth-default condition, leads people to believe information without thoroughly checking its truthfulness. As a result, users are more likely to trust and spread misinformation or fake news on social media (Levine et al., 1999; McCornack & Parks, 1986). According to the hypothesis, social media users' frequently view information from popular or credible-looking sources as trustworthy, even if it is erroneous (Ceron et al., 2021). The more recent study by Guess et al. (2020) supports Truth Default Theory and found that a higher level of digital media literacy helps users distinguish between true and false news, suggesting that users with higher fake news awareness are more likely to make informed trust judgments. Higher levels of self-efficacy in detecting misinformation positively influence users' authentication behavior and trust, suggesting that users with higher fake news detection ability are more likely to evaluate information before trusting it. A recent study by Sousa and Bates (2021) found that author credibility positively influences the perceived credibility of news, and users are more likely to trust news from credible sources.

Empirical Review

Fake news awareness and users trust in social media as a news source: Talwar et al. (2020) identified Sharing of fake news on social media: Application of the honeycomb framework and the third-person effect hypothesis in India. Specifically, the SEM

Table 1
Summary of previous studies

Author (s)	Year	Country	Methodology	Findings
Guess et al.	2020	USA and India	OLS regression	Showed that digital media literacy had a negative significant effect on belief in fake news and improved users' ability to distinguish between true and false news.
Pennycook et al.	2020	USA	Linear regression	Found that warning labels had a negative significant effect on the perceived accuracy of fake news, while verification improved users' ability to identify reliable information.
Majerczak and Strzelecki	2022	Poland	Regression analysis	Found that media credibility had a positive significant effect on information verification behavior.
Olan et al.	2022	USA	Regression analysis	Found that fake news had a negative significant impact on trust in information and highlighted the importance of fact-checking.
Bachmann and Valenzuela	2023	Chile	OLS regression	Found that fact-checking had a negative significant effect on misinformation beliefs and improved belief accuracy.
Zoonen et al.	2023	Netherlands and Finland	Regression analysis	Found that perceived self-efficacy in detecting misinformation had a positive significant effect on authentication behavior.
Mahlous	2024	Saudi Arabia	Trend and pattern analysis	Found that fake news awareness is important to reduce social, political, and cultural divisions caused by misinformation.
Negi and Bedi	2024	India	Regression analysis	Evaluated that authenticating news before sharing had a negative significant effect on fake news sharing and increased trust in social media news.
Atlay et al.	2025	France and Germany	Experimental study	Found that higher exposure to false news had a negative significant effect on trust in news and increased overconfidence in ability to distinguish true and false news.
Nguyen et al.	2025	Vietnam	Multivariate regression analysis	Found that exposure to fake news had a significant impact on users' responses to misinformation.
Vu and Saling	2026	Australia	Mixed-effects linear regression	Found that expert and crowdsourced fact-checking had a negative significant impact on confidence in misinformation and willingness to share it.

Table 2
Summary of prior studies

Author (s)	Year	Country	Methodology	Findings
Kožuh and Cakš	2021	Slovenia	Regression analysis	Found that the need for cognition and engagement in news had a positive significant impact on users' trust in social media news.
Orhan	2023	Turkey	Regression analysis	Evaluated that critical thinking and news media literacy had a positive significant on fake news detection ability.
Park and Lee	2023	Australia, UK and USA	Regression analysis	Found that incidental exposure to news on Facebook had a negative significant effect on trust in social media news.
Zoonen et al.	2023	Netherland and Finland	Regression analysis	Found that perceived self-efficacy in detecting misinformation had a positive significant effect on authentication behavior and users' trust.
Lan and Tung	2024	Vietnam	Thematic analysis	Evaluated that familiarity and repeated exposure to content have a positive significant impact on perceived reliability and trust.
Melchior et al.	2025	Finland, Canada and Portugal	Regression analysis	Analyzed that literacy skills and trust had a positive significant on fake news sharing behavior.
Soumya and Babu	2025	India	Trend analysis	Determined that users often share fake news due to trust in sources and inability to identify misinformation.

analysis discovered that instantaneous sharing of news for creating awareness and active corrective action on fake news has a positive significant impact on sharing fake news due to religiosity and sharing fake news due to lack of time.

H_1: Fake news awareness has positive and significant impact on users trust in social media as news source.

Fake news detection ability and users trust in social media as a news source: Cheng and Chen (2021) found that encountering misinformation online: Antecedents of trust and distrust and their impact on the intensity of Facebook use in the USA. Using structural equation modeling it was evaluated that factors such as information trustworthiness, information elaboration, self-efficacy, and prescriptive expectancy have positive significant on user levels of trust and distrust toward social media information.

H_2: Fake news detection ability has positive and significant effect on users trust in social media as news source.

Social media credibility and users trust in social media as news source: Cheng and

Table 3
Summary of earlier studies

Author (s)	Year	Country	Methodology	Findings
Sousa and Bates	2021	United Kingdom	Experimental study	Found that the credibility of the author had a positive significant effect on user's perceived credibility of news.
Majerczak and Strzelecki	2022	Poland	Regression analysis	Observed that social media credibility had a positive significant on information verification behavior.
Park and Lee	2023	Australia, UK andUSA	Regression analysis	Found that incidental exposure to news on Facebook had a negative significant effect on users' trust in social media news.
Lan and Tung	2024	Vietnam	Thematic analysis	Evaluated that repeated exposure to similar content had a positive significant impact on perceived reliability and trust.
Kuorsoh and Nkrumah	2025	Ghana	Content Analysis	Found that misinformation on social media had a negative impact on users' perceptions of information credibility and highlighted the importance of content verification.

Chen (2021) investigated that Encountering misinformation online: Antecedents of trust and distrust and their impact on the intensity of Facebook use in USA. The that structural equation modeling revealed that factors such as information trustworthiness, information elaboration, self-efficacy, and prescriptive expectancy has positive significant effect on user levels of trust and distrust toward social media information.

H_3: Social media credibility has positive and significant influence on users trust in social media as a news source.

Based on the literature review, the study developed the research framework presented in figure 1.

METHODOLOGY

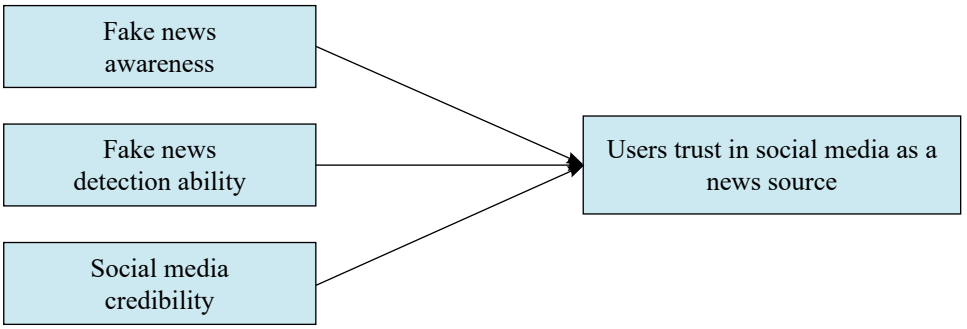
Research design

The study adopts a deductive research approach. Further the study employed positivist research philosophy. This study used a quantitative research design; it includes descriptive, relational, and explanatory research design. The descriptive research design was employed to delineate the fundamental properties of the investigated variables (Budhathoki et al., 2025). The relational research design was used to examine the relationship between the antecedent and consequent variables (Budhathoki et al., 2023). Explanatory research design was employed to investigate the influence of independent variables on dependent variables.

Population and sample

The targeted population of this study consists of social media users in the Lalitpur district especially in Dhobighat, who uses social media platforms such as Facebook, X, Instagram, and TikTok. The exact population was unknown so it is difficult to collect data from the entire population.

Figure 1
Theoretical framework



So that sample of 391 respondents was selected for the study. This study used convenience sampling techniques to select respondents. Convenience sampling was suited for this study because it allows to efficiently collecting data from a wide population of social media users in the Lalitpur district while remaining within the time and resource constraints. If the population size is unknown but expected to be large, use statistical formulas to determine the sample size (Cochran, 1977). The Cochran's formula is shown below:

$$n = \frac{z^2 * p * q}{e^2}$$

(Where n = required sample size (384); Z = Z-value (e.g., 1.96 for 95% confidence level); p = estimated proportion (0.5 if unknown); q = 1 – p; *e* = margin of error (5 %))

The close-ended five Likert-scale questionnaire was distributed online through social media platforms such as Facebook, Instagram, WhatsApp, and Messenger. Respondents were asked to fill out the questionnaire during their free time from June 24 to July 10.

Sources of data and analysis tools

This study used primary data collected through a structured close ended questionnaire. The questionnaire includes three sections: demographic information, general questions and measurement items. The measurement items were assessed using a five-point Likert-scale. The questionnaire is designed based on the findings from the literature study. The measurement items for fake news awareness, fake news detection ability, social media credibility, and users' trust in social media as a news source were taken from previous studies (Cheng & Chen,

Table 4
Reliability test

Variable dimensions	Number of items	Cronbach's Alpha
Fake news awareness	5	0.785
Fake news detection ability	5	0.876
Social media credibility	5	0.820
Trust in social media as a news source	5	0.758

2021; Zoonen et al., 2023; Le, 2024; Obadă & Dabija, 2022). The study employed the SPSS software version 32.0.0 for necessary data analysis. Table 4 shows the reliability analysis:

Table 4 represents the reliability analysis of the study. A pilot study with 51 participants was undertaken to ensure its reliability and utility, and if the calculation was satisfactory, further data gathering began. The Table 4 shows the Cronbach's alpha coefficients for fake news awareness (0.785), detection abilities (0.876), social media credibility (0.82), and trust in social media (0.758). All calculated alpha values exceed 0.7, indicating good internal consistency across questions assessing each construct.

Analytical model

This study used the regression model to examine the cause-and-effect correlations between antecedent and subsequent variables. The model was used in the previous study by (Budhathoki & Khadka, 2024).

$$Y = i + a_1x_1 + a_2x_2 + a_3x_3 + e$$

(Where, x_1 = Fake news awareness (FNA), x_2 = Fake news detection ability (FNDA), x_3 = Social media credibility (SMC), a_1, a_2, a_3= coefficients of predictors, e = error term, i = constant, and Y = Users trust in social media as a news source).

Definition of variables

Independent variables

Fake news awareness: Fake news awareness is defined as an individual's knowledge and understanding of fake news, including its characteristics and potential implications (Omar et al., 2024). It allows users to identify disinformation and critically evaluate the authenticity of online material before trusting or spreading it (Barakat et al., 2021; Pennycook & Rand, 2019). As a result, those who are more aware of fake news are more inclined to double-check material and make informed decisions regarding its veracity. As a result, raising knowledge about fake news is critical in molding peoples faith in social media as a news source.

Fake news detection ability: Fake news detection skill is an individual's capacity to identify and separate fake or misleading information from correct and reliable news by critically evaluating the content and its source. Furthermore, those with greater detection abilities are more likely to verify information before believing or sharing it, making them less vulnerable to disinformation (Khan & Idris, 2019). In addition, media literacy, critical thinking, and confidence in information evaluation all help improve this skill (Bandura, 1977). As a result, people's faith in social media as a news source is heavily influenced by its capacity to detect fake news.

Social media credibility: Social media credibility relates to users opinions of the trustworthiness, dependability, and correctness of information posted on social media platforms. It expresses the degree to which consumers believe the content and its sources are reputable and reliable. As a result, perceived credibility influences users' desire to use social media for news and information (Flanagin & Metzger, 2000; Westerman et al., 2014). As a result, social media credibility is a significant aspect in determining peoples trust in social media as a news source.

Dependent variables

Users trust in social media as a news source: Users trust in social media as a news source

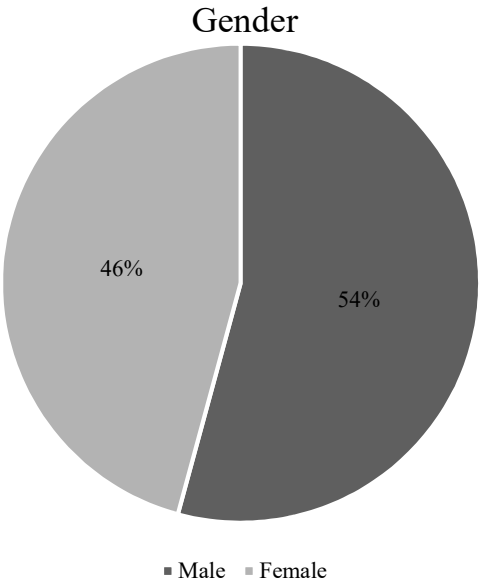
refers to how much people feel the news and information, they get from social media platforms is reputable, dependable, and accurate. In other words, it represents users trust in the legitimacy of news material, as well as their tendency to access and share news through social media. As a result, consumers with higher levels of trust are more likely to accept and engage with information offered on social media. As a result, people's faith in social media as a news source is critical to understanding news consumption behavior in the digital environment.

FINDINGS AND DISCUSSIONS

Findings

Demographic response: Table 5 indicates that the majority of respondents (69.6%) held a bachelor's degree, with +2 level respondents (18.6%) and master's degree holders (7.9%) following. The qualifications of SLC (2.6%), below SLC (0.8%), or PhD (0.5%) were only possessed by a small number of respondents.

Figure 2
Gender of the respondents



The below Figure 2 the represents gender of the respondents.

According to Figure 2, 54% of the 391 respondents were men and 46% were women.

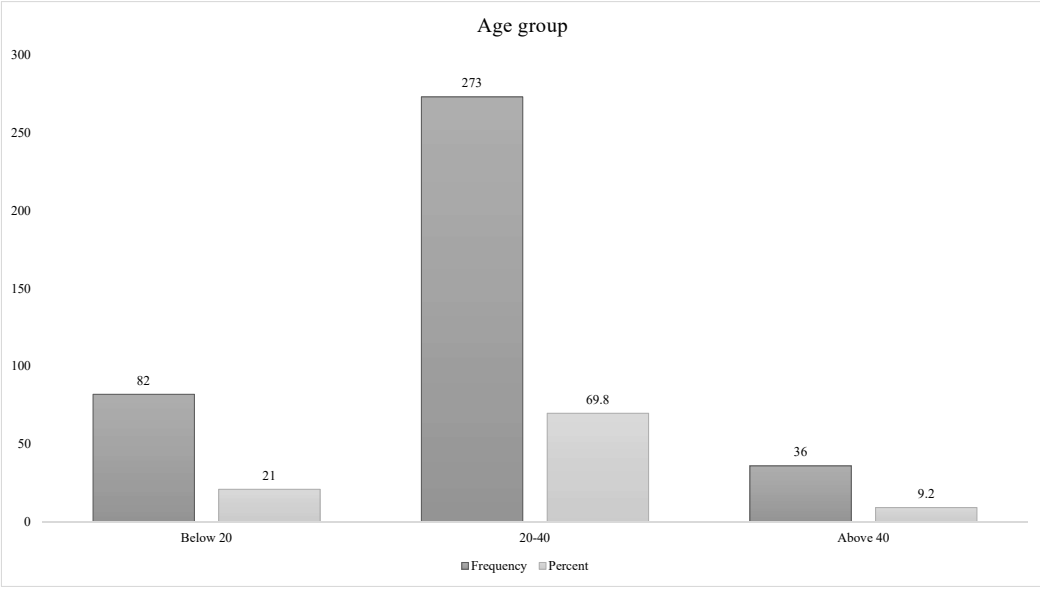
Table 5
Academic qualification of respondents

Academic qualification	Frequency	Percent	Cumulative Percent
Bachelor	272	69.6	69.6
Master	31	7.9	77.5
SLC	10	2.6	80.1
Below SLC	3	0.8	80.9
+2	73	18.6	99.5
PhD	2	0.5	100

Table 6
Time spent by respondents

Time spent	Frequency	Percent	Cumulative Percent
Below 2 hours	86	22	22
2-4 hours	198	50.6	72.6
Above 4 hours	107	27.4	100

Figure 3
Age group of respondents



This suggests that there were somewhat more male respondents than female respondents in the study. Table 6 represents time spent by respondents on social media.

Table 6 shows that 50.6% of respondents (198) spend 2–4 hours on social media daily. This was followed by 107 respondents (27.4%) who spent over 4 hours and 86 (22.0%) who spent less than 2 hours. The majority of respondents spent 2–4 hours each day on social media, indicating moderate to high usage. The below Figure 3 shows the age groups of respondents.

Figure 3 shows that 273 (69.8%) of respondents were aged 20 to 40. This was followed by 82 (21%) under-20 respondents and 36 (9.2%) over 40. The majority of participants were young, indicating that the study is representative of the most socially active age group. The below Table 7 represents the basic information of respondents.

Table 7 shows that 99.2% of respondents use social media to obtain news and information, while 94.1% have encountered fake news. Although 83.6% verify news before sharing, 40.7% have still shared false news. Moreover, 95.4% believe that fake news influences users trust in social media as a news source.

Descriptive analysis: Based on Table 8, fake news awareness was reported to have the highest mean value (mean value 4.30), followed by fake news detection ability and social media credibility. Similarly, trust in social media as a news source has the lowest average value (mean value 3.47). Social media credibility has the largest standard deviation (0.74), followed by trust in social media as a news source and fake news detection ability, with fake news awareness having the lowest standard deviation value (0.61). Similarly, social media credibility has the highest variance (0.55), followed by trust in social media as a news source and

Table 7
Basic information of respondents

Questions	Responses				Total	
	Yes	Percent	No	Percent	Count	Percent
Do you use social media to obtain news and information?	388	99.2	3	0.8	391	100
Have you ever encountered fake news on social media?	368	94.1	23	5.9	391	100
Do you verify the truth of the news before sharing it on social media?	327	83.6	64	16.4	391	100
Have you ever shared news that was false?	159	40.7	232	59.3	391	100
Do you believe that fake news influences users trust in social media as a source of news?	373	95.4	18	4.6	391	100

Table 8
Descriptive statistics

Statistics/Variables	FNA	FNDA	SMC	TSMN
N	391	391	391	391
Mean	4.29	4.23	4.01	3.47
Median	4.4	4.4	4.4	3.6
Mode	4.4	4.4	4.4	3.8
Std. Deviation	0.61	0.63	0.74	0.63
Variance	0.376	0.398	0.55	0.408

Table 9
Correlation analysis

Variables	FNA	FNDA	SMC	TSMN
Fake news awareness	1			
Fake news detection ability	.765*** (.001)	1		
Social media credibility	.580*** (.001)	.673*** (.001)	1	
Trust in social media news	.482*** (.001)	.561*** (.001)	.758*** (.001)	1

fake news detection ability, with fake news awareness having the lowest variance (0.376).

Correlation analysis: The Table 9 shows a positive and statistically significant relationship between fake news awareness (FNA) and trust in social media as a news source ($r = 0.482$, $p < 0.01$). Similarly, fake news detection ability (FNDA) has a positive and statistically significant link with trust in

Table 10
Regression analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.646	0.156		4.131	0.001
Fake news awareness	0.022	0.054	0.021	0.402	0.688
Fake news detection ability	0.079	0.058	0.078	1.375	0.17
Social media credibility	0.597	0.039	0.693	15.411	0.001
Adjusted R square	0.576	F	177.712	Sig.	0.001

social media as news source ($r = 0.561$, $p < 0.01$). Furthermore, social media credibility (SMC) is strongly favorable and statistically connected with trust in social media as a news source ($r = 0.758$, $p < 0.01$).

Regression analysis: According to Table 10, fake news awareness has an insignificant impact on users' trust in social media as a news source ($r = 0.022$, $p > 0.05$), which rejects the alternate hypothesis (H_1). This implies that the awareness of fake news alone may not be sufficient to affect the general trust of the users. Furthermore, fake news detection ability has an insignificant effect on users' trust in social media as news source ($r = 0.079$, $p > 0.05$), which rejects the alternate hypothesis (H_2). It means that a person's ability to identify fake news does not significantly influence how much they trust social media as a source of news. Also, social media credibility has a positive significant effect on users' trust in social media as a news source ($r = 0.597$, $p < 0.01$), which supports the alternate hypothesis (H_3). This indicates that users tend to trust social media more as a news source when they perceive the information credible and reliable. The regression model is statistically significant, as shown by the F-statistic of 177.712 ($p = 0.01$), which is significant at the 1% significance level. The linear regression equation is estimated as follows:

$$Y = 0.646 + 0.022\ FNA + 0.079\ FNDA + 0.597\ SMC + e$$

Discussion

Fake news awareness has insignificant influence on users' trust in social media as a news source. This finding contradicts with Guess et al. (2020); Pennycook et al. (2020); Negi and Bedi (2024); who reported that media literacy, verification, and news authentication significantly affect users' evaluation of misinformation and trust in social media news. This may be because awareness of fake news does not always translate into changes in users trust decisions, as users may still rely on familiar sources or existing perceptions when evaluating news. Similarly, fake news detection ability has an also insignificant impact on users' trust. This result has the opposite view with the findings of Cheng and Chen (2021); Zoonen et al. (2023); Orhan (2023); who found significant relationships between information trust, detection self-efficacy and fake news detection. However, Park and Lee (2023) found that incidental exposure to social media news has a negative significant effect on trust. Users self-reported ability to detect fake news may not reflect their

actual ability to identify deceptive material hence, detection ability may have less impact on trust when other factors are considered. Furthermore, social media credibility has a positive and significant impact on users' trust and is the strongest predictor of the three variables. This finding is similar with the results of Sousa and Bates (2021); Cheng and Chen (2021); Lan and Tung (2024). This phenomenon may be because users are more likely to trust social media news when they perceive the source or content as credible, reliable, and accurate. From the perspective of Truth Default Theory, perceived credibility may reinforce users' tendency to accept information as truthful unless clear cues of deception are present.

CONCLUSION

This study examined how users' perceptions of fake news and social media information relate to their trust in social media news. The findings provide insight into the relative importance of awareness, detection ability, and credibility in shaping users' trust. Fake news awareness has an insignificant impact on trust in social media news. The findings reported that only being aware of fake news awareness is not sufficient to change users' trust in social media as a news source. Also, fake news detection ability has insignificant effect on trust on social media news. This suggests that users' ability to detect fake news may not be an important factor influencing users' overall trust in social media news. Furthermore, social media credibility was the most influential factor affecting users' trust. The finding suggests that users are more likely to trust social media as a news source when they perceive the information available on it to be credible and reliable. This finding is significant to the Truth Default Theory, which indicates that users are more likely to trust social media news when they find the source and information credible and reliable. Therefore, high social media credibility strengthens users' tendency to perceive information as true, even without extensive verification. Therefore, improving the credibility and reliability of information on social media, along with encouraging users to develop skills in detecting fake news, can contribute to more informed and responsible use of social media as a news source.

IMPLICATION

The findings determined that in order to increase customer trust in social media news, social media platforms and news providers should improve the information's validity, accuracy, and dependability because social media credibility was strongest predictor of users' trust. Policymakers, local news writers, and the Nepalese government should also promote media literacy and responsible news practices to reduce the spread of fake news. Programs for media literacy should also encourage consumers to double-check information and improve their ability to identify fake information. The findings also suggest that before accepting information as legitimate, consumers should be encouraged to critically evaluate the credibility of news sources.

There are some limitations of this study, the study was based on the Lalitpur area, which may restrict its application to other parts of Nepal. It examined only three variables, while factors such as media literacy, source familiarity, and social media usage may also affect users' trust. Moreover, this study does not explore differences in content, algorithm

and user behavior separately between social media platforms. To provide more through insights, future research can combine these characteristics and use larger, more diverse sample sizes and should include interviews, cross-country responses, and rural area.

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ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Determinants of Consumer Spending Behavior: *The Role of Digital Payment Awareness, Convenience, Security, Trust, and Ease of Use*

Yugesh Karki
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
ka.yugesh23@ncmt.edu.np

Received: 17 Jul., 2026 | Revised: 5 Aug., 2026 | Accepted: 9 Sept., 2026

Abstract: *The rapid adoption of digital payment systems has changed the way consumers conduct transactions and potentially influence their spending behavior. The objective of this study is to investigate factors that influence consumer spending behavior through digital payment systems. The study considers digital payment awareness, convenience, security, trust, and ease of use as independent variables and consumer spending behavior as the dependent variable. The study is based on the Technology Acceptance Model (TAM) and uses an alternative hypothesis. A quantitative research approach was used, and primary data were collected from digital payment users in the Samakhusi area of Nepal through Google Forms circulated via social media platforms. The sample size was 385 respondents. Data were analyzed using SPSS software, descriptive statistics, correlation analysis, and multiple regression analysis to explore the relationships and influence among the variables. The regression outcomes demonstrate that convenience, trust, and ease of use positively and significantly influence consumer spending behavior. In contrast, security has a positive but insignificant influence while digital payment awareness has a negative and insignificant effect. The findings suggest that consumers are more likely to engage in digital payment transactions when the systems are convenient, easy to use, and trustworthy. Additionally, this study offers valuable implications for digital payment providers, enterprises, lawmakers, and governments to enhance the usability, convenience, and trustworthiness of digital payment systems in Nepal. Limitations include geographical coverage. Additional variables such as perceived usefulness, financial literacy, rewards, social impact, and consumer attitude may be incorporated to provide more a comprehensive understanding of consumer spending behavior.*

Keywords: Consumer spending behavior, conveniences, digital payment awareness, ease of use, security, trust

JEL Classification: D12, E42, O33, G23

Cite as: Karki, Y. (2026). Determinants of consumer spending behavior: The role of digital payment awareness, convenience, security, trust, and ease of use. *NCMT Journal of Multidisciplinary Studies, 1*(1), 17-34.

INTRODUCTION

Digital payment systems have transformed the way consumers conduct financial transactions in today's technology-driven economy. The rapid advancement of smartphones, internet connectivity, and financial technology (fintech) has accelerated the adoption of payment methods such as unified payments interface (UPI), mobile wallets, debit and credit cards, internet banking, and QR code payments, making them an essential part of everyday transactions (Bharathi et al., 2026). Digital payment systems are incorporated into everyday living and this not only allows consumers to enjoy more convenient and efficient transactions but also influences their purchase decisions and spending patterns. Our use of money is based not simply on our principles and our financial intelligence, but also on the way we pay. The switch from cash to digital payment systems has drastically affected the way consumers spend and save money (Stavins, 2017). However, the adoption and continuous usage of digital payment systems depend on various aspects like awareness of the users, perceived security, trust and existence of banking infrastructure (Halaweh & Qaisi, 2016).

The rise of digital payment methods has transformed not only how people pay for things but also their overall purchasing habits. Digital payments are more popular than traditional cash-based methods because of their features, such as rapid payments, easy access, and smooth transaction procedures, which encourage consumers to purchase more frequently and with more ease (Sahi et al., 2021)**.** The simplicity of digital payment also reduces the work needed in making payments and often encourages impulse purchases or unexpected buying, as consumers are less likely to see the rapid outflow of money compared to cash transactions. Consequently, experts have claimed that the popularization of digital payment systems may influence consumers' behavior of expenditure, financial decisions, and overall consumption behavior (Kurniawan et al., 2019).

Previous studies have examined digital payment adoption and consumer behavior in various countries (Pradhan & Karn, 2025; Adekunle et al., 2020; Gupta & Gupta, 2026; Fauziah & Berakon, 2024); their findings remain inconsistent and may not be directly applicable across different economic and cultural contexts. Thus, the present study aims to evaluate the impact of digital payment systems on consumer spending behavior by providing empirical evidence on the relationship between the use of digital payments and the consumer's purchasing behavior. The results are expected to assist businesses, financial institutions, and politicians in promoting the efficient use of digital payment systems. Prior research had mostly focused on analyzing the association between digital payments and consumer behavior using a variety of mediating and moderating variables. For instance, Agarwal and Subnani (2025); Underdown and Tamara (2025); Jagapur and Singh (2025) investigated the mediating role of perceived pain of paying and consumer attitude incorporating behavioral intention as a mediator. Similarly, Fauziah and Berakon (2024) analyzed the moderating effects of digital savviness, financial literacy, and demographic factors. Furthermore, limited empirical research has been conducted in the Nepalese context (Lamichhane, 2025; Pradhan & Karn, 2025). Lamichhane (2025) studied only qualitative research,

but this study uses quantitative research. Although earlier research has looked into the relationship between digital payment systems and consumer spending behavior, the majority of these studies were conducted outside of Nepal and included mediating or moderating variables in their models. There has been little quantitative study on the direct effects of major digital payment parameters on consumer buying behavior in Nepal. These elements include digital payment awareness, convenience, security, trust, and ease of use. Furthermore, prior studies in Nepal have shown little evidence of how these characteristics directly influence consumers' buying habits. As a result, there was a contextual and methodological gap, which the current study filled by looking at the direct effects of these five factors on consumer buying behavior among digital payment users in Kathmandu's Samakhusi area.

The study contributes to the existing literature by providing quantitative information on how digital payment systems affect consumer spending behavior in Nepal. Unlike previous research, which focuses on mediating or moderating effects, this study investigates the direct effects of digital payment knowledge, convenience, security, trust, and simplicity of use on consumer buying behavior. The findings are likely to provide valuable insights for digital payment providers, financial institutions, enterprises, legislators, and consumers into the elements that may influence spending behavior via digital payment systems.

Research question

- What is the relationship between digital payment awareness, ease of use, trust, security, convenience, and consumer spending behavior?
- Do digital payment awareness, ease of use, trust, security, and convenience affect consumer spending behavior?

Objectives of the study

The rapid growth of digital payment systems has changed how consumers conduct financial transactions and manage their spending. The growing usage of mobile banking, e-wallets, QR payments, and other cashless payment methods has sparked interest in how they affect consumer buying behavior. The study focuses on understanding how different characteristics of digital payment systems may influence consumers' spending patterns. The major objective of the study is to examine the effect of the digital payment system on the consumer spending behavior of digital payment users in the Samakhusi area. Hence, the specific purpose of the study includes the following:

- To analyze the relationship between digital payment awareness, ease of use, trust, security, convenience and consumer spending behavior.
- To examine the effects of digital payment awareness, ease of use, trust, security, and convenience on consumer spending behavior.

LITERATURE REVIEW

Theoretical review

Technology Acceptance Model (TAM): Davis et al. (1989) developed and verified the Technology Acceptance Model (TAM), which describes how people accept and use technology. The model was based on Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA), which identified perceived usefulness (PU) and perceived ease of use (PEOU) as important predictors of technological

acceptance. Perceived usefulness is the level to which a person believes that utilizing a system increases performance, whereas perceived ease of use is the degree to which using the system involves little effort (Davis et al., 1989). TAM established a theoretical framework for comprehending the acceptance and use of digital payment systems (Ramesh et al., 2015). In this study, ease of use was connected with PEOU, whereas convenience was associated with perceived usefulness, owing to the fact that digital payments made transactions faster and easier. Similarly, digital payment awareness, trust, and security were identified as critical elements impacting customer confidence and utilization of digital payment systems. As a result, TAM provided a theoretical foundation for studying digital payment awareness, convenience, security, trust, and ease of use as influences on consumer spending behavior.

Theory of Planned Behavior (TPB): The Theory of Planned Behavior (TPB) was developed by Ajzen (1991) for prediction and explanation of human behavior. The theory suggests that behavioral intention is a function of attitude, subjective norms, and perceived behavioral control, which in turn predict actual conduct. In the digital payment environment, simplicity and ease of use may help to create favorable attitudes and perceived behavioral

Table 1
Summary of previous studies

Authors	Year	Country	Methodology	Findings
Fauziah and Berakon	2024	Indonesia	Regression analysis	Indicated that ease of use shows a strong and significant influence on consumptive behavior.
Joshi et al	2024	India	Correlation and regression analysis	Showed that ease of use has a positive and significant impact on spending habits.
Lamichhane	2025	Nepal	Qualitative research	Confirmed that consumer spending behavior is influenced by ease of use.
Malik and Rana	2025	India	Logistic and multiple regression analysis	Found that ease of use has a significant positive impact on consumer spending behavior.
Pradhan and Karn	2025	Nepal	Regression analysis	Highlighted that ease of use has a positive impact on consumer spending habits.
Underdown and Tamara	2025	Indonesia	Regression analysis	Found that ease of use has an insignificant impact on consumer spending behavior.
Gupta and Gupta	2026	India	Regression analysis	Demonstrated that ease of use has a significant influence on consumer spending behavior.

Table 2
Summary of prior studies

Authors	Year	Country	Methodology	Findings
Kanwal and Singh	2025	India	Correlation and regression analysis	Found that convenience has a positive significant impact on the log of monthly spending.
Malik and Rana	2025	India	Logistic and multiple regression analysis results	Found that convenience has a significant positive impact on consumer spending behavior.
Pradhan and Karn	2025	Nepal	Correlation and regression analysis	Highlighted that convenience has a positive impact on consumer spending habits.
Gupta and Gupta	2026	India	Regression analysis	Demonstrated that convenience has a significant influence on consumer spending behavior.

control, while trust and security may enhance the confidence of customers in utilizing the digital payment systems. Similarly, awareness of digital payment may increase the understanding of consumers about digital payment services and their benefits. The study by Adhikari and Chalise (2025) on the use of electronic payment system in Kathmandu Valley used TAM and TPB, which showed the usefulness of these theories in relation to Nepalese digital payment. Therefore, TPB is a complementary theory to TAM that provides a behavioral perspective to study the impact of digital payment elements on consumer buying behavior.

Empirical review

Ease of use and consumer spending behavior: Deviarti et al. (2023) determined the impact of e-wallets on consumer behavior in Indonesia. The regression analysis stated that perceived ease of use and perceived usefulness significantly influenced users' attitudes toward e-wallets.

H_1: Ease of use has a significant impact on consumer spending behavior.

Convenience and consumer spending behavior: Adekunle et al. (2020) determined electronic payment adoption and consumer spending growth: Empirical evidence from Nigeria. The regression analysis stated that convenience and security significantly influence e-payment adoption.

H_2: Convenience has a significant impact on consumer spending behavior.

Security and consumer spending behavior: Adekunle et al. (2020) investigated electronic payment adoption and consumer spending growth: empirical evidence from Nigeria. The regression analysis stated that security significantly influences e-payment adoption and spending behavior.

H_3: Security has a significant effect on consumer behavior.

Digital payment awareness and consumer spending behavior: Adekunle et al. (2020) examined electronic payment adoption and consumer spending growth: Empirical evidence from Nigeria. The

Table 3
Summary of earlier studies

Authors	Year	Country	Methodology	Findings
Fauziah and Berakon	2024	Indonesia	Regression analysis	Indicated that security has positive and significant effect on the consumptive behavior.
Malik and Rana	2025	India	Logistic and multiple regression analysis	Found that Security perception has a significant negative impact.
Pradhan and karn	2025	Nepal	Correlation and regression analysis	Highlighted that Security has insignificant impact on consumer spending habit.
Gupta and Gupta	2026	India	Regression analysis	Demonstrated that security has a significant influence on consumer spending behavior.
Pawar	2026	India	Regression analysis	Revealed that security factor has insignificant impact on consumer spending behavior.

regression analysis indicated that showed that awareness has positive significant relationship with consumers' spending behavior. Furthermore, Jagapur and Singh (2025) highlighted the impact of digital payments on consumer spending behavior in India. The regression analysis findings found that digital payment awareness has a significant influence on consumer spending behavior. Likewise, Gupta and Gupta (2026) also studied digital payments and consumer behavior in urban India. The regression analysis findings demonstrated that awareness has a significant influence on consumer spending behavior.

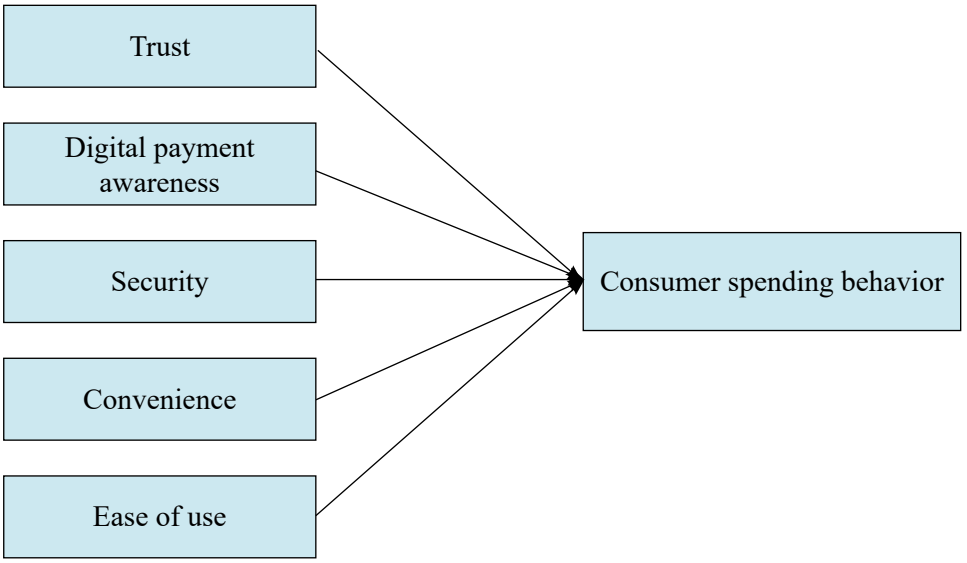
H_4: Digital payment awareness has a significant impact on consumer spending behavior.

Trust and consumer behavior: Fauziah and Berakon (2024) showed the effect of trust, ease of use, and security of digital payment transactions on individual consumptive behavior in Indonesia. The regression analysis stated that trust has a significant positive effect on individual consumptive behavior. Likewise, Adekunle et al. (2020) investigated the electronic payment adoption and consumer's spending growth in Nigeria. The findings from regression model revealed that awareness has positive significant relationships with consumer spending behavior. Furthermore, Pradhan and Karn (2025) revealed the impact of cashless transactions on consumer spending habits and consumer satisfaction in Nepal. The correlation and regression model findings highlighted that security has an insignificant impact on consumer spending habits.

H_5: Trust has significant impact on consumer spending behavior.

Based on the literature review, the study developed the research framework presented in figure 1.

Figure 1
Research framework of study



Note. Fauziah and Berakon (2024); Jagapur and Singh (2025).

METHODOLOGY

Research design

The research approach adopted in the study was deductive. Moreover, the study adopted positivism as a research philosophy. This quantitative study used descriptive, relational, and explanatory research designs (Budhathoki et al., 2023). A descriptive study approach was used to describe the basic characteristics of the variables under inquiry (Budhathoki & Khadka, 2024). The relationship between the antecedent and consequent variables was examined utilizing the relational research approach. An explanatory study design was used to explore the effect of independent variables on dependent variables (Budhathoki et al., 2025).

Population and sample

The study's target group was individuals who utilize digital payment systems for financial transactions. They encompass mobile banking users, e-wallets, internet banking, QR code payments, and debit or credit card payment systems. Since the exact number of digital payment users in the study area was not known and was always changing, the population was considered to be limitless. Thus, the convenience sample method was used to pick 384 respondents who have experience utilizing at least one of the digital payment methods. This method facilitated the collection of data from a large population of digital payment users in the Kathmandu District, Samakhusi area. Sample size was calculated using Cochran's methods for when the size of the population was unknown but assumed to be big (Cochran, 1977). The sample size can be calculated using Cochran's formula as follows:

$$n = \frac{z^2 * p * q}{e^2}$$

(Where n = required sample size (384); Z = Z-value (e.g., 1.96 for 95% confidence level); p = estimated proportion (0.5 if unknown); q = 1 – p; e = margin of error (5%))

A structured questionnaire with close-ended questions was prepared utilizing Google Forms and sent through several social media sites like Facebook, Instagram, WhatsApp, and Messenger. A Google Form questionnaire was circulated over various social media platforms from June 26 to July 3.

Sources of data and analysis tools

This study used primary data collected through a structured closed-ended questionnaire. The questionnaire includes demographics and a five-point Likert scale. The questionnaire was developed based on the findings of the literature study. The measurement items for trust, security, digital payment awareness and convenience and ease of use in the Likert-scale questionnaire were extracted from (Adekunle et al., 2020). The study employed the SPSS software version 32.0 for necessary data analysis.

Table 4
Reliability test

Variable dimension	Number of items	Cronbach's Alpha
Digital payment awareness	4	0.769
Convenience	5	0.902
Security	4	0.879
Trust	4	0.888
Ease of use	4	0.894
Consumer spending behavior	5	0.908

Pilot research with 49 participants was conducted to ensure its reliability and utility, and if the calculation was successful, additional data collection commenced. Cronbach's alpha coefficients are shown in Table 4 for digital payment knowledge (0.769), convenience (0.902), security (0.879), trust (0.888), simplicity of use (0.894), and customer purchasing behavior (0.908). All estimated Cronbach's alpha values are more than 0.7, showing strong internal consistency across questions assessing each component.

ANALYTICAL MODEL

This study used the regression model to examine the cause-and-effect correlations between antecedent and subsequent variables. The model was used in the previous study by (Pradhan & Karn, 2025).

$$CSH = \beta_0 + \beta_1 C + \beta_2 E + \beta_3 T + \beta_4 S + \beta_5 DPA + e$$

(Where, E= Ease of use, T= Trust, S= Security, C= Convenience, e= Error term, DPA= Digital payment awareness, CSH= Consumer spending habits, β_0= Constant term, $\beta_1 \ldots \beta_5$= Coefficients of predictors)

Definition of variables

Independent variable

Ease of use: Ease of use is defined as the degree to which an individual believes that the use of a certain technology or system is simple and understandable and needs minimal physical or mental effort. Technology that is easy to learn, explore, and operate that allows people to accomplish their responsibilities more efficiently and confidently (Davis,1989). The more perceived user friendliness and the ease of use of the system, the greater the probability of continuing adoption and use (Ilieva et al., 2023).

Trust: Trust is defined as the extent to which consumers think that a digital payment system is reliable, secure, and can consistently and accurately execute transactions (Sahabuddin et al., 2025). It reflects users' confidence that their personal and financial information will

be protected, and service providers will conduct transactions in a fair and responsible way. Higher levels of trust lessen the users' concerns about prospective hazards and facilitate the continuous usage of digital payment systems in daily transactions (Beheri et al., 2025).

Digital payment awareness: Digital payment awareness (DPA) refers to the knowledge and understanding of the digital payment system, its characteristics, benefits, functions, and use by people (Adhikari & Chalise, 2025). It shows users' perception of convenience, availability, and security of digital payment services, which enables them to make educated decisions on the adoption and continued usage of digital payment services (Franciska & Sahayaselvi, 2024).

Convenience: Convenience is the extent to which customers believe that using a digital payment system is simple, is accessible, and is practical to utilize in their regular activities (Prakosa & Wintaka, 2020). It allows the users to do transactions fast and at any time and from anywhere (Sari, 2021). A convenient payment system can save time and make users more likely to continue using electronic payment methods (Latief & Dirwan, 2020).

Security: Security is the measure to which users think that a digital payment system can secure their personal and financial information, maintain the confidentiality of transactions, and prevent unauthorized access or fraudulent activity (Rahmawati & Yuliana, 2020). It indicates that customers believe in the ability of security measures such as authentication procedures, data protection, encryption, and privacy policy to protect the financial transaction (Rahmawati & Yuliana, 2020). The level of perceived security is higher, which lessens the users' concerns about the possible hazards and boosts their confidence and readiness to adopt and continue utilizing digital payment systems (Patel & Patel, 2018).

Dependent variables

Consumer spending behavior: Consumer spending behavior (CSB) is a pattern of decision-making and behaviors that people do while buying products and services with their available financial resources (Mynarikova & Posta, 2023). It represents the rate at which customers spend, make buying decisions, and spend money and may be influenced by the simplicity and accessibility of digital payment systems (Faraz & Anjum, 2025).

FINDINGS AND DISCUSSION

Findings

Demographic response: Based on Table 5, the majority of the respondents were bachelor degree holders with a total of 202 (52.5%) of the total respondents. Table 5 shows that 202 (52.5%) respondents have bachelor's degrees. Next, 82 (21.3%) had +2 qualifications. Additionally, 38 (9.9%) participants had master's degrees, 37 (9.6%) SLC degrees, 20 (5.2%) below SLC degrees, and 6 (1.6%) PhD degrees. The bulk of responders were male (n=254, 66.0%) and female (n=131, 34.0%). Only 127 (34.0%) were married, while 258 (67.0%) were single. Classification also used respondent age. The bulk of respondents were 25–45. There were 203 (52.7%) responses in this age group. Then 166 (43.1%) responders were under 25, and 16 (4.2%) were above 50. Students dominated the occupations category with 173 (44.9%). Other occupations included 155 (40.3%) respondents, 29 (7.5%) jobless,

Table 5
Demographic profile of respondents

		Frequency	Percent	Cumulative Percent
Academic qualification	Below SLC	20	5.2	5.2
	SLC	37	9.6	14.8
	+2	82	21.3	36.1
	Bachelor	202	52.5	88.6
	Master	38	9.9	98.4
	Phd	6	1.6	100
Gender	Male	254	66	66
	Female	131	34	100
Marital status	Single	258	67	67
	Married	127	33	100
Age group	Below 25	166	43.1	43.1
	25-45	203	52.7	95.8
	Above 50	16	4.2	100
Occupations	Student	173	44.9	44.9
	Business	28	7.3	52.2
	Unemployed	29	7.5	59.7
	Others	155	40.3	100
Monthly income	Below NPR 20,000	71	18.4	18.4
	NPR 20,000-60,000	107	27.8	46.2
	NPR 60,000-90,000	64	16.6	62.9
	Above NPR 80,000	15	3.9	66.8
	None	128	33.2	100
Digital payment method	Mobile banking	281	73	73
	E-sewa	77	20	93
	Khalti	18	4.7	97.7
	FonePay	9	2.3	100
Frequency of digital payment use	Daily	128	33.2	33.2
	Several times a week	216	56.1	89.4
	Occasionally	30	7.8	97.1
	Rarely	11	2.9	100
Duration of digital payment use	Less than 1 year	26	6.8	6.8
	1-3 years	135	35.1	41.8
	3-5 years	145	37.7	79.5
	More than 5 years	79	20.5	100

Table 6
Descriptive statistics

Statistics/Variables	Convenience	Security	Trust	EOU	CSB
N	385	385	385	385	385
Mean	3.86	3.85	3.82	4.25	3.85
Median	4	4	4	4.5	4
Mode	4	4	4	4.5	4
Std. Deviation	0.647	0.692	0.613	0.672	0.744
Variance	0.419	0.48	0.377	0.452	0.555

Table 7
Correlation analysis

Variables	DPA	S	T	EOU	CSB
Digital payment awareness	1				
Convenience	.706***				
	(0.001)				
Security	.634***	1			
	(0.001)				
Trust	.616***	.758***	1		
	(0.001)	(0.001)			
Ease of use	.726***	.677***	.649***	1	
	(0.001)	(0.001)	(0.001)		
Consumer spending behavior	.488***	.570***	.597***	.562***	1
	(0.001)	(0.001)	(0.001)	(0.001)	

*** *Correlation is significant at the 0.001 level (2-tailed)*

and 28 (7.3%) businesspeople.

The largest percentage of respondents, 128 (33.2%), reported no monthly income. This was followed by 107 (27.8%) respondents earning NPR 20,000–60,000. Only 15 (3.9%) respondents earned above NPR 80,000, while 71 (18.4%) earned below NPR 20,000, and 64 (16.6%) earned between NPR 60,000 and NPR 90,000. Respondents were also categorized by digital payment preference. Most digital payments were made via mobile banking (281, 73.0%). E-sewa was second with 77 (20.0%) responders, followed by Khalti (18 (4.7%)) and FonePay (9, 2.3%). Most respondents (216, 56.1%) used digital payment services several times a week, while 128 (33.2%) used them daily, 30 (7.8%) occasionally, and 11 (2.9%) rarely. Finally, respondents were split by digital payment duration. Most respondents (145, 37.7%) utilized digital payment systems for 3–5 years. The second group, 135 (35.1%), had utilized digital payment systems for 1–3 years. Moreover, 79 (20.5%) respondents had used digital payment systems for more than five years, while 26 (6.8%) had used them for less than one year.

Table 8
Regression analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.486	0.209		2.327	0.021
Digital payment awareness	-0.031	0.073	-0.027	-0.429	0.668
Convenience	0.191	0.076	0.166	2.509	0.013
Security	0.122	0.073	0.113	1.66	0.098
Trust	0.321	0.078	0.265	4.1	0.001
Ease of use	0.249	0.07	0.225	3.58	0.001
Adjusted R-Square	0.422	F	57.009	Sig	0.001

Descriptive analysis: According to Table 6, among the study factors, ease of use (EOU) was reported to have the highest mean value (mean value 4.26), followed by convenience and consumer spending behavior. Likewise, the mean value of trust was the lowest at 3.83. The highest standard deviation value was in the consumer spending behavior of 0.74, security of 0.69, and the lowest was trust of 0.61. Likewise, consumer spending behavior had the highest variance (0.555), followed by ease of use and security (0.480), and trust had the lowest variance (0.377).

Correlation analysis: As shown in Table 7, the association between digital payment awareness (DPA) and consumer spending behavior (CSB) is positive and statistically significant ($r = 0.488$, $p < 0.01$). Furthermore, convenience (C) has a significant and favorable effect on consumer spending behavior ($r = 0.563$, $p < 0.01$). Security (S) was positively and strongly associated with consumer spending behavior ($r = 0.570$, $p < 0.01$). Trust (T) was positively and significantly related with consumer spending behavior (CSB) ($r = 0.597$, $p < 0.01$), making it the strongest relationship among the independent variables and CSB. Ease of use (EOU) has a significant relationship with customer spending behavior ($r = 0.562$, $p < 0.01$).

Regression analysis:According to Table 8 digital payment awareness revealed a negative and statistically insignificant effect on consumer spending behavior ($r = -0.031$, $p = 0.668$), rejecting the alternate hypothesis (H_4). This suggests that digital payment awareness did not boost consumer spending behavior. Convenience has a positive and significant effect on consumer spending ($r = 0.191$, $p < 0.05$) accepting the alternative hypothesis (H_2), which indicated that the convenience of digital payment systems increased customer spending behavior, accepting the alternate hypothesis. Furthermore, the security has a positive but insignificant effect on consumer spending behavior ($r = 0.122$, $p = 0.098$), rejecting the hypothesis (H_3), showing that security did not significantly influence consumer spending behavior. Similarly, trust has a positive and significant effect on consumer spending behavior ($r = 321$, $p < 0.001$), indicating that consumer spending behavior increased when customers trusted digital payment systems, accepting alternative

hypothesis (H_5). Likewise, ease of use showed a positive and significant impact on consumer spending behavior ($r = 0.249$, $p < 0.01$) accepting the hypothesis (H_1). The adjusted R^2 of 42.2 percent demonstrated that all independent variables together explained 42.2 percent of the variation in customer spending behavior. The comprehensive regression model demonstrated statistical significance ($F = 57.009$, $p = 0.001$), which fit the regression model significantly at the 1% significance level. The linear regression equation is estimated as follows:

$$Y = 0.486 - 0.031\ DPA + 0.191\ C + 0.122\ S + 0.321\ T + 0.249\ EOU + e$$

Discussion: Digital payment awareness (DPA) has an insignificant impact on consumer spending behavior (CSB). This result differs from the studies of Adekunle et al. (2020); Jagapur and Singh (2025); and Gupta and Gupta (2026) who found a significant positive impact of digital payment awareness on CSB. The insignificant result may be because consumers may already be adequately aware of digital payment systems; therefore, changes in awareness may not significantly influence their spending behavior. Likewise, convenience has a positive and significant effect on consumer spending behavior. The result is consistent with Kanwal and Singh (2025); Malik and Rana (2025); Pradhan and Karn (2025); and Gupta and Gupta (2026). The significant result may be because convenient digital payment methods reduce the time and effort required to complete transactions, making consumers more likely to make purchases and spend more frequently. Also, security has a positive but insignificant effect on consumer spending behavior. The results are similar to those of Pradhan and Karn (2025); and Pawar (2026). However, the studies of Kanwal and Singh (2025); Malik and Rana (2025); Fauziah and Berakon (2024); and Gupta and Gupta (2026) concluded a significant influence of security on CSB. The insignificant effect could be due to consumers viewing security as a necessary component of digital payment services rather than a factor that directly improves their spending. Furthermore, trust has a positive and significant effect on CSB. The results were similar to studies of Pradhan and Karn (2025) and Fauziah and Berakon (2024). The considerable benefit could be due to consumers who trust digital payment providers feeling more confident that their transactions and financial information are handled safely, reducing reluctance during purchases and driving further use of digital payments. Similarly, ease of use has significant and positive impact on CSB. The outcomes are identical with those published by Fauziah and Berakon (2024); Joshi et al. (2024); Malik and Rana (2025); Pradhan and Karn (2025); and Gupta and Gupta (2026). However, Underdown and Tamara (2025) found an insignificant effect, indicating that the effects of ease of use vary by circumstance. The current study's intriguing finding could be attributed to the fact that simple and user-friendly digital payment systems lower the effort necessary to execute transactions, making customers more comfortable and eager to use digital payments for purchases.

CONCLUSION

Consumer spending behavior is not significantly influenced by awareness of digital payment methods. According to the research, simply being aware of a digital payment system does not influence customer spending behavior. Furthermore, convenience has a positive and considerable

impact on consumer buying habits. The findings show that consumers are more likely to utilize digital payment solutions that make transactions faster, easier, and more convenient. Similarly, trust has a favorable and considerable impact on consumer spending habits. The most influential aspect is trust, which suggests that when customers consider digital payment systems trustworthy and reliable, they are more likely to use them and spend more. Furthermore, ease of use has a positive and considerable impact on customer spending habits. This finding is backed by the Technology Acceptance Model (TAM), which identifies the simplicity of use as an important factor influencing user acceptance and use of technology. This indicates that consumers are more likely to adopt digital payment systems for transactions that are simple to learn, understand, and operate. The ease of the payment process reduces the amount of work required to execute transactions and encourages more frequent use of digital payment systems, which may eventually lead to increased consumer spending behavior. Overall, the findings confirm the TAM perspective that users' views of a technology's simplicity and usefulness influence their behavior, while also demonstrating the importance of trust and convenience in the digital payment environment.

IMPLICATIONS

This study has significant implications for digital payment providers, businesses, consumers, the Nepal Rastra Bank, and the Ministry of Finance. Since convenience, trust, and ease of use were discovered to have a favorable and considerable impact on customer buying behavior, digital payment providers should concentrate on providing simple, user-friendly, convenient, and dependable payment systems. As trust was the most important factor, service providers should increase transaction transparency, system reliability, customer assistance, and user personal and financial information security. According to the Technology Acceptance Model, improving the usability of digital payment systems can minimize consumers' effort and encourage them to use them more frequently. Although security did not have a substantial impact on consumer purchasing, effective security measures are still necessary to protect customers from fraud, unwanted access, and data misuse. Similarly, digital payment awareness had no significant effect, indicating that awareness campaigns should emphasize the practical benefits, ease of use, and safety of digital payments. The Nepal Rastra Bank can improve payment system laws, consumer protection, and security requirements, while the Ministry of Finance can back policies and programs that encourage safe and responsible digital payment uptake. Overall, the study suggests that increasing digital payment systems' usability, convenience, trustworthiness, and security can help Nepalese consumers utilize them more effectively and responsibly.

There are several limitations of this study. First, the survey was conducted among digital payment users in the Samakhusi area; hence, the findings may not be fully relevant to customers in other locations of Nepal. Second, the study used a quantitative approach and a convenience sample and this may use qualitative, mixed, and stratified sampling techniques. Third, the study only focused on a few variables; further, researchers should use variables such as reward and cashbacks, social influence, and financial

literacy, which may also influence the customer's buying behavior. Finally, the study only evaluated the direct effect of the selected factors and did not include mediating or moderating variables that may help provide further knowledge of the relationship between digital payment systems and consumer spending behavior.

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NCMT JOURNAL OF
MULTIDISCIPLINARY STUDIES (NJMS)

ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Examining the Effect of Smartphone Notifications on Psychological Well-being: *The Mediating Role of Attention Disruption among Smartphone Users*

Lex Yonjan Lama

National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College,
la.lexyonjan23@ncmt.edu.np

Received: 18 Jul., 2026 | Revised: 5 Aug., 2026 | Accepted: 9 Sept., 2026

Abstract: *In our daily lives, digital communication is pervasive, with smartphone notifications everywhere. Yet constant, loud, and intrusive notifications can take a toll on attention and mental health. This study examined the relationship between smartphone notifications and mental health and attentional disruption. The independent variables were notification frequency, volume, interruptions, and push notifications. Psychological well-being (PWB) was the dependent variable, and attention disruption (AD) was the mediating variable. The study was guided by Action Regulation Theory. A quantitative approach using descriptive, correlational, and causal research designs was employed. Primary data were collected from smartphone users through a Google Form-structured questionnaire. The study examined 12 hypotheses on the direct, indirect, and total effects of four types of smartphone notifications on psychological well-being. Relationships among smartphone notifications, attention disruption, and psychological well-being were examined using descriptive statistics, correlation analysis, regression analysis, and mediation analysis in IBM SPSS Statistics Version 32 with Hayes' PROCESS Macro Model 4.3. Mediation effects were tested using Model 4. Findings revealed that frequency of notification, volume of notification, interruption of notification, and push notifications have significant direct and total effects on psychological well-being. There were also significant indirect effects of notification on psychological well-being through attention disruption. The results indicated that users would benefit from having control over unnecessary notifications and that app developers could provide more control and customization options for notifications. Policymakers and relevant organizations have a role to play in encouraging responsible notification practices and digital well-being.*

Keywords: Attention disruption, frequency, interruptions, notifications, psychological well-being, smartphone notifications, volume

JEL Classification: D91, I31, O33, I12

Cite as: Lama, L.Y. (2026). Examining the effect of smartphone notifications on psychological well-being: The mediating role of attention disruption among smartphone users. *NCMT Journal of Multidisciplinary Studies, 1*(1), 35-53.

INTRODUCTION

The effects of digital technology on human well-being have been studied extensively in psychological research (Montag et al., 2023). Especially, smartphone notifications have been linked to attentional disruption, as they are unpredictable and interruptive. The notifications contain possibly useful but misleading information to sustain the users' engagement and motivation by reward-seeking behaviors (Nasti et al., 2021). Turning off notifications has been associated with greater attention and well-being in daily life (Fitz et al., 2019). That is, notifications interrupt the execution of ongoing tasks because you have to quickly shift your limited attention to the current task.

On the other hand, attentional capabilities are considered to be a finite asset with bounds. Previous research has described this as an attention bottleneck, suggesting that there exist boundaries regarding both the things we have access to and what we can take action on if multitasking is crucial (Tombu et al., 2011). In addition, carrying out multiple activities simultaneously needs extra cognitive capacity, increasing the cognitive load (Liefooghe et al., 2008) and making push notifications more interruptive. Interruptions generated by notifications have adverse effects on users' mental well-being. Several studies have made comments on users' anxiety and dissatisfaction with untimely notifications, measured by analyzing distinct interruption scenarios and how they impact users' mental well-being (Adamczyk & Bailey, 2004).

Research on the usefulness of digital well-being features, which include batching summaries, focus/do not disturb settings, and quiet hours, is lacking. Past intervention methods have led to inconsistent results, with a bit of research demonstrating slight behavioral changes with notification silencing (Nesbit & Lole, 2026), while others demonstrate slight improvements from stronger restrictions or design nudges (Giovanniello et al., 2023). Previous study have shown a various kinds of research methodologies, which include qualitative, mixed-methods, labroratory, and field experiments, offering significant findings including smartphone notification behavior (Fourniera et al., 2026; Kaminske et al., 2022; Khanday et al., 2025; Kim & Park, 2025; Li et al., 2022; Mukhdoom & Villarama, 2025; Ohly & Bastin, 2023; Özdemir et al., 2025) but this study used quantitative research approach. Along with that, previous research has mostly focused on other psychological traits, such as Fear of Missing Out (FoMO), boredom proneness, distress tolerance, and the frequency of interruptions caused by notifications, as mediating variables (Elhai et al., 2021; He & Zeng, 2024; Ohly & Bastin, 2023). While traits such as FoMO, telepressure, internal interruptions, age, and sex have been analyzed as moderators (Elhai et al., 2021; Ohly & Bastin, 2023). However, this study used the mediating variable attention disruption and did not use any moderating variables. In addition, most of the present findings have been collected from undergraduate or college student samples (Khanday et al., 2025; Upshaw et al., 2022; Upshaw et al., 2024). However, this study used a sample of smartphone users. To the best of the researcher's knowledge, research on the impact of smartphone notification interruption on attention disruption and psychological well-being among smartphone users remains limited in the context of Nepal. To fill this research gap, this research was conducted.

This study adds to the literature by examining smartphone notifications from the perspective of attention disruption and psychological well-being of smartphone users. Most prior studies have examined specific psychological traits, student populations, or individual notification behaviors, but this study examines four dimensions of smartphone notifications (notification frequency, notification volume, notification interruptions, and push notifications) and explores the mediating role of attention disruption. Moreover, this study contributes to the existing empirical evidence in the setting of Nepal, where research on the psychological effects of smartphone notifications is scarce. The findings may provide useful insights for smartphone users, application developers, and policymakers for promoting more effective notification management and supporting digital well-being.

Research questions

- Is there any relationship between smartphone notification characteristics and psychological well-being among smartphone users in Tokha Municipality?
- What is the effect of smartphone notification characteristics on psychological well-being and attention disruption of smartphone users in Tokha Municipality?
- Do the smartphone notification characteristics significantly impact attention disruption among smartphone users in Tokha Municipality?
- Does attention disruption play a mediating role in the relationship between smartphone notification characteristics and psychological well-being among smartphone users in Tokha Municipality?

Objectives of the study

The aim of this study is to examine the effect of smartphone notifications on psychological well-being, using attention disruption as a mediating variable. This study has the following very specific purposes:

- To analyze the relationship between smartphone notifications, attention disruption, and psychological well-being.
- To examine the effect of smartphone notifications on psychological well-being and attention disruption among smartphone users in Tokha Municipality.
- To examine the effect of smartphone notifications on attention disruption.
- To examine the mediating role of attention disruption in the relationship between smartphone notifications and psychological well-being.

LITERATURE REVIEW

Theoretical review

Action Regulation Theory: Human behavior is goal-oriented (Hacker, 2003; Altmann & Trafton, 2002), which suggests that humans act to achieve specific goals, as described by the Action Regulation Theory (ART). The theory holds that humans perform actions by employing cognitive processes such as planning, monitoring, and behavior control to manage their behavior in the pursuit of desired goals (Hacker, 2003). Effective regulation of action involves the ongoing surveillance and successful coordination of multiple sub-goals (Baethge et al., 2015). If

disruptions occur while people are engaged in a task, it becomes more difficult for them to remain consistent and achieve their goals, since the action regulation process is hampered (Baethge & Rigotti, 2013). The pre-interruption stage of the interruption process begins with concentration on an initial goal. During this time, all other data in the sensory register is filtered out (inhibited), and only the most relevant data for the main task or the current attentional focus is selected for interpretation (Couffe & Michael, 2017). The second period is called the "interruption phase" and starts after the interruption signal has been detected (not filtered in the early stage) and the attention focus has been re-directed (Anderson et al., 2018). The number of notifications and how often people check them can affect how people process information, but the time spent on notifications has less impact (Fourniera et al., 2026). Özdemir et al. (2025) demonstrated that inappropriate timing of notifications could cause interruptions, annoyance, and stress. Fewer interruptions can also improve people's performance and reduce their stress, as found by Ohly and Bastin (2023). The findings are consistent with Action Regulation Theory, as notifications can interrupt people's tasks and thus reduce their ability to focus and perform well on their work.

Empirical review

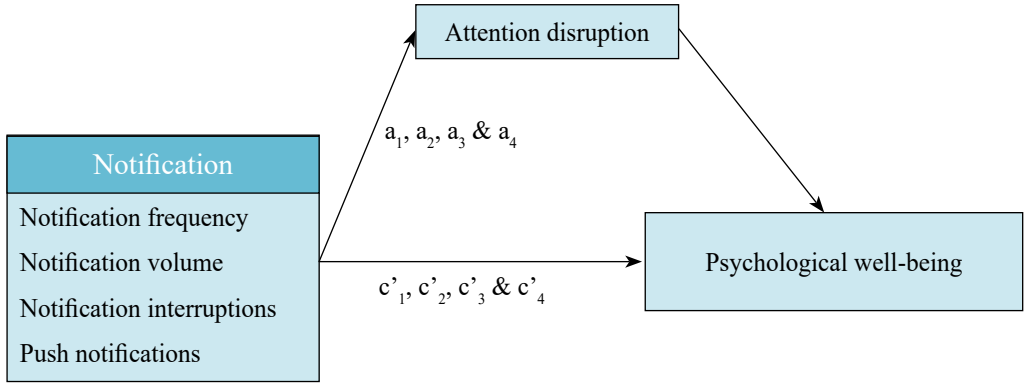
Prior work has indicated that more frequent notifications were associated with greater negative emotional responses, but receiving more messages and updates about participants' social networks also increased participants' feelings of social connectedness (Pielot et al.,2014). In addition, Kim et al. (2016) discovered that smartphone push notifications affect cognitive performance, as indicated by decreased N200 and P300 ERP components and increased reaction time and error rates, especially for smartphone overuse high-risk users. Kushlev et al. (2016) also found that inattention owing to smartphone use was associated with lower productivity and reduced psychological well-being. Furthermore, Pielot and Rello (2017) also demonstrated that alerts were bad for focused work, with participants reporting that they were less distracted and more productive when push notifications were switched off. However, turning off notifications also increased fear about losing important information and lowered a feeling of being awake. Likewise, Morrison et al. (2018) also showed that frequent push notifications increased the exposure of users to the intervention content, where participants who received daily or intelligent notifications viewed and acted on more notifications than those who received occasional notifications. However, the adaptive timing of notifications did not significantly increase the overall application usage. Peper and Harvey (2018) also showed that the lonelier people were, the more anxious and depressed they felt, indicating that digital addiction behaviors had broader psychological effects.

Based on earlier research, Elhai et al. (2021) investigated the relationship between disruptive smartphone notifications and psychological states such as susceptibility to melancholy, anxiety, and boredom. Similarly, Kaminske et al. (2022) showed that cell phone notifications had a large negative impact on attention, increasing the time needed to complete cognitive tasks regardless of cell phone ownership or difficulty of the task, thus providing evidence to suggest that notifications are distractions. Furthermore, Kim and Park (2022) showed that the excessive use of

smartphone notifications causes cognitive load and fatigue, and that customization of notifications by users can greatly reduce notification overload, compulsive phone-checking behavior, and smartphone addiction, resulting in better digital well-being. Likewise, Li et al. (2022) investigated smartphone users' notification preferences and found that users prefer to suppress or control interruptions rather than defer the notification, and content factors have a stronger influence on preference formation than contextual factors. In addition, Upshaw et al. (2022) discovered that the trial frequency and sound condition have significant and positive effects on cognitive control behavior. Moreover, Ohly and Bastin (2023) revealed that reducing interruptions through notifications is beneficial for performance and strain reduction. FoMO and tele pressure significantly moderated performance. Another study by He and Zeng (2024) also confirmed that the entertainment value and timeliness of smart push notifications increase the fear of missing out (FoMO), which mediates and amplifies smartphone addiction, and thus highlights the psychological risks of notification-based engagement systems.

Upshaw et al. (2024) reported that smartphone notifications negatively affect neural correlates of cognitive control, while brief mindfulness training may reduce this distraction effect. Similarly, Bhumithavara and Sun (2025) found that social expectations encouraged rapid responses to notifications, while repeated notification interruptions fragmented attention and delayed task re-engagement. The study further revealed that frequent phone checking became a habitual behavior, contributing to notification dependence as an everyday psychological experience. However, Dekker et al. (2025) noticed the notification has an insignificant relationship with fear of missing out. Likewise, Khanday et al. (2025) showed that notification frequency did not significantly predict cognitive or emotional outcomes. Instead, alert fatigue and attention disruption emerged as the strongest predictors of reduced well-being. Furthermore, Mukhdoom and Villarama (2025) reported that high-frequency notifications increase cognitive load, reduce heart rate variability, and impair task performance, while batching strategies and structured notification control systems significantly reduce stress and improve cognitive efficiency. Moreover, Özdemir

Figure 1
Conceptual framework



et al. (2025) showed that smartphone push notifications are often received in ill-timed contexts, leading to interruptions, annoyance, and stress. Finally, Fourniera et al. (2026) revealed that notification volume and frequency of checking have significant and beneficial effects on cognitive processing, whereas time spent has a minor impact on cognitive processing.

From the literature review, the study constructed the conceptual framework shown in Figure 1.

METHODOLOGY

Research design

A quantitative approach with descriptive, correlational, and causal research designs was used in this study. The descriptive research design was used to describe the study variables and respondents' characteristics (Budhathoki et al., 2025). The study employed a correlational research design to examine the relationship between smartphone notifications, attentional disruption, and psychological well-being. This study employed an explanatory research design to evaluate the impact of smartphone notifications on psychological well-being and the mediating role of attention interruption. The model included one mediator (attention disruption), one dependent variable (psychological well-being), and four independent variables.

Population and sample

The target population of this study involves smartphone users in Tokha Municipality, Kathmandu District. For sampling purposes, the population is considered expansive because the exact number of smartphone users is unknown and constantly changing. Therefore, a sample size of 384 was selected to be consistent with the 95% confidence level standards and a 5 % margin of error (Cochran, 1977). The sample size was selected using a sample calculator (Qualtrics & Fisher, 2023). The study's population of focus consists of smartphone users in Tokha Municipality. The necessary sample size was determined using Cochran's method for an unknown or large population. The formula is shown below.

$$n = \frac{z^2 * p * q}{e^2}$$

(Where, n = Sample size (384); Z= Z-score (e.g., 1.96 for 95% confidence level); p = estimated proportion (use 0.5 to maximize variability); e = margin of error (5%))

A closed-ended, well-organized questionnaire created with Google Forms was employed to obtain primary data from 23 June to 6 July. To take the survey at their ease, the questionnaire was distributed online through several digital mediums, including Facebook, Instagram, WhatsApp, and Messenger, and respondents were encouraged to participate.

Sources of data and analysis tools

This study depends on primary data obtained through a structured questionnaire. The questionnaire has two parts, which are demographic information and five-point Likert-scale questions regarding smartphone notifications, attention disruption, and psychological well-being.

The obtained data were evaluated with IBM SPSS Statistics Version 32. Furthermore, Hayes (2022) PROCESS Macro (Version 4.3) for SPSS was applied to analyze the mediating role of attention disruption in the relationship between the independent variable and dependent variable. The

Table 1
Reliability test

Variable dimensions	Number of items	Cronbach's Alpha
Notification frequency	4	0.780
Notification volume	4	0.718
Notification interruptions	4	0.917
Push notification	4	0.747
Attention disruption	4	0.922
Psychological well-being	5	0.755

PROCESS Macro employs Ordinary Least Squares (OLS) regression to calculate the direct, indirect, and total effects among the research variables.

Before starting the crucial data collection, a pilot study of 67 respondents was performed to determine the questionnaire's reliability and feasibility. All alpha values determined were higher than the acceptable level of 0.70, proving that the measuring items were internally consistent and reliable.

Analytical model

In this study, regression analysis was used to determine the relationships among notification frequency (X_1), notification volume (X_2), notification interruptions (X_3), push notifications (X_4), attention disruption (M), and psychological well-being (Y). The study used four multiple Ordinary Least Squares (OLS) regression models with path model statistics to investigate the cause-and-effect relationships among the predictor variables, the mediating variable, and the response variable (Budhathoki & Khadka, 2024). According to Hayes (2022), the regression coefficients a_j denotes a_1b, a_2b, a_3b, and a_4b denote the indirect effect (IE) of indirect variables on the dependent variable through the mediating variable (i.e., X→M →Y) (Budhathoki & Khadka, 2024). Similarly, the direct effects (DE) of independent variables on the dependent variable were measured by the regression coefficients of (a_1, a_2, a_3, a_4) and (c'_1, c'_2, c'_3, c'_4) (i.e., X→M; X/M →Y). The total effect (TE) was measured by the sum of a_jb and c'_j (i.e., total effect = $a_jb + c'_j$). If a^*b^*c' is positive, then the model is complementary mediation. Whereas a^*b^*c' is negative, the model is competitive mediation. The indirect effect model presented the t-statistics, which are calculated as the effect divided by BootSE. When the t-statistic is greater than 1.96, the indirect effect model is significant, whereas when the t-statistic is less than 1.96, the indirect effect model is insignificant. If the direct and indirect effect model is significant, then the model is partial mediation, and direct and indirect effect model is insignificant, then the model is full mediation (Budhathoki et al., 2023). The existence of a mediating impact gets proved by the equation below:

Model 1 (DE): AD (M) = $i_M + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + e_M$

Model 2 (DE): PWB (Y) = $i_Y + c'_1x_1 + c'_2x_2 + c'_3x_3 + c'_4x_4 + bM + e_Y$

Model 3 (IE): PWB (Y) = $i_Y + a_1b + a_2b + a_3b + a_4b + e_y$

Model 4 (TE): PWB = $i_Y + (c'_1x_1 + a_1b) + (c'_2x_2 + a_2b) + (c'_3x_3 + a_3b) + (c'_4x_4 + a_4b) + e_Y$

Where AD (M) = Attention disruption, PWB (Y) = Psychological well-being, X_1 = Notification frequency, X_2 = Notification volume, X_3 = Notification interruptions, X_4 = Push notifications, a_1-a_4 = regression coefficients representing the effects of the predictor variables on the mediating variable, b = regression coefficient representing the effect of the mediating variable on the response variable, $c'_1 - c'_4$ = direct effects of the predictor variables on the response variable after controlling for the mediating variable, i = intercept, e = error term.

Definition of variable

Independent variable

Notification frequency: Notification frequency means the rate at which a user receives push notifications during a particular period of time (Wohllebe et al., 2021). Additionally, frequent contact with smartphone alerts has been associated with higher cognitive costs and may negatively influence attentional performance (Fourniera et al., 2026).

H_1: Notification frequency has a positive direct effect on psychological well-being

H_2: Notification frequency has a positive indirect effect on psychological well-being through attention disruption.

H_3: Notification frequency has a positive total effect on psychological well-being.

Notification volume : The average amount of notifications that a user receives per day is known as notification volume (Fourniera et al., 2026). Continuous smartphone usage is encouraged with high notification volume, and users' daily patterns develop a habit of frequent checking (Bhumithavara & Sun, 2025). Furthermore, being exposed to smartphone notification sounds has been associated with spontaneous focus and increased pre-attentive neural activity, suggesting that alerts have the power to automatically grab users' attention (Upshaw et al., 2024).

H_4: Notification volume has a positive direct effect on psychological well-being

H_5: Notification volume has a positive indirect effect on psychological well-being through attention disruption.

H_6: Notification volume has a positive total effect on psychological well-being.

Notification interruptions: Notifications that seek to capture users' focus to alert them regarding a new event or content of information, such as a new message from a friend, are known as interruptive notifications (Paul et al., 2015). It takes effort to deal with interruptions; in most cases, task interruptions degrade performance and cause stress, especially when interruptions arrive from external sources (Baethge et al., 2015; Puranik et al., 2020).

H_7: Notification interruptions have a positive direct effect on psychological well-being

H_8: Notification interruptions have a positive

indirect effect on psychological well-being through attention disruption.

H_9: Notification interruptions have a positive total effect on psychological well-being.

Push notification: A notification, according to Iqbal and Bailey (2008), was a visible cue, auditory signal, or haptic alert provided by an application or service that sends information to a user that was not directly in their point of view. Push notifications are short messages that are sent directly to the user's smartphone from an application server or apps. Also, if the phone is locked and the app isn't opened, they still pop up on the screen as usual (Matuszewska, 2026). Furthermore, smartphone push notifications offer users updates on how we interact with others, and this is important for everyone's well-being. Yet numerous alerts may turn into a disruption from group survival, so the users of smartphones have to make decisions about deciding whether to turn off notifications or consistently concentrate on just one (Lee et al., 2016).

H_{10}: Push notifications have a positive direct effect on psychological well-being

H_{11}: Push notifications have a positive indirect effect on psychological well-being through attention disruption.

H_{12}: Push notifications have a positive total effect on psychological well-being.

Mediating variable

Attention disruption: Attention disruption can be defined as interruptions that make people pivot and change their attention from doing something to something else. It is the adverse impact on an important task (Arroyo & Selker, 2011). In addition, smartphone notifications can produce problems with focused attention through distraction of attentional switching, leading to degradation of memory function and reduction of task performance, especially during tasks that require focus. (Khanday et al., 2025)

Dependent variable

Psychological well-being: Psychological well-being is a multifaceted attribute beyond just feeling happy. It includes your sense of purpose, your capacity for self-development, the value of your relationships, and your ability to cope with the challenges of daily life. Psychological well-being, compared to temporary feelings, is a deep and more permanent feeling of existing intentionally and functioning well (Ryff, 1989). The frequent use of smartphone notifications has led to higher levels of stress, emotional exhaustion, and less emotional balance that can negatively affect psychological well-being (Khanday et al., 2025).

FINDINGS AND DISCUSSION

Finding

Demographic responses:

Based on Table 2, regarding gender, 239 respondents (61.9%) were male and 147 (38.1%) were female, showing that the majority of the sample consisted of male respondents. On the question of age, the highest number of respondents were between the ages of 20-29 years, with 165 (142.7), closely followed by those below 20 years, with 131 (33.9%). 67 (17.4%) of respondents were between the ages of 30 and 39 years, with 23 (6.0%) being above the age of 40 years. As for academic qualification, 39 respondents (10.1%) were below SEE/SLC, 41 (10.6%) respondents were SEE/SLC, 88 (22.8%) respondents were +2 /Higher Secondary, 145 (37.6%) respondents were bachelor's degree,

Table 2
Demographic characteristics of the respondents

		Frequency	Percent	Cumulative percent
Gender	Male	239	61.9	61.9
	Female	147	38.1	100
Age group	Below 20 years	131	33.9	33.9
	20-29 years	165	42.7	76.7
	30-39 years	67	17.4	94
	40 years and above	23	6	100
Academic qualification	Below SEE/SLC	39	10.1	10.1
	SEE/SLC	41	10.6	20.7
	+2/Higher secondary	88	22.8	43.5
	Bachelor's degree	145	37.6	81.1
	Master's degree	57	14.8	95.9
	MPhil/PhD	16	4.1	100
Occupation	Student	195	50.5	50.5
	Government employee	26	6.7	57.3
	Private employee	85	22	79.3
	Self-employed	54	14	93.3
	Unemployed	26	6.7	100
Average daily smartphone usage	Less than 2 hours	40	10.4	10.4
	2-4 hours	54	14	24.4
	4-6 hours	130	33.7	58
	More than 6 hours	162	42	100
	Total	386	100	

57 (14.8%) respondents were master's degree, and 16 (4.1%) respondents were MPhil/PhD. Occupation-wise, 195 (50.5%) were students, 26 (6.7%) were government employees, 85 (22.0%) were private employees, 54 (14.0%) were self-employed, and 26 (6.7%) were unemployed. Regarding the average daily usage of smartphones, 40 respondents (10.4%) reported use of smartphones less than 2 hours a day, 54 (14.0%) reported 2-4 hours, 130 (33.7%) reported 4-6 hours, and 162 respondents (42.0%) reported more than 6 hours. Overall, the data indicate that the respondents in the sample were characterized by a broad spectrum of demographic characteristics, most of whom were male, between the ages of 20 and 29, had a bachelor's degree, were students, and were smartphone users for more than 6 hours a day.

According to Table 3, regarding ownership and regular usage of smartphones, 374 respondents (96.9%) reported that they owned and regularly used a smartphone, while 12 respondents (3.1%) reported otherwise. As for smartphone notification receiving, 347 respondents (89.9%) said that they receive notifications every day, whereas 39 respondents (10.1%) said that they did not receive notifications. As for interruptions,

Table 3
General background of the respondents

Questions	Responses				Total	
	Yes	Percent	No	Percent	Count	Percent
Do you own and regularly use a smartphone?	374	96.9	12	3.1	386	100
Do you receive smartphone notifications every day?	347	89.9	39	10.1	386	100
Have smartphone notifications ever interrupted your work, study, or daily activities?	330	85.5	56	14.5	386	100
Have you ever felt distracted because of smartphone notifications?	333	86.3	53	13.7	386	100
Do you think smartphone notifications influence your psychological well-being?	330	85.5	56	14.5	386	100

Table 4
Descriptive statistics

Statistics/Variables	NF	NV	NI	PN	AD	PWB
N	386	386	386	386	386	386
Mean	3.58	3.39	3.52	3.47	3.42	3.41
Median	4.00	3.62	3.75	3.75	3.75	3.40
Mode	4.00	4.00	4.00	4.00	3.00	3.00
Std. Deviation	1.09	1.14	1.12	1.06	1.12	1.03
Variance	1.20	1.31	1.26	1.12	1.26	1.06

330 respondents (85.5%) reported that smartphone notifications had interrupted their work, study, or daily activities, while 56 respondents (14.5%) reported that they had not experienced such interruptions. Similarly, 333 respondents (86.3%) stated that they had felt distracted by smartphone notifications, and 53 respondents (14.5%) stated that they had not. Finally, 330 respondents (85.5%) said smartphone notifications influence their psychological well-being. While 56 respondents (13.5%) said they did not think smartphone notifications influence their psychological well-being.

Descriptive analysis: Table 4 showed that frequency of notification (NF) had the highest mean across all study variables (M = 3.58), while notification volume (NV) had the lowest (M = 3.39). The highest median was notification frequency (4.00), which was followed by notification volume, notification interruptions, and push notifications. The lowest median was psychological well-being (PWB) (3.40). The highest mode was 4.00 in NF, NV, NI, and PN, and the lowest mode was 3.00 in AD and PWB. The notification volume (NV) showed the highest standard deviation (1.14) and variance (1.31), indicating the highest variability in responses. The lowest standard deviation (1.03) and variance (1.06) were observed in PWB.

Correlation analysis: As shown in Table 5, notification frequency (NF) was highly positively correlated with PWB (r =.755, p

Table 5
Correlation analysis

Variable	NF	NV	NI	PN	AD	PWB
NF	1					
NV	.594***	1				
	(.001)					
NI	.731***	.626***	1			
	(.001)	(.001)				
PN	.731***	.623***	.780***	1		
	(.001)	(.001)	(.001)			
AD	.742***	.645***	.822***	.769***	1	
	(.001)	(.001)	(.001)	(.001)		
PWB	.755***	.628***	.777***	.792***	.787***	1
	(.001)	(.001)	(.001)	(.001)	(.001)	

*** *Correlation is significant at the 0.001 level (2-tailed).*

Table 6
Direct effect of the independent variables on attention disruption

Variables	Coefficient	Se	t	P	LLCI	ULCI
Constant	-0.1780	0.1093	-0.1633	0.8703	-0.2327	0.197
NF	0.2011	0.0425	4.7334	0.0000	0.1176	0.2847
NV	0.1224	0.0343	3.5734	0.0004	0.0550	0.1897
NI	0.4420	0.0455	9.7096	0.0000	0.3525	0.5315
PN	0.2146	0.0480	4.4675	0.0000	0.1202	0.3091
F-statistics	279.6919	R=0.8637	R^2=0.7460	df_1=4.0000	df_2=381.0000	
P value	(.001)	MSE=0.3235				

<.01). Notification volume (NV) correlated strongly and positively with PWB (r =.628, p <.01). Notification interruptions (NI) was also highly and positively correlated with PWB (r = .777, p <.01). Push notifications (PN) showed the strongest positive correlation with PWB (r =.792, p < .01). These findings indicate that within the sample, higher levels of each smartphone notification characteristic were associated with higher levels of reported psychological well-being. Further, AD was significantly and positively correlated with PWB (r = .787, p < .01).

Regression analysis:

As shown in Table 6, Model 1 is statistically significant (F = 279.6919, p < .01) and (R^2 = 0.7460) explains 74.60% of the variance in attention disruption by the independent variables. We found that notification frequency had a significant and positive influence on attention disruption (a_1 = 0.2011, p < .01), suggesting that frequent notifications could lead users to repeatedly distract their attention from ongoing activities. Notification volume also had a significant effect on attention disruption

Table 7
Direct effect of the independent and mediating variables on psychological well-being

Variables	Coefficient	Se	t	P	LLCI	ULCI
Constant	0.2493	0.1015	2.4450	0.0145	0.0496	0.4489
NF	0.1997	0.0406	4.9144	0.0000	0.1198	0.2796
NV	0.0666	0.0324	2.0571	0.0404	0.0029	0.1302
NI	0.1552	0.0472	3.2844	0.0011	0.0623	0.2481
PN	0.2815	0.0458	6.1463	0.0000	0.1914	0.3715
AD	0.2026	0.0476	4.2547	0.0000	0.1090	0.2962
F-statistics	271.3818	R=0.8606	R^2=0.7410	df_1=5.0000	df_2=380.000	
P value	(.001)	MSE=0.2794				

(a_2 = 0.1224, p < .01), which shows that the higher volume of notifications may increase the possibility of users' attention being diverted. Notification interruptions had the most positive effect on attention disruption (a_3 = 0.442, p < .01), meaning that respondents who had more notification interruptions are likely to have more attention disruption. We also observed a positive and significant effect of push notifications on distraction of attention (a_4 = 0.2146, p < .01), which suggests push notifications can be a distraction from users' current activities.

According to Table 7, Model 2 is statistically significant (F = 271.3818, p < .01) and (R^2 = 0.7410) accounts for 74.10% of the variance in psychological well-being by four independent variables and the mediating variable. Notification frequency (NF) has a positive and significant direct effect on psychological well-being (c'_1 = 0.1997, p < .01), indicating that changes in notification frequency are significantly associated with psychological well-being among respondents. Similarly, notification volume (NV) has a positive and significant effect on psychological well-being (c'_2 = 0.0666, p < .05), suggesting that differences in notification volume are associated with variations in psychological well-being. Notification interruptions also have a positive and significant effect on psychological well-being (c'_3 = 0.1552, p < .01), indicating that interruptions caused by notifications are significantly related to respondents' psychological well-being. Among the independent variables, push notifications have the highest positive effect on psychological well-being (c'_4 = 0.2815, p < .01), suggesting that push notifications have the strongest association with psychological well-being among the four notification variables. Attention disruption also has a positive and significant effect on psychological well-being (b = 0.2026, p < .01), indicating that greater attention disruption is significantly associated with changes in psychological well-being.

Table 8 showed that Model 4 is statistically significant (F = 255.7226, p <.01) and (R^2 = 0.7286) accounted for 72.86% of the variance of psychological well-being by the independent variable. The total effect of notification frequency (NF) on psychological well-being is positive and significant (coefficient = 0.2404, p < .01). Notification volume (NV) has a positive, significant effect on psychological well-being (coefficient = 0.0914, p = .0052). Notification interruptions

Table 8
Total effect model

Variables	Coefficient	Se	t	P	LLCI	ULCI
Constant	0.2457	0.1038	2.3669	0.0184	0.0416	0.4497
NF	0.2404	0.0404	5.9564	0.0000	0.1611	0.3198
NV	0.0914	0.0325	2.8079	0.0052	0.0274	0.1553
NI	0.2447	0.0432	5.6591	0.0000	0.1597	0.3297
PN	0.3250	0.0456	7.1210	0.0000	0.2352	0.4147
F-statistics	255.7226	R=0.8536	R^2=0.7286	df_1=4.0000	df_2=381.0000	
P value	(.001)	MSE=0.2919				

Table 9
Indirect effect model

Independent variables	Mediating variable	Effect	BootSE	BootLLCI	BootULCI	t-statistics
NF	AD	0.0407	0.0164	0.0116	0.0761	2.482
NV	AD	0.0248	0.0112	0.0050	0.0490	2.214
NI	AD	0.0895	0.0275	0.0395	0.1464	3.255
PN	AD	0.0435	0.0205	0.0119	0.0916	2.122

(NI) have a positive, significant effect on psychological well-being (coefficient = 0.2447, $p < .01$). The total effect of push notification (PN) on psychological well-being is the strongest among the four notification variables (coefficient =.3250, $p <.01$).

Based on Table 9, the indirect effect of notification frequency (NF) on psychological well-being (PWB) via attention disruption (AD) is significant (effect = 0.0407, t = 2.482). In the same way, notification volume (NV) also has a significant indirect effect on PWB through AD with an effect of 0.0248 (t = 2.214). The most significant indirect effect on PWB was through AD through notification interruptions (NI) with an effect of 0.0895 (t = 3.255). Finally, push notification (PN) has an important indirect effect on PWB through AD, with an effect of 0.0435 (t = 2.122).

Table 10 present all four notification variables have direct, total, and indirect significant effects on psychological well-being (PWB). Therefore, all twelve alternative hypotheses are accepted. It presents partial mediation.

Discussion

The notification frequency (NF) significantly and positively affected psychological well-being. This is consistent with the findings of Pielot et al. (2014); Morrison et al. (2018) but differs from Khanday et al. (2025), who found no significant relationship. Also, volume of notifications (NV) has a significant effect on psychological well-being. This is in agreement with Fourniera et al. (2026) but differs from Mukhdoom and Villarama (2025); Özdemir et al. (2025). Moreover, notification interruptions (NI) were positively associated with psychological well-being, in line with the findings of Elhai et al. (2021); Kaminske et al. (2022); Ohly and Bastin

Table 10
Mediation analysis summary

Variables effect	Direct effect	Total effect	Indirect effect	Relationship	Conf. Interval		t- statistics	Conclusion
					Lower Bound	Upper Bound		
NF→ PWB	0.1997 (.001)	0.2404 (.001)	0.0407	NF→AD→ PWB	0.0116	0.0761	2.482	Partial mediation
NV→ PWB	0.0666 0.0404	0.0914 0.0052	0.0248	NV→AD→ PWB	0.0050	0.049	2.214	Partial mediation
NI→ PWB	0.1552 0.0011	0.2447 (.001)	0.0895	NI→AD→ PWB	0.0395	0.1464	3.255	Partial mediation
PN→ PWB	0.2815 (.001)	0.325 (.001)	0.0435	PN→AD→ PWB	0.0119	0.0916	2.122	Partial mediation

(2023); Bhumithavara and Sun (2025). Positive effects of push notifications (PN) on mental well-being. This finding is important and consistent with the findings of Kim et al. (2016); Pielot and Rello (2017); Özdemir et al. (2025). Attention disruption (AD) was also found to have a significant effect on psychological well-being, indicating that the change in attention disruption is significantly associated with PWB. The results support the mediating role of AD in the relationship between smartphone notifications and PWB. Finally, the mediating role of attention disruption is consistent with the results of Kushlev et al. (2016); Kaminske et al. (2022); Ohly and Bastin (2023); Bhumithavara and Sun (2025).

CONCLUSION

The present study was designed to investigate the impact of smartphone notifications on psychological well-being and the mediating role of attention disruption among smartphone users. Results indicated that notification frequency, notification volume, notification interruptions, and push notifications significantly direct and total impact psychological well-being. Furthermore, all four notification characteristics have significant indirect effects on psychological well-being through attention disruption. The findings suggest that an increase in smartphone notifications is related to an increase in attention disruption, which affects psychological well-being. This implies that attention disruption is one of the mechanisms by which smartphone notifications affect users' psychological well-being. The results support Action Regulation Theory (ART) explaining how interruption of ongoing activities can lead to disruption of attention and interfere with individuals' capacity to regulate and complete their actions. In real life, smartphones might send frequent and interruptive notifications that distract users' attention repeatedly, which may create additional psychological pressure and affect their well-being. Thus, management of unnecessary notifications through customization, reduction, and focus or do-not-disturb features may help in the reduction of attention disruption and may contribute toward better psychological well-being.

IMPLICATIONS

The findings of the study indicate that app developers, policymakers, and smartphone users need to pay more attention to the design and management of smartphone notifications. App creators may include features that help users with attention disruption, including the ability to customize, batch, prioritize, and reduce unnecessary interruptions from notifications. Smartphone users should also review their notification settings and cut down on unnecessary notifications. Policymakers and related organizations could advocate for campaigns on digital wellbeing and responsible notification design. The findings also indicate that intelligent notification management systems could be helpful, giving users control over how often, how many, how disruptive, and what type of push notifications they receive. It might help reduce unnecessary interruptions of attention and improve mental health. Better smartphone usage and psychological health require managing smartphone notifications and cutting down unnecessary distractions, the study recommends.

There are some limitations to this study. The study was conducted in a limited geographical area, which may not be representative of the smartphone users from different regions of Nepal. Thus, the findings may not be generalizable to smartphone users in other geographical locations with different social, cultural, and technology contexts. This study only tested four types of smartphone notifications and attention distraction as the mediating variable; other factors can also affect psychological well-being, including the amount of time spent on the smartphone, notification content, application type, social pressure, individual notification preference, etc. Secondly, the study used self-reported data, which are affected by the perceptions and recall of the respondents. The cross-sectional design did not permit examination of changes in the notification behavior and psychological well-being over time. Future research could include more and diverse samples from different geographical and demographic backgrounds and other factors associated with smartphone notifications, attention disruption, and psychological well-being.

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ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Impact of influencer marketing on Gen-Z purchase decision: *Analyzing the impact of social media influencers, trustworthiness, and content quality on purchase decisions among Gen Z*

Minisha Pulami Magar
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College,Malaysia
ma.minisha23@ncmt.edu.np

Received: 18 Jul., 2026 | Revised: 5 Aug., 2026 | Accepted: 10 Sept., 2026

Abstract: *This study examined the impact of social media influencer, trustworthiness and content quality on purchase decision of Gen Z consumers in Kathmandu Metropolitan City. The independent variables of the study are social media influencer, trustworthiness, and content quality, while purchase decision is the dependent variable, and the study is based on Signaling Theory. A quantitative research approach was adopted which included descriptive, correlational and explanatory research designs. In this study, primary data were collected from 384 Gen Z respondents selected through convenience sampling technique using a structured questionnaire based on a five-point Likert scale, and the collected data were analyzed using SPSS software through descriptive statistics, correlation analysis, and regression analysis. The results of the correlation analysis showed that there was a positive and significant relationship between social media influencer, trustworthiness, content quality and purchase decision. The regression analysis also resulted that social media influencer and content quality have a positive and statistically significant effect on purchase decision, while trustworthiness has a positive but statistically insignificant effect when the variables are considered together. The results indicate that businesses, brands and advertising agencies can strategically select the appropriate influencers and generate relevant, informative and engaging content to effectively reach Gen Z, enhance brand visibility and improve purchase results.*

Keywords: Content quality, purchase decision of Gen Z, social media influencer, trustworthiness

JEL Classification: M31, M37, D12

Cite as: Magar, M. P. (2026). Impact of influencer marketing on Gen-Z purchase decision: Analyzing the impact of social media influencers, trustworthiness, and content quality on purchase decisions among Gen Z. *NCMT Journal of Multidisciplinary Studies, 1*(1), 55-72.

INTRODUCTION

The widespread adoption of social media platforms has drastically transformed the marketing environment, providing digital content creators, also known as social media influencers, a great opportunity to influence consumers' perceptions and behaviors when they make purchasing decisions. Influencer marketing strategies are increasingly being

adopted, particularly among Gen Z consumers in emerging market contexts, but the processes through which influencer qualities and content characteristics influence consumer purchase intention are not well understood (Muthulingam & Amirtharaj, 2026). Gen Z refers to the generation born from the mid-1990s to the early 2010s. The digitally native group is characterized by a high demand for authenticity, recommendations from peers, and interactive participation (Williams et al., 2010). Similarly, this Gen also possesses the main channels of communication with influencers and businesses on social media platforms like YouTube and Instagram. Previous research has discovered that relatable and authentic influencers who are consistent in their values with those of Gen Z consumers are more likely to be trusted by these consumers, and that this trust increases the persuasive power of influencer marketing (Djafarova & Trofimenko, 2019).

Social media and influencer marketing play a crucial role in influencing consumer behavior in today's rapidly evolving digital marketing world. Social media platforms have become increasingly important in modern marketing strategies due to their extensive reach and interactive capabilities (Li et al., 2021). One of the variants of the digital space is influencer marketing, which uses the reach and credibility of popular people to influence consumer perceptions and purchase decisions (Vrontis et al., 2021). As influencers become trusted voices in their respective domains, their recommendations and content become influential in shaping followers' opinions and actions (Kapitan et al., 2021). However, a better understanding of the link between social media, influencer marketing, and consumer intentions is required to fully comprehend how these dynamics emerge (Migkos et al., 2025).

Previous studies used brand awareness, engagement, trust, perception, brand credibility, and brand perception as mediating variables (Gunawan et al., 2021; Muthulingam & Amirtharaj, 2026; Sunilkumar et al., 2026). However, this study has no mediating variables. Furthermore, previous research used moderating variables such as green consumption values (Rizomyliotis et al., 2024), but this study does not use any moderating variable. Similarly, a previous study by Sharma and Sanu (2025) had used qualitative research methodology, but this study has used quantitative research methodology. Moreover, research on the influence of social media influencers on Gen Z's purchase decisions in the Nepalese context is limited (Khanal & Pradhan, 2025). Given the exponential growth of social media usage among Gen Z in Nepal, it is important to understand how the influencer-related factors influence their purchasing decisions. Therefore, this research investigates the combined impact of social media influencers, trustworthiness, and content quality on the purchase decisions of Gen Z consumers. This study addresses these gaps and adds to the existing literature and offers practical implications to businesses and marketers who intend to develop more effective influencer marketing strategies for targeting Gen Z.

This study primarily contributes to businesses, brands, and advertising agencies by providing practical suggestions on how to develop more effective influencer marketing strategies for reaching Gen Z consumers. The findings assist marketers in determining that selecting the right social media influencers and focusing on high-quality, relevant, and engaging content are more important for driving purchase decisions than relying solely on

trustworthiness. This enables organizations to better spend marketing budgets by investing in influencer connections and content strategies that produce measurable results rather than distributing resources across less significant elements. Furthermore, the study increases Gen Z's understanding of how influencer marketing secretly impacts their purchase behavior, urging them to analyze promoted material more closely before making purchasing decisions. Overall, the study provides industry practitioners with evidence-based solutions for increasing brand awareness, strengthening consumer interactions, and improving purchasing outcomes among Gen Z.

Research questions

- Is there any relationship between social media influencer, trustworthiness, content quality and purchase decision?
- Do social media influencers, trustworthiness, content quality affect purchase decision?

Objectives of the study

This study aims to examine the extent to which social media influencer, trustworthiness, and content quality influence the purchase decisions of Gen Z consumers in Kathmandu Metropolitan City. The specific goals of this study are as follows:

- To analyze the relationship between social media influencer, trustworthiness, content quality and the purchase decisions of Gen Z in Kathmandu Metropolitan City.
- To examine the effect of social media influencers, trustworthiness, and content quality on the purchase decisions of Gen Z in Kathmandu Metropolitan City.

LITERATURE REVIEW

Theoretical review

Signaling Theory: According to signaling theory (Spence, 1973), individuals use signals to reduce uncertainty and support decision-making in situations (Donald et al., 2014). The theory aims to resolve information asymmetries between parties by the transmission of credible signals (Connelly et al., 2011). The theory has three key elements: the signaler, the signal, and the receiver (Connelly et al., 2011). This study mentions that social media influencers are the signalers as they share information and recommendations about products or brands on social media platforms. Trustworthiness and content quality are important signals that convey the credibility, reliability, and value of the promoted products. These signals are received by Gen Z consumers, who tend to reach out to social media for product-related information. When influencers are seen as trustworthy and provide valuable and interesting content, it helps people feel sure about a product and more confident in buying it.

Duffett and Mxunyelwa (2025) found that source credibility, especially trustworthiness, positively signals product value to Gen Z audiences and improves purchase intent. However, Migkos et al. (2025) discovered that trustworthiness alone does not always translate into a statistically significant effect on purchase behavior when analyzed alongside other influencer-related signals, implying that its signaling strength may be dependent on the presence of complementary signals such as content quality. Similarly, Muthulingam and Amirtharaj (2026) discovered that content quality acts as a powerful signal, improving message processing and

increasing favorable consumer responses, thereby playing an important role in influencing purchase decisions. Taken together, these findings indicate that social media influencer presence, trustworthiness, and content quality are all connected signals in the influencer marketing environment. When Gen Z customers see these signals as strong and credible, they feel less hesitant and more confident in their purchasing decisions. Even if the influencer is popular, weak or inconsistent signals like low-quality content or an untrustworthy influencer may fail to persuade consumers.

Table 1

Summary of previous studies

Author(s)	Year	Country	Methodologies	Findings
Gunawan et al.	2021	Indonesia	Regression analysis	Discovered the relevance and resonance of Social Media Influencer had positive and significant influences on brand awareness and purchase intention.
Nguyen et al.	2022	Vietnam	Correlation analysis	Found positive and significant effect of perceived influencers' credibility and perceived expertise of influencers on Gen Z customer purchase intention.
Fatima and Erdoğdu	2023	Turkey	Correlation analysis	Resulted the relation between influencers and Gen Z's purchasing decision was positive.
Ghalib and Ardiansyah	2023	Indonesia	Regression analysis	Found that Instagram influencers' expertise significantly affect customer purchase intention.
Nadanyiova and Sujanska	2023	Slovakia	Correlation analysis	Showed a positive effect of influencer on purchasing behavior.
Dharma et al.	2024	Indonesia, Malaysia, India, and Nigeria	Regression analysis	Highlighted that perceived influencer credibility and perceived expertise significantly impact Gen Z's purchasing intention.
Ge	2024	UK and China	Regression analysis	Found a positive effect of similarity between influencers and Gen Z on purchase decision.
Rizomyliotis et al.	2024	China	Regression analysis	Revealed that social media influencers' credibility positively effects brand consideration and purchase intention.
Wahyuni and Ratnasari	2024	Indonesia	Regression analysis	Highlighted a positive impact and significance of influencer marketing on purchasing decision.
Duffett and Mxunyelwa	2025	South Africa	Correlation analysis	Found a significant positive relationship between Instagram mega-influencer expertise and intention to purchase among Gen Z consumers.
Estrada and Zavala	2025	Mexico	Regression analysis	Found a positive effectiveness of influencer marketing on social media factored by influencer empathy, reciprocity and perceived benefits and consistency on Gen Z's purchase decisions.

Author(s)	Year	Country	Methodologies	Findings
Guled and Rajkumar	2025	India	Regression analysis	Discovered a positive and significant effect of influencers' authentic vulnerability, narrative creativity and ethical alignment on purchase decision among Gen Z and Millennial.
Khanal and Pradhan	2025	Nepal	Correlation analysis	Showed a positive impact of social media influencer popularity and engagement level on consumer buying behavior.
Migkos et al.	2025	Greece	Regression analysis	Found influencer ads, influencer marketing, website design, clear promotional offers and usability have significant impact on customer loyalty, satisfaction, profitability and consumer purchasing behavior.
Sharma and Sanu	2025	India	Mann-Whitney and Kruskal-Wallis test	Revealed influencing consumers' buying behavior was the credibility of influencers and social influence on purchase decisions.
Yao et al.	2025	China	Regression analysis	Found the significant role of certain influencer characteristics, particularly socioeconomic status, visual aesthetics, and denotative inspiration, in shaping customer perceptions and purchase intentions.
Chavan et al.	2026	India	Regression analysis	Revealed a positive and significant relationship between influencer marketing and purchase decisions in shaping consumer behavior.
Khan and Nadar	2026	India	Regression analysis	Found a strong positive relationship between influencer credibility and purchase intention.
Muthulingam and Amirtharaj	2026	India	Correlation analysis	Demonstrated social media influencer has positive effects on purchase intention.
Sunilkumar et al.	2026	United Arab Emirates	Regression analysis	Found influencers' brand credibility and brand familiarity have positive and significant impact on purchase decision.

This theoretical foundation supports the current study's methodology, which examines how social media influencer trustworthiness and content quality, three distinct but connected signals, affect Gen Z consumers' purchasing decisions in Kathmandu Metropolitan City.

Empirical review

Social media influencer on purchase decision of Gen Z: Dwidienawati et al. (2020) examined customer review or influencer endorsement: Which one influences purchase intention more in Indonesia. The regression model result found that influencer review has a positive impact on purchase intention.

H_1: Social media influencer has a positive or negative and significant effect on purchase decision.

Trustworthiness on purchase decision of Gen Z:

H_2: Trustworthiness has a positive or negative and significant impact on purchase decision.

Table 2
Summary of prior studies

Author(s)	Year	Country	Methodologies	Findings
Ghalib and Ardiansyah	2023	Indonesia	Regression analysis	Found that Instagram influencers' trustworthiness significantly affect customer purchase intention.
Dharma et al.	2024	Indonesia, Malaysia, India, and Nigeria	Regression analysis	Highlighted that perceived influencer trustworthiness significantly impact Gen Z's purchasing intention.
Migkos et al.	2025	Greece	Regression analysis	Found influencer trust has significant impact on customer loyalty, satisfaction, profitability and consumer purchasing behavior.
Sharma and Sanu	2025	India	Mann-Whitney and Kruskal-Wallis test	Revealed influencing consumers' buying behavior is trustworthiness of influencers on purchase decisions.
Chavan et al.	2026	India	Regression analysis	Revealed a positive and significant relationship between influencer marketing and purchase decisions and found factors like authenticity and trust were the most influential in shaping consumer behavior.

Content quality on purchase decision of Gen Z:
H_3: Content quality has a positive or negative and significant effect on purchase decision.

Based on the literature review, the study developed the research framework presented in figure 1.

METHODOLOGY

Research design

The study used a deductive research approach. The investigation also applied a positivist research philosophy. The study adopted a quantitative research design, which involved descriptive, relational, and explanatory research methods. The descriptive research design was used to outline the fundamental characteristics of the variables under investigation (Budhathoki et al., 2025). The relationship between the antecedent and consequent variables was investigated using the relational research design (Budhathoki et al., 2023). The impact of independent variables on dependent variables was examined using an explanatory research approach (Budhathoki & Khadka, 2024).

Population and sample

The targeted population of this study was the Gen Z consumers of Kathmandu Metropolitan City who actively used social media platforms like Facebook, Instagram, and TikTok, where they were exposed to influencer-generated content that could influence their purchase decisions. It was challenging to gather statistical data from the entire population because the precise number is unclear. Thus, a sample of 384 respondents was chosen for the research. Convenience sampling methods were used in this study to choose participants. Convenience sampling was appropriate for this study because it enabled effective data

collection from a large population of social media users in Kathmandu Metropolitan City while considering time and resource constraints. The Cochran's Sample Size Formula (Cochran, 1977) was used to calculate the sample size, as the population size was unknown but expected to be large.

$$n = \frac{Z^2 * P * (1-P)}{e^2}$$

Where, n = sample size (384); Z = Z-score (e.g., 1.96 for 95% confidence level); P = estimated proportion (use 0.5 to maximize variability); e = margin of error (5 %)

Facebook, Instagram, WhatsApp, Messenger, and other social media platforms were used to circulate the closed-ended questionnaire from June 24 and July 5. The questionnaire was given to respondents to complete in their spare time.

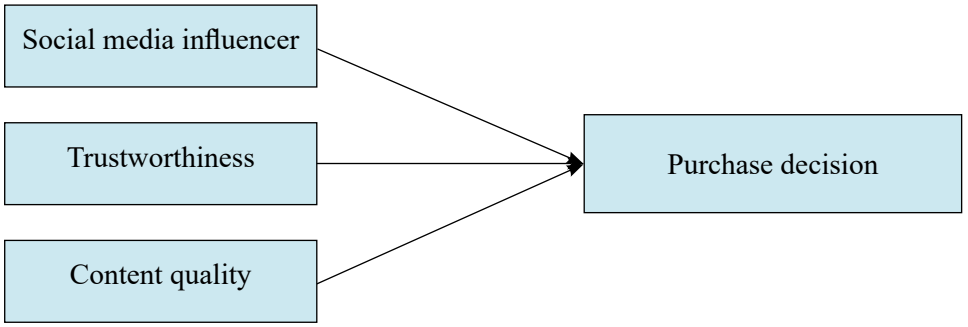
3.3 Sources of data and analysis tools

The Likert scale questionnaire used in this study was adapted from Muthulingam & Amirtharaj (2026) and modified to suit the context and objectives of the present research. This study used primary data collected through a structured close-ended questionnaire. The study focused on Gen Z consumers in Kathmandu Metropolitan City who actively used social media platforms like Facebook, Instagram, TikTok, and X. Data were collected using a Google Forms questionnaire, which was distributed online through various social media platforms to reach the target respondents. Similarly, the questionnaire consisted of measurement items assessed using a five-point

Table 3
Summary of earlier studies

Author(s)	Year	Country	Methodologies	Findings
Nguyen et al.	2022	Vietnam	Correlation analysis	Found positive and significant effect of entertainment value of influencers' content on Gen Z customer purchase intention.
Khanal and Pradhan	2025	Nepal	Correlation analysis	Showed a positive impact of social media influencer' information content on consumer buying behavior.
Migkos et al.	2025	Greece	Regression analysis	Found high-quality content have significant impact on customer loyalty, satisfaction, profitability and consumer purchasing behavior.
Chavan et al.	2026	India	Regression analysis	Revealed a positive and significant relationship between influencer marketing and purchase decisions and found factor like content quality is the most influential in shaping consumer behavior.
Khan and Nadar	2026	India	Regression analysis	Found a strong positive relationship between influencer' content quality and engagement on purchase intention.
Muthulingam and Amirtharaj	2026	India	Correlation analysis	Demonstrated that content quality has a positive effect on purchase intention.

Figure 1
Research framework



Note. Muthulingam and Amirtharaj (2026).

Likert scale. The Statistical Package for the Social Sciences (SPSS) software, IBM SPSS Statistics Version 32.0.0.0 (134), was used to analyze the gathered data.

A Cochran's alpha value beyond 0.7 often signifies acceptable reliability. Preliminary research was performed ahead to the distribution of the questionnaire; the questionnaire was distributed to 50 participants to verify its reliability and effectiveness. In this research, the computed Cochran's alpha values for the variables are as follows: social media influencers (0.85), trustworthiness (0.88), content quality (0.87), and purchase decision (0.932), as detailed in Table 4. All the alpha values computed are above the normal requirement of 0.7, showing a considerable amount of internal consistency among the items evaluating each construct.

Table 4
Reliability test

Variable dimension	Number of items	Cronbach's Alpha
Social media influencers	5	0.85
Trustworthiness	5	0.88
Content quality	5	0.87
Purchase decision	5	0.932

Analytical model

The cause-and-effect relationships between antecedent and subsequent variables were investigated in this study using the regression model. The model had been used in the earlier research by Wahyuni and Ratnasari (2024).

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

(Where, X_1 = Social media influencer, X_2 = Trustworthiness, X_3 = Content quality, ϵ = Error term, α = Constant, β_1 - β_3 = Coefficient of independent variable, Y = Purchase decision).

Definition of variables

Independent variable

Social media influencer: Social media influencers are those who use social media to influence how communities interact with goods, concepts, and activities; they often act as brand ambassadors and are either funded by businesses or self-identified individuals who aim to influence consumer purchase decisions (Hahn, 2021). Influencers become well-known online by focusing on user-generated content or consumer-generated content in particular industries, such as fitness, beauty, travel, fashion, and lifestyle. They are able to interact with and provide

relevant information to customers who are interested in these topics by utilizing their knowledge, skills, and personality (Veirman et al., 2017).

Trustworthiness: Trust represents a critical determinant of persuasion in digital environments (Muthulingam & Amirtharaj, 2026). Trust is one of the main psychological mechanisms that explain how influencer characteristics affect consumer behavior. The consumer's belief in the influencer's honesty, reliability, and credibility is represented by trust (Ohanian, 1990). Influencer recommendations are more convincing when trust is a key factor in reducing perceived risk. Influencers who are viewed as transparent and trustworthy have a higher chance of influencing purchase decisions through processes based on trust (Muthulingam & Amirtharaj, 2026).

Content quality: Content quality refers to the perceived relevance, clarity, and aesthetic appeal of influencer-generated content (Veirman et al., 2017). Content quality plays a crucial role in shaping how influencer messages are evaluated. High-quality content improves message processing and has a positive effect on consumer reviews. High-quality content enhances positive reviews, which influences consumer decision-making (Muthulingam & Amirtharaj, 2026).

Purchase decision: Purchase decision refers to a person's thought-out desire to buy a good or service in consideration of the information at hand and its perceived worth (Ajzen, 1991). Social media influencers are important individuals in the buying process since Gen Z is tech-savvy and digitally connected, and they rely heavily on them for product information and recommendations (Sharma & Sanu, 2025). Previous research has repeatedly shown that purchase intention is positively influenced by influencer credibility, trust, and perceived authenticity, highlighting the significance of psychological mediators in consumer decision-making (Muthulingam & Amirtharaj, 2026).

FINDINGS AND DISCUSSION

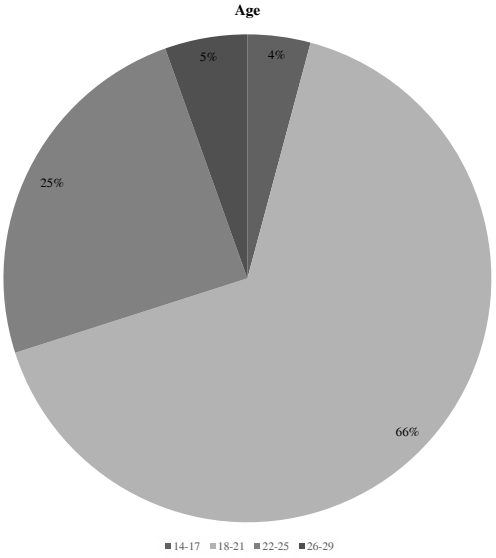
Findings

Demographic responses: The Figure 2 represents the gender of the respondents

Figure 2
Gender of the respondents



Figure 3
Age of the respondents



who participated in the study. Among 384 Gen Z individuals from Kathmandu Metropolitan City, 205 respondents (53.4%) identified as male, while 167 respondents (43.5%) identified as female. Additionally, 12 respondents (3.1%) preferred not to disclose their gender. The findings indicate that male respondents constituted the largest proportion of the sample, followed by female respondents, with only a small percentage choosing not to specify their gender.

According to the Figure 3, the majority of respondents, 253 (65.9%), belonged to the 18–21 years age group, making it the largest segment of the sample. This was followed by 94 respondents (24.5%) aged 22–25 years. Meanwhile, 21 respondents (5.5%) were between 26–29 years, and only 16 respondents (4.2%) fell within the 14–17 years age group. Table 5 presents the educational qualifications of the respondents who participated in the study.

Based on Table 5, the majority, 265 (69.0%), had attained a Bachelor's degree. This was followed by 73 respondents (19.0%) with a Master's degree. Additionally, 24 respondents (6.3%) reported having other educational qualifications, while 22 respondents (5.7%) had completed Higher Secondary (+2) education.

Figure 4 illustrates the monthly income distribution of the respondents. Among the 384 participants, the largest proportion, 201 respondents (52.3%), reported earning between NPR 10,000 and NPR 20,000 per month. This was followed by 98 respondents (25.5%) with a monthly income above NPR 20,000. In contrast, 65 respondents (16.9%) reported having no personal income, while only 20 respondents (5.2%) earned below NPR 5,000 per month.

As shown on Table 6, Instagram was the most frequently used platform, with 228 respondents (59.4%), followed by Facebook and TikTok, each accounting

Table 5
Education level of the respondents

Education level	Frequency	Percent	Cumulative Percent
Higher Secondary (+2)	22	5.7	5.7
Bachelor's	265	69	74.7
Master's	73	19	93.8
Other	24	6.3	100
Total	384	100	

Figure 4
Monthly income of the respondents

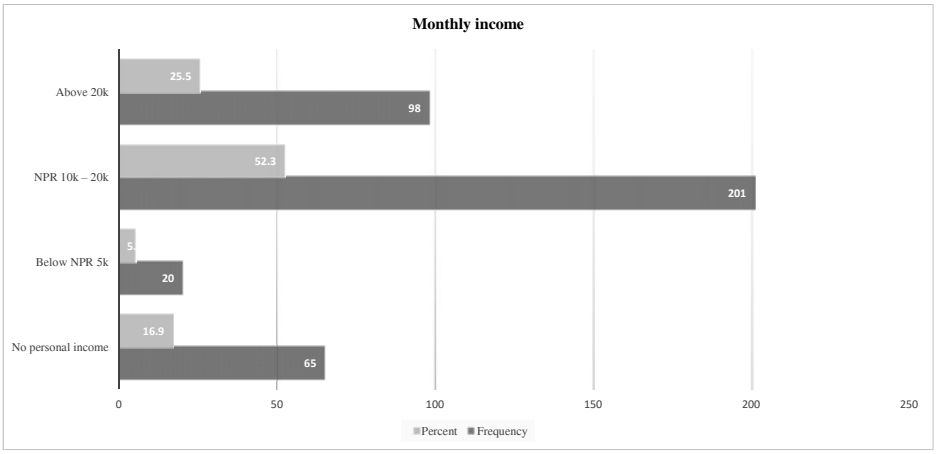


Table 6
Basic information of the respondents

		Frequency	Percent	Cumulative Percent
Social media platform	Facebook	68	17.7	17.7
	Instagram	228	59.4	77.1
	TikTok	68	17.7	94.8
	YouTube	16	4.2	99
	Twitter	4	1	100
Time spend on social media	Less than 1 hour	3	0.8	0.8
	1-2 hours	31	8.1	8.9
	3-4 hours	139	36.2	45.1
	5-6 hours	184	47.9	93
	More than 6 hours	27	7	100
View influencer-generated content	Several times a week	44	11.5	11.5
	Daily	185	48.2	59.6
	Once a week	102	26.6	86.2
	Occasionally	36	9.4	95.6
	Rarely	17	4.4	100
Years of use of social media	Less than 1 year	4	1	1
	1–2 years	13	3.4	4.4
	2–4 years	87	22.7	27.1
	More than 4 years	280	72.9	100
Total		384	100	

Table 7
Basic information of the respondents

Questions	Responses				Total	
	Yes	Percent	No	Percent	Count	Percent
Do you follow one or more social media influencers?	277	72.1	107	27.9	384	100
Have you ever purchased a product or service based on a social media influencer's recommendation?	175	45.6	209	54.4	384	100

for 68 respondents (17.7%). YouTube and Twitter were the least preferred platforms, representing 4.2% and 1.0% of the respondents, respectively. Regarding daily usage, nearly half of the respondents (47.9%) spent 5–6 hours on social media, while 36.2% reported spending 3–4 hours per day, indicating a high level of engagement with social networking platforms. In terms of exposure to influencer-generated content, 48.2% of respondents viewed such content daily, followed by 26.6% who viewed it once a week, suggesting that influencer content is regularly encountered by most participants. Furthermore, the majority of respondents (72.9%) had been using social media for more than four years, while only a small proportion reported less than one year of usage. Table 7 presents the respondents' engagement with social media influencers and their purchasing behavior based on influencer recommendations.

Out of the 384 respondents, 277 (72.1%) reported following one or more social media influencers, while 107 (27.9%) indicated that they did not. This suggests that a substantial majority of Gen Z respondents actively follow influencers on social media platforms. Regarding purchasing behavior, 175 respondents (45.6%) stated that they had purchased a product or service based on a social media influencer's recommendation, whereas 209 respondents (54.4%) reported that they had not.

Descriptive analysis: It is found that the mean value for the independent variable, content quality, is the highest among all variables, with a mean of 3.40, followed by trustworthiness, social media influencer, and purchase decision, with the lowest. Similarly, the median value for content quality is found to be the highest among the variables, with a value of 3.20, followed by social media influencer, trustworthiness, and purchase decision, each with a median value of 3.00. The mode is found to be 3.00 for all four variables. Standard deviation is found to be highest for purchase decisions with a value of 0.925, followed by trustworthiness, social media influencers, and content quality with the lowest value. Similarly, variance is highest for purchase decisions with a value of 0.855, followed by trustworthiness, social media influencers, and content quality with the lowest value.

Table 8
Descriptive statistics

Statistics/Variables	SMI	TW	CQ	PD
N	384	384	384	384
Mean	3.31	3.33	3.4	3.26
Median	3	3	3.2	3
Mode	3	3	3	3
Std. Deviation	0.9	0.902	0.88	0.925
Variance	0.81	0.813	0.775	0.855

Table 9
Correlation analysis

Variables	SMI	TW	CQ	PD
Social Media Influencer	1			
Trust-worthiness	.922*** (.001)	1		
Content Quality	.876*** (.001)	.895*** (.001)	1	
Purchase Decision	.882*** (.001)	.864*** (.001)	.873*** (.001)	1

***. *Correlation is significant at the 0.001 level (2-tailed).*

Correlation analysis: The relationship between social media influencer and purchase decision is found to be positive and statistically significant ($r = 0.882$, $p < 0.01$). This indicates that higher levels of social media influencer influence are associated with higher purchase decision among Gen Z consumers. Likewise, trustworthiness also demonstrates a positive and significant relationship with purchase decision ($r = 0.864$, $p < 0.01$). In addition, content quality is positively and significantly correlated with purchase decision ($r = 0.873$, $p < 0.01$).

Regression analysis: As depicted in Table 10, the impact of social media influencers on purchase decisions is found to be positive and significant at the 99 percent confidence level. The standardized coefficient (beta) of 0.438 indicates that social media influencers have a positive impact on purchase decisions, accepting the alternative hypothesis (H_1). This implies that an increase in the influence of social media influencers leads to an increase in the purchase decisions of Gen Z consumers. Likewise, the impact of trustworthiness on purchase decisions is found to be positive but statistically insignificant ($r = 0.113$, $p = 0.081$), rejecting the alternative hypothesis (H_2). This indicates that trustworthiness has no impact on purchase decisions. Similarly, the impact of content quality on purchase decisions is found to be positive and significant ($r = 0.41$, $p < 0.01$), accepting the alternative hypothesis (H_3). This finding indicates that an increase in the quality of content provided by social media influencers leads to an increase in the purchase decision of Gen Z consumers.

The adjusted R^2 value of 0.821 indicates that 82.1 percent of the variation in purchase decision is explained by the three independent variables, while the remaining 17.9 percent is explained by other variable which is not included in the regression model. Furthermore, the F-statistic of 587.626 with a significance value of less

Table 10
Regression analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Adjusted R square	F	Sig
	B	Std. Error	Beta					
(Constant)	0.002	0.081		0.03	0.976	0.821	587.626	0.01
SMI	0.45	0.06	0.438	7.494	0.001			
TW	0.113	0.065	0.11	1.749	0.081			
CQ	0.41	0.053	0.391	7.712	0.001			

than 0.01 indicates that the overall regression model is statistically significant. The linear equation is estimated as follow:

$$Y = 0.002 + 0.45\ SMI + 0.113\ TW + 0.41\ CQ + \epsilon$$

Discussion

Social media influencers are found to have a positive and statistically significant effect on purchase decisions among Gen Z consumers in Kathmandu Metropolitan City. This finding is consistent with Dwidienawati et al. (2020); Gunawan et al. (2021); Nguyen et al. (2022); Fatima and Erdoğdu (2023); Ghalib and Ardiansyah (2023); Nadanyiova and Sujanska (2023); Dharma et al. (2024); Ge (2024); Rizomyliotis et al. (2024); Wahyuni and Ratnasari (2024); Duffett and Mxunyelwa (2025); Estrada and Zavala (2025); Guled and Rajkumar (2025); Khanal and Pradhan (2025); Migkos et al. (2025); Sharma and Sanu (2025); Yao et al. (2025); Chavan et al. (2026); Khan and Nadar (2026); Muthulingam and Amirtharaj (2026); and Sunilkumar et al. (2026). The significant effect may be because influencers provide accessible and relatable product information, recommendations, and reviews that help Gen Z evaluate products and reduce uncertainty. Therefore, social media influencers can play an important role in shaping Gen Z consumers' purchase decisions.

Trustworthiness is found to have a positive but statistically insignificant effect on purchase decisions among Gen Z consumers. This finding is inconsistent with Ghalib and Ardiansyah (2023); Dharma et al. (2024); Migkos et al. (2025); Sharma and Sanu (2025); and Chavan et al. (2026). The insignificant result may be because purchase decisions are determined not only by trustworthiness but also by the influencer's overall influence and content quality. Its effect may also overlap with social media influencers and content quality when all variables are analyzed together. Thus, trustworthiness may support consumer perceptions without independently determining their purchase decisions.

Content quality is found to have a positive and statistically significant effect on purchase decisions among Gen Z consumers in Kathmandu Metropolitan City. This finding is consistent with Nguyen et al. (2022); Khanal and Pradhan (2025); Migkos et al. (2025); Chavan et al. (2026); Khan and Nadar (2026); and Muthulingam and Amirtharaj (2026). The significant effect may be due to the fact that relevant, informative, and engaging content aids Gen Z in comprehending and assessing products more efficiently. Attractive and useful content can also increase consumers' interest in promoted products, encouraging purchase decisions. Therefore, content quality is an important factor in shaping Gen Z consumers' purchase decisions.

CONCLUSION

Social media influencers and content quality have a positive and significant impact on purchase decisions, whereas trustworthiness has a positive but statistically insignificant impact on purchase decisions among Gen Z when all three variables are considered simultaneously. Based on signaling theory, social media influencers act as signalers who provide information and recommendations that help consumers evaluate products and reduce uncertainty in their purchase decisions. Thus, the significant impact of social media influencers suggests that influencer recommendations and presence serve as important signals that shape consumers' perceptions and purchase

decisions. Similarly, the significant impact of content quality indicates that clear, relevant, informative, and engaging content offers more powerful signals to consumers, helping them evaluate products and encouraging purchase decisions. However, trustworthiness alone might not be enough to influence purchase decisions significantly when other factors related to influencers are present. Overall, the study concludes that social media influencers and content quality are the key factors influencing the purchase decisions of Gen Z consumers in Kathmandu Metropolitan City.

IMPLICATIONS

The findings of this study possess useful implications for the consumers and marketers, organizations, and social media influencers targeting Gen Z consumers of Kathmandu Metropolitan City. Social media influencers have to focus on creating relevant, informative, engaging, and high-quality content that will influence consumers' purchase decisions in a positive way. By collaborating with the most suitable influencers, marketers can more effectively reach and market to Gen Z. The strongest predictor was social media influencer, suggesting that selecting influential and appropriate creators can improve promotional effectiveness. The findings also suggest that content quality should be a top priority when developing influencer marketing strategies. The study additionally provides useful insights for researchers and marketers who would like to understand the behavior of Gen Z consumers in the social media environment.

Several limitations of the study will need to be considered. First, the study was limited to Gen Z consumers of Kathmandu Metropolitan City, which may limit the generalizability of the findings to other geographical areas, and future research may include respondents from different areas of Nepal. Similarly, the convenience sampling used in the current study might have resulted in sampling bias. Future studies could use probability-based sampling to obtain a more representative sample. The study also considered only three independent variables, so future studies may consider other variables such as influencer credibility, expertise, authenticity, engagement, and attractiveness. Moreover, the lack of mediators and moderators does not allow us to explore the mechanisms and conditional relationships between variables. Future research can include relevant mediators and moderators. Finally, the study did not differentiate between types of influencers or types of social media platforms. Future research could conduct comparative analyses between types of influencers, as well as types of platforms.

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NCMT JOURNAL OF
MULTIDISCIPLINARY STUDIES (NJMS)

ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Examining the Effect of Academic Procrastination on Academic Performance among BIT Students

Dal Kumari Ghale

National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malayisa
gh.dalkumari23@ncmt.edu.np

Received: 18 Jul., 2026 | Revised: 8 Aug., 2026 | Accepted: 10 Sept., 2026

Abstract: *The study addresses the need to understand how the delaying of academic tasks may affect the academic outcomes of students. The present study is an attempt to investigate the effect of academic procrastination on academic performance of the BIT students of Texas College, Nepal. The independent variable was procrastination, while the dependent variable was academic performance and Temporal Motivation Theory was used for this research article. A quantitative research approach and deductive technique were utilized in the study, which included descriptive statistics, the independent-samples t-test, Pearson correlation, and linear regression. A standardized questionnaire with a five-point Likert scale was utilized to collect primary data from 337 Texas College of Management students using convenience sampling method. The collected data was analyzed by using SPSS software. The correlation analysis showed a moderate negative relationship between academic procrastination and academic performance. The regression analysis revealed that academic procrastination has a significant negative effect on academic performance. According to the study, students may perform better in their academic life if they stop procrastinating and learn how to manage their time and self-control. The study was limited by its cross-sectional design, quantitative approach, convenience sampling, and focus on students from a single college, which may limit the applicability of the findings.*

Keywords: Academic performance, academic procrastination, Temporal Motivation Theory

JEL Classification: I21, I23, D91, D03

Cite as: Ghale, D. K. (2026). Examining the effect of academic procrastination on academic performance among BIT students. *NCMT Journal of Multidisciplinary Studies, 1*(1), 73-86.

INTRODUCTION

Procrastination is the intentional postponement of work despite the probable negative consequences. But not all delay is procrastination. Delays may be due to urgent needs, limited options or prioritization of different tasks but they are not considered procrastination (Sirois, 2022).Academic procrastination is the intentional delay of academic work such as studying, writing essays, or projects without any valid reason. Procrastination is frequent among college students, studies suggest that approximately

95% of students procrastinate academically on occasions (Solomon & Rothblum, 1984). For students who are enrolled in associate degrees, academic procrastination is common because of the combination of pressures of academic studies, job, and family duties.

There are many factors that cause academic procrastination in students such as lack of capability in academic achievement, fear of failure, reduced tolerance for frustration, perfectionism, anxiety, excessive academic load, lack of academic assistance, and distracting study environment (Ying & Lv, 2012; Steel, 2007). Smartphones and social media are everywhere to provide that instant satisfaction, which is the opposite of what academic aims for in the long term, and it distracts students from their studies (Jin et al., 2024). Students who manage their time well and have good self-regulation skills perform better academically and are less likely to procrastinate (Baumeister & Scher, 1988). However, procrastination can be linked to lower satisfaction, increased level of tension, poor quality of sleep and lower academic success (Steel, 2007).Therefore, the relationship between academic procrastination and academic achievement is importance in developing strategies to improve academic performance.

A lot of studies have examined the relationship between academic procrastination and academic performance, but most of these researches were performed in countries like the Netherlands, Turkey, India, Pakistan, Iran and Ethiopia (Afzal et al., 2026; Akyol, 2025; Kooren et al., 2024; Hayat et al., 2019). Also, previous studies have focused on students from different academic disciplines, such as medical students (Hayat et al., 2019) and physics students (Erdemir, 2019), limiting the applicability of their findings to Bachelor of Information Technology students. In addition, previous research has used different methodological approaches, including qualitative and conceptual studies (Nayak & Tayeng, 2026), providing overall understanding of academic procrastination. To address these gaps, the present study employs a quantitative research methodology to investigate the association between academic procrastination and academic performance among BIT students enrolled at Texas College of Management and IT.

The study adds to what's already been written by giving real-life examples of academic procrastination and poor academic performance among BIT students in Nepalese higher education. Findings could help students, teachers, academic counselors, and schools understand the effects of putting things off and come up with useful ways to help students learn how to manage their time, plan their studies, and control themselves. The study could also be used as a starting point for more research with students from different schools and programs.

Research question

- Is there relationship between academic procrastination and academic performance?
- Does academic procrastination affect the academic performance of students?

Objectives of the study

The aim of this project is to learn more about the relationship between academic procrastination and academic achievement and to provide recommendations to help students achieve better academic results. The specific objectives are:

- To analyze the relationship between academic procrastination and academic performance.
- To examine the impact of academic procrastination on the academic performance.

LITERATURE REVIEW

Theoretical review

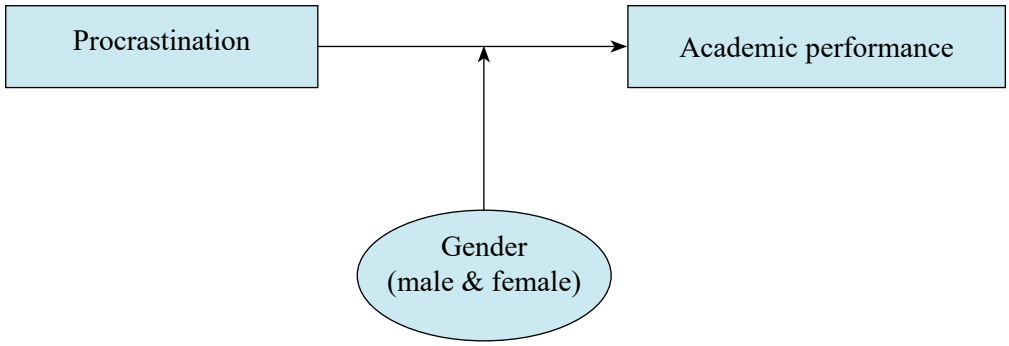
Temporal Motivation Theory: Temporal Motivation Theory (TMT) is an integrative behavioral theory created by Piers Steel and König (2006) that describes the effects of time, deadlines, and delays on human motivation and procrastination. TMT identifies four major factors that influence procrastination: impulsivity (the tendency to prefer immediate gratification over a longer-term benefit), expectancy (a person's confidence in successfully completing a task), value (the importance or reward associated with the task), and time sensitivity or delay. The hypothesis is that people procrastinate more when they have low expectations for their performance, believe the activity is trivial, are very impulsive, or have long-term deadlines (Steel & König, 2006). Students lose motivation to begin on time, and this lowers their marks, when they have self-doubt, see little purpose in a task, lack self-control or perceive deadlines to be far off. Many students view procrastination as more than just a poor habit. It gradually drains their mental and emotional resources. In the long term, procrastination causes stress, stops students from completely engaging with and understanding the courses, and eventually weakens their overall performance. However, there is usually a valid cause for the delay. A lot of students worry that their work won't be good enough, feel like they have to be perfect, or have anxiety. Because of these feelings, starting seems scarier than waiting to do it, so they put it off. It gets easier for them to

Table 1
Summary of previous studies

Author (s)	Year	Country	Methodology	Finding
Savithri	2014	India	Correlational analysis	Found the academic procrastination has been linked to poor academic performance and low life satisfaction.
Balkis and Duru	2017	Turkey	Regression analysis	Research has shown that academic procrastination has a negative impact on academic performance and well-being.
Yilmaz	2017	Turkey	Correlational analysis	Investigated those students who procrastinated more did worse on homework and exams.
Dev	2018	India and UAE	Regression analysis	Revealed the academic achievement was influenced by procrastination, study habits, and stress tolerance.
Mostafa	2018	Egypt	Correlational analysis	Found that students with higher procrastination had lower academic achievement.
Erdemir	2019	Turkey	Quasi-experimental research	Found that reducing academic procrastination improved students' physics achievement.

Author (s)	Year	Country	Methodology	Finding
Hayat et al.	2019	Iran	Correlational analysis	Showed that academic procrastination had a moderate negative effect on academic achievement.
Akpur	2020	Turkey	Meta-analysis	Identified that higher levels of academic procrastination were associated with poorer study habits and weaker executive functioning.
Gutiérrez-García et al.	2020	Mexico	Correlational analysis	Found that higher levels of academic procrastination were associated with poorer study habits and weaker executive functioning.
Siddiqui et al.	2020	Pakistan	Regression analysis	Found meta cognitive awareness and academic procrastination have a significant influence on academic performance.
Fentaw et al.	2022	Ethiopia	Regression analysis	Reported that academic procrastination was common and linked to poor academic performance.
Svartdal et al.	2022	Norway	Correlational analysis	Found that academic self-efficacy mediated the relationship between study habits and academic procrastination.
Ahmed et al.	2023	India	Correlational analysis	Revealed that academic procrastination led to stress, guilt, low self-esteem, and poor academic performance.
K.S. et al.	2023	India	Regression analysis	Decision-making and affective styles were substantially associated with academic procrastination.
Kooren et al.	2024	Netherlands	Regression analysis	Passive academic procrastination had a negative impact on academic attainment, whereas aggressive procrastination had a minor beneficial effect.
Akyol	2025	Turkey	Correlational Study	Academic procrastination was discovered to have a considerable impact on academic achievement.
Gayary and Kalita	2025	India	Regression analysis	More frequent academic procrastination was associated with worse academic attainment.
Afzal et al.	2026	Pakistan	Correlational analysis	Academic procrastination was found to be significantly associated with poor academic achievement.
Nayak and Tayeng	2026	India	Conceptual review study	Academic procrastination was found to be linked to poor academic achievement and personal issues.

Figure 1
Research Framework



avoid the longer they wait.Some students put things off because they are worried, scared, or want to be perfect, which can make them avoid them even more (Cao, 2012).

Empirical review

Procrastination and academic performance: Akinsola et al., (2007) investigated the relationships between academic procrastination and mathematics achievement of Nigerian undergraduate students The regression study found that students with higher levels of academic procrastination performed worse in math, while children with lower procrastination had better academic outcomes.

H_1: Female students have a significantly higher level of academic procrastination than male students.

H_2: Female students have a significantly higher level of academic performance than male students.

H_3: Academic procrastination has a significant relationship with academic performance.

H_4: Academic procrastination has a significant effect on academic performance.

Based on the literature review, the study develops the research framework presented in figure 1.

METHODOLOGY

Research design

In this study, a deductive methodology was applied to examine the relationship between academic procrastination and performance. The study's research philosophy was positivism. Research design this study employed a quantitative research design with descriptive, correlational and explanatory methods. Descriptive research was used to describe the characteristics of respondents and the main variables in this study (Budhathoki et al., 2025). The correlational research method was used in the study to examine the association between academic procrastination and academic achievement (Budhathoki et al., 2023). Moreover, an explanatory research approach was used to examine the effect of academic procrastination on academic achievement among associate degree students (Budhathoki et al., 2024). In this study, the independent variable was academic procrastination while the dependent variable was academic success.

Sample and population

The study targeted population was undergraduate BIT students at Texas College of Management and IT, Kathmandu, Nepal. According to the Texas College of Management and IT administration report (2026), the college currently has approximately 2,000 undergraduate BIT students enrolled. Respondents were chosen through a convenience sampling method based on their availability and willingness to participate. Adam (2020) used Yamane's (1967) formula to determine the required sample size. The confidence level was set to 95%, with a margin of error of 5%. According to the formula below, the sample size was 334 respondents.

$$n = \frac{N}{(1+N(e)^2)} ; n = \frac{2000}{(1+2000(0.05)^2)}$$

$$n = 333.33$$

(Where, n = Sample size; N = Population size = 2000; e = the acceptable sampling error (0.05))

Sources of data and analysis tools

This study was based on the main data acquired by a systematic, closed ended questionnaire. The respondents are BIT students from the Texas College of Management and IT. Data were collected from June 27th to July 5th, 2026 by an online survey using Google Form which was sent to students' email addresses. The college administration approved the questionnaire before distributing it to the students. Participation was purely voluntary and respondents were informed of the objective of the study. The questionnaire is organized into two sections: a demographic section and five point Likert scale. All measuring items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Data were processed with IBM SPSS Statistics version 30.

Table 2
Reliability test

Variable dimensions	Number of Items	Cronbach's Alpha
Academic procrastination	6	0.835
Academic performance	6	0.764

For the reliability test, the internal consistency of the questionnaire items was measured using Cronbach's Alpha. The Academic procrastination scale was comprised of 6 items with a Cronbach's Alpha of 0.835 indicating good reliability. Similarly, the Academic performance scale of 6 items had a Cronbach's Alpha value of 0.764 indicating acceptable to good reliability.

Analytical model

In an effort to investigate the cause-effect relationship between academic procrastination and academic performance, linear regression model was used. Similar analytical method was used in previous work (Budhathoki et al., 2025). The regression model is expressed as:

$$Y = i + a_1x_1 + e$$

(Where; a_1 = Coefficient of the academic procrastination; X_1 = Academic procrastination; e = Error term; i = Constant (Intercept); Y = Academic performance)

Definition of variable

Independent variable

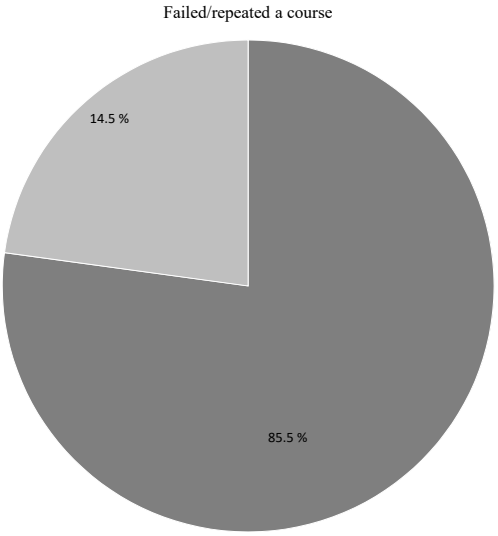
Academic procrastination: Procrastination is the intentional delay of work that needs to

be done. Academic procrastination is defined as the irrational delay of educational work, including studying, doing assignments, preparing for examinations, or performing other educational tasks, when the individual knows that such delay may have negative consequences. In addition, academic procrastination has been the subject of academic attention since the 1980s because of its widespread occurrence among students and its impact on academic success (Qian & Zhao, 2018). The approach is mainly concerned with procrastination in the academic setting. Students have huge academic responsibilities and hard deadlines to meet which could be stressful and pressuring. Therefore, many students defer their academic responsibilities while knowing it could negatively impact their learning and academic performance.

Dependent variable

Academic performance: Academic performance is the extent to which a student has met the learning goals and learning outcomes intended. It is generally measured through grades, test scores, GPA, completion of assignments and overall academic achievement. But academic achievement is not only about academic scores. Academic performance is also influenced by students' study habits, classroom behavior, attention, organization, assignment completion, and productivity (Taimur et al., 2024). Moreover, academic success is impacted by other factors such as motivation, study habits, self-efficacy, academic stress, and procrastination. Academic procrastination has attracted much attention because of its negative effect on students' learning outcomes. Previous studies have consistently reported that students who procrastinate on academic assignments have lower academic achievement and poorer educational outcomes (Afzal et al., 2026).

Figure 2
Failed/Repeated a course



FINDING AND DISCUSSION

Finding

Demogaraphics response: Figure 2 shows that 49 (14.5%) of the 337 respondents reported that they has failed or repeated a course, and 288 (85.5%) reported that they has not. This shows that the majority of respondents did not fail or repeat a course.

Table 3 shows the demographic and academic profile of the 337 respondents. Most of them were male (68.2%) and aged between 21 and 23 years (43.6%). The second and fourth semesters represented the largest percentage of respondents (22.3% each). Most of the respondents (35.9%) were living with the family or were renters. In terms of academic characteristics, about half of the respondents had a GPA of 3.00-3.49 (49.0%) and they studied for 1 to 2 hours a day (40.9%). Most (32.3%) reported sometimes using social media. In terms of assignment submission, majority of the respondents reported that they rarely delay their assignments (35.3%),

Table 3
Demographic profile of respondent

		Frequency	Percent	Cumulative Percent
Gender	Male	230	68.2	68.2
	Female	107	31.8	100
Semester	1st	30	8.9	8.9
	2nd	75	22.3	31.2
	3rdt	38	11.3	42.4
	4th	75	22.3	64.7
	5th	23	6.8	71.5
	6th	48	14.2	85.8
	7th	27	8	93.8
	8th	21	6.2	100
Age	18-20	114	33.8	33.8
	21-23	147	43.6	77.4
	24-26	62	18.4	95.8
	Above 26	14	4.2	100
Current living arrangement	With family	121	35.9	35.9
	Hostel	87	25.8	61.7
	Rent Room	113	33.5	95.3
	Other	16	4.7	100
Current GPA	Below 2.50	22	6.5	6.5
	2.50-2.99	103	30.6	37.1
	3.00-3.49	165	49	86.1
	3.50 and above	47	13.9	100
Average study hours per day	Less than 1 hour	95	28.2	28.2
	1-2 hours	138	40.9	69.1
	3-4 hours	73	21.7	90.8
	More than 4 hours	31	9.2	100
Social media use	Never	31	9.2	9.2
	Rarely	87	25.8	35
	Sometimes	109	32.3	67.4
	Often	71	21.1	88.4
	Always	39	11.6	100
Assignment submission delay	Never	78	23.1	23.1
	Rarely	119	35.3	58.5
	Sometimes	92	27.3	85.8
	Often	22	6.5	92.3
	Always	26	7.7	100
	Total	337	100	

Table 4
Descriptive analysis

Statistics	Academic procrastination	Academic performance
N	337	337
Mean	2.48	3.80
Median	2.33	4
Mode	2	4
Std. Deviation	0.88	0.81
Variance	0.77	0.66

Table 5
Group statistics

Variables	Gender	N	Mean	Std. Deviation	Std. Error Mean
Academic procrastination	Male	230	2.420	0.816	0.054
	Female	107	2.636	0.998	0.097
Academic performance	Male	230	3.838	0.791	0.052
	Female	107	3.735	0.871	0.084

Table 6
I*ndependent sample t-test*

Variables	Equal variances	Levene's test for equality of variances		t-test for Equality of Means			
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference
Academic procrastination	1	10.266	0.001	-2.096	335.000	0.037	-0.215
	2			-1.948	174.244	0.053	-0.215
Academic performance	1	0.844	0.359	1.072	335.000	0.285	0.102
	2			1.035	190.087	0.302	0.102

1 = Equal variances assumed 2 = Equal variances not assumed

followed by those who occasionally delay submission (27.3%).

Descriptive analysis: Based on Table 5, the mean score for academic procrastination was 2.48, a median of 2.33 and a mode of 2. The standard deviation was 0.88 and variance was 0.77, which means that the respondents' ratings of academic procrastination were varied by about 88% respectively compared to the mean. Similarly, the mean of academic performance was 3.80 while the median and mode were 4. The standard deviation was 0.81. This means that the scores of academic achievement of the respondents differ from the mean by about 81%.

Independent sample t-test for equality of means across gender : According to Table 5 the

average score for academic procrastination for male students (N = 230) was 2.420 while for female students (N = 107) it was higher 2.636. Thus, female students were shown to have a little higher level of academic procrastination than their male counterparts. The mean score of academic performance of male students was 3.838 whereas the mean score of female students was 3.735. Therefore, male students performed marginally better than female students in academic performance.

Based on Table 6, Levene's test for academic procrastination was significant; $p < .01$, the equal variances was not assumed. There was no statistically significant difference between male and female learners (P = .053, mean = -0.215), reject hypothesis H_1. Academic achievement Levene's test was not significant (F = 0.844, p = 0.359) showing equal variances assumed. The results revealed no significant gender differences, p = 0.285, mean difference = 0.102, reject hypothesis H_2.

Table 7
Correlation analysis

Variables	Academic procrastination	Academic performance
Academic procrastination	1	
Academic performance	-.512*** (0.001)	1

Correlation analysis: Based on Table 8 the result shows a moderate negative relationship between academic procrastination and academic performance ($r = -0.512$, $p < 0.01$) support the hypothesis H_3. This indicates that students with higher levels of academic procrastination tend to have lower academic performance, while students with lower procrastination tend to have higher academic performance.

Regression analysis: According to Table 8, academic procrastination also has significant negative impact on academic success ($r = -0.475$, $p < 0.01$), supporting hypotheses H_4. The adjusted $R^2 = 0.26$ indicates that academic procrastination accounts for approximately 26% of the variation in academic performance, with the remaining 74% explained by other variables. The regression model showed statistical significance and fit ($F = 119.135$, $p < 0.001$).

$$Y = 4.987 - 0.475x_1 + e$$

Discussion

The study found that academic procrastination has a significant and negative impact on academic performance among BIT students. This finding is consistent with the findings of Akinsola et al. (2007); Savithri (2014); Balkis and Duru (2017); Yilmaz (2017); Fentaw et al. (2022); Gayary and Kalita (2025) and Afzal et al. (2026); which

Table 8
Regression analysis

Variables	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	4.987	0.115		43.431	0.001
Academic procrastination	-0.475	0.043	-0.512	-10.915	0.001
Adjusted R	0.26	F	119.135	Sig.	0.001

suggest that delaying studying, assignments, and examination preparation may reduce effective learning and negatively affect academic outcomes. Another explanation is that by postponing studying, homework and exam preparation, the time available for learning is reduced and the pressure near the deadlines is increased. Thus, students who procrastinate may have less opportunity to review course materials, practice skills, and correct errors. The finding is also consistent with the Temporal Motivation Theory that low task value or expectancy, impulsivity, and perceived distance of deadlines can reduce motivation to act in a timely manner (Steel & König, 2006). Repeated delays can therefore interfere with effective study habits and results in worse academic results.

CONCLUSION

This study looked at the impact of academic procrastination on the academic performance of BIT students. The data demonstrated a statistically significant and negative association between academic procrastination and academic performance, showing that students who delay academic assignments are more likely to perform poorly academically. The findings also imply that academic procrastination is a significant behavioral factor influencing students' academic achievements. The findings are consistent with Temporal desire Theory (TMT), which states that desire to finish a work declines as deadlines approach, and that delays might eventually impair task completion and performance. In the academic setting, often postponing studying, assignments, and other learning tasks can diminish effective study time, raise last-minute stress, and impair students' ability to fully prepare for academic exams. As a result, eliminating procrastination may help students improve their academic performance by allowing them to better manage their study time and complete academic activities on time. Based on these findings, BIT students should be encouraged to adopt effective skills for time management, study planning, goal setting, and self-regulation. Similarly, academic institutions may help by offering academic advice, supporting disciplined study routines, tracking students' progress, and encouraging timely completion of academic responsibilities. Overall, the study shows that tackling academic procrastination is critical for developing more effective learning habits and improving academic achievement in BIT students.

IMPLICATION

The findings have practical implications for students, teachers, academic counselors and educational institutions. The study result findings indicating that reducing procrastination may help students improve their academic achievement. Students should be encouraged to develop regular study schedules, break down large academic tasks into smaller tasks, set earlier personal deadlines, and monitor their progress. By setting clear deadlines, intermediate milestones and timely feedback, teachers can enable the timely completion of tasks. Time-management, study-planning and self-regulation programs can be used by academic counselors and institutions for students who procrastinate. These recommendations are in line with the study's finding that higher procrastination is associated with poorer academic achievement.

There are several limitations to the study. It was carried out on BIT students in one

college. This limits the generalization of the findings. Because of the cross-sectional design, temporal causality cannot be assessed. Convenience sampling may also lead to sampling bias. Moreover, the study is limited to academic procrastination and academic performance and does not consider other potentially relevant factors such as motivation, academic stress, self-efficacy, and study habits. Future studies might include students from different colleges and academic programs, geographical area, employ probability sampling when possible, and explore other variables using cross-section data or mixed-method.

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NCMT JOURNAL OF
MULTIDISCIPLINARY STUDIES (NJMS)

ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Impact of Security, Privacy, Trust and Perceived Risk on Online Purchase Intention of Clothing Items

Siddhishree Khanal

National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
kh.siddhishree23@ncmt.edu.np

Received: 18 Jul., 2026 | Revised: 8 Aug., 2026 | Accepted: 10 Sept., 2026

Abstract: *Online shopping has grown in popularity because of the rapid advancement of digital technology and e-commerce platforms; nonetheless, consumers frequently express worries about security, privacy, trust, and perceived risk while making purchases online. The study investigated the factors that influence people's online clothes purchases. The independent variables in this study were security (S), privacy (P), trust (T), and perceived risk (PR), while the dependent variables were online purchase intention (PI), with different age groups acting as moderators. The study was based on the Theory of Planned Behavior (TPB). A quantitative research approach was used, including descriptive statistics, ANOVA, correlation analysis, and regression analysis. Primary data were gathered using a structured questionnaire, and 402 respondents were chosen using convenience sample procedures. The data was analyzed by using SPSS software. The regression study found that privacy and trust have a positive and significant impact on online purchase intention, whereas perceived risk has a significant negative effect. However, security was discovered to have a favorable but minor impact on online purchase intention. The findings show that privacy and trust are crucial elements in persuading consumers to buy clothing online, but perceived risk diminishes consumers' willingness to buy online. To lessen perceived dangers, online retailers should prioritize customer privacy, creating consumer confidence, providing accurate product information, dependable delivery services secure payment choices, and clear return and refund policies.*

Keywords: Perceived risk, privacy, purchase intention, security, trust

JEL Classification: M31, L81, D12, D83

Cite as: Khanal, S. (2026). Impact of security, privacy, trust and perceived risk on online purchase intention of clothing items. *NCMT Journal of Multidisciplinary Studies, 1*(1), 87-102.

INTRODUCTION

The rapid advancement of information and communication technology has significantly transformed the way consumers purchase products and services. As a result, online shopping has become an integral part of modern commerce due to its convenience, accessibility, wider product selection, and time-saving benefits (Tiwari & Verma, 2026; Imtiyaz & Yasin, 2025). However, the growth of e-commerce platforms has enabled consumers to make purchasing decisions anytime and anywhere using

digital devices. Despite these advantages, online shopping also exposes consumers to various uncertainties because transactions occur without physical interaction between buyers and sellers. Consequently, consumers carefully evaluate several factors before making online purchase decisions, particularly those related to trust, security, privacy, and perceived risk (Kim et al., 2007; Pavlou, 2003). Therefore, understanding these factors has become increasingly important for online retailers seeking to enhance consumer confidence and encourage purchase intention.

Purchase intention is widely recognized as a strong predictor of actual purchasing behavior and reflects a consumer's willingness to buy products or services through online platforms (Dodds et al., 1991; Pavlou, 2003). Previous studies have consistently reported that consumer trust plays a fundamental role in reducing uncertainty and encouraging online purchasing behavior (Gefen, 2000; McKnight et al., 2002). Similarly, perceptions of website security and privacy protection enhance consumers' confidence by assuring them that their financial and personal information is protected during online transactions (Flavián & Guinalíu, 2006; Malhotra et al., 2004). In contrast, perceived risk including concerns about financial loss, product quality, delivery, and information misuse negatively influences consumer's willingness to purchase online (Masoud, 2013; Jarvenpaa et al., 2000). Moreover, recent empirical studies have further confirmed that trust, security, privacy, and perceived risk significantly influence consumer behavior, satisfaction, and purchase decisions across various e-commerce platforms (Tran & Nguyen, 2022; Balli, 2025; Ahmed & Siddiqui, 2025).

Although numerous studies have examined the determinants of online shopping behavior in different countries, the relative influence of perceived risk, security, privacy, and trust on consumers' purchase intention continues to vary across different contexts and markets. Moreover, rapid technological advancement and changing consumer expectations require continuous investigation of these factors to better understand online purchasing behavior (Decatoria-Condino & Caballero, 2025; Buba et al., 2025). Therefore, this study aims to examine the effects of perceived risk, security, privacy, and trust on consumers' purchase intention in online shopping. Specifically, guided by the Theory of Planned Behavior (Ajzen, 1991), this research seeks to provide empirical evidence regarding the factors that influence online purchase strategies that enhance consumer confidence and promote sustainable online purchasing behavior. There was single study in Nepal (Sharma & Pradhan, 2025). Previous studies used mediating variables such as perceived value, e-Wom, trust (Jusuf Zeqiri, 2023; Al-Debei, 2014). But this study does not used meditating variables. Similarly, Tiwari and Verma (2026); Imtiyaz (2025) had qualitative research design. But this study used the quantitative research design. To fulfill the research gap, this study was conducted.

The study contributes significant empirical evidence from Nepal on security, privacy, trust and perceived risk in online clothing purchase. The Theory of Planned Behavior (TPB) has been utilized to study the effect of these factors on the intention of customers to buy clothes online in Nagarjun Municipality. Privacy protection, trust building and reduced perceived risk are beneficial for online retailers; e-commerce platforms, government and customers, and these can

promote online purchase intention. The data also contribute to the perception of Nepalese buyers' desires to purchase clothes online.

Research question

- Is there a relationship between security, trust, privacy, perceived risk and online purchase intention?
- Does security, trust, privacy, perceived risk effect on online purchase intention?

Objectives of the study

With the rapid growth of e-commerce and online shopping for clothing items, it is increasingly important to understand the factors that influence consumers purchase intention. Online shopping has brought convenience and more product choice but consumers often face security, privacy, trust and perceived risk issues in making online purchase decisions. Previous studies have had mixed results regarding the effect of these factors on consumers online buying behavior. the objective of this study is to examine the impact of security, privacy, trust and perceived risk on online purchase intention of clothing items among the consumers of Nagarjun Municipality. The study aims to have a better understanding of its impact on the willingness of consumers to purchase clothing products online by analyzing these significant factors.The specific objectives of the study are detailed below:

- To analyze the relationship between security, trust, privacy and perceived risk with consumers' online purchase intention.
- To examine the impact of security, privacy, trust and perceived risk on the consumers' online purchase intention.

LITERATURE REVIEW

Theoretical review

Theory of planned behavior: Ajzen's theory of planned behavior (TPB) was developed in 1991 to explain and predict human behavior. This concept connects beliefs, attitudes, intentions, and behaviors. According to TPB, attitude, subjective norms, and perceived behavioral control have a considerable influence on behavioral intention, which predicts actual conduct. Behavioral beliefs influence people's desire to engage in an action by shaping their perceptions of the consequences (Ajzen, 1991). Customers' perceptions and beliefs regarding online safety, reliability, and potential consequences impact their online purchasing decisions. This planned behavior study looks at how security, privacy, trust, and perceived risk influence online clothes purchase intentions in Nagarjun Municipality. When consumers trust online merchants, transactions, and personal information, they are more inclined to purchase clothing online (Imtiyaz & Yasin, 2025). However, financial loss, privacy, product quality, delivery, and transaction uncertainty may discourage online customers (Tiwari & Verma, 2026). Security, privacy, trust, and perceived risk all have an impact on consumers' online apparel purchasing decisions and preferences. TPB gives a solid theoretical foundation for understanding how these variables influence online clothing. purchases.

According to TPB theory, a recent study by Suardhita et al. (2024) discovered that customer trust in the security of online transactions is important in developing long-term relationships between customers and e-commerce platforms, implying that stronger perceptions of security may encourage consumers to feel more confident when purchasing online. Similarly,

Decatoria-Condino and Caballero (2025) discovered customer trust as a significant predictor of online purchase choices which corroborate the TBP hypothesis, demonstrating that consumers are more inclined to purchase when they perceive that their personal information is securely secured. Furthermore, Habib et al. (2022) found that trust directly influences customers' intention to purchase, whereas perceived risk adversely affects trust, suggesting that stronger trust might motivate consumers to make online purchases. Likewise, Tran and Nguyen (2022) observed an indirect association between perceived risk and buy intention, showing that higher perceived risk may limit consumers' propensity to purchase online that support the Theory of Planned Behaviors. These findings demonstrate the relevance of security, privacy, trust, and perceived risk in determining consumers' online purchase intention.

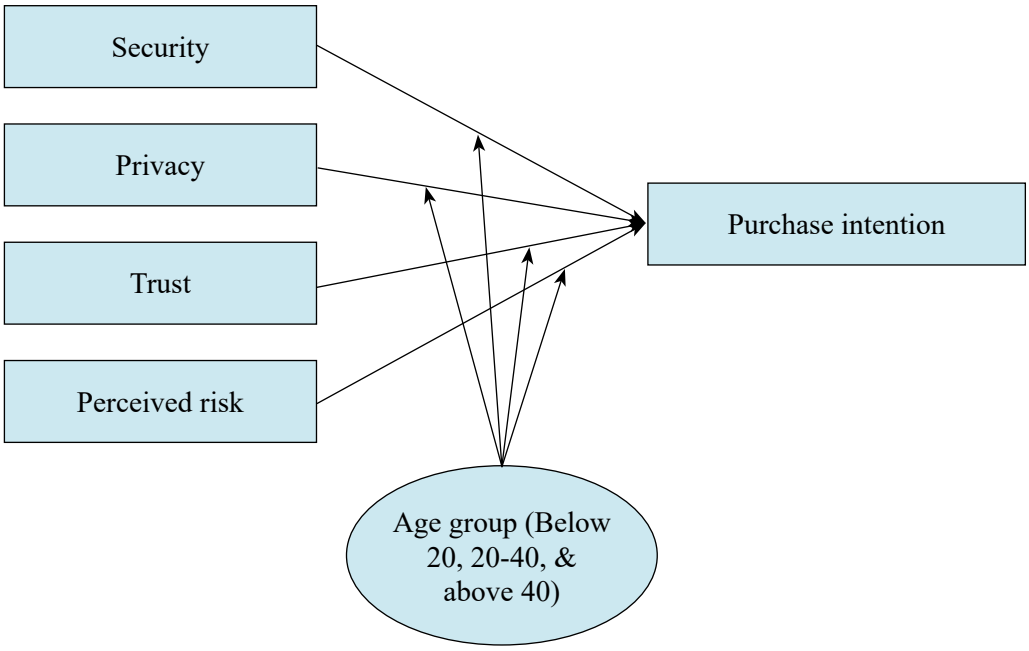
Empirical review

According to prior research, Wu et al. (2010) indicated that both consumer perceived interactivity and perceived web assurance positively influence their initial online trust. Similarly, Al-Debel et al. (2015) focused that consumer attitudes on online shopping are determined by trust and perceived benefits. Additionally, Mofokeng (2021) examined that product delivery, perceived security, information quality, and product variety have influence on customer satisfaction. Likewise, Abbas et al. (2022) based on the study; there was a positive and significant influence on consumer perception variables and trust in consumer satisfaction in shopping online. Furthermore, Habib et al. (2022) revealed that trust directly affects a consumer's intention to purchase, and the consumer trust is negatively affected by perceived risk, but trust is positively affected by customer's expectation, and perceived benefit. Also, Tran and Nguyen (2022) presented cognitive trust, perceived risk and purchase intention have indirect relationship which contribute to a better insight into consumer behavior. Moreover, Tuyapala and Nuangjamnong (2022) identified factor that affecting customer loyalty in online shopping.

However, Maulana et al. (2023) showed there are several factors to consider while examining consumer behavior and gaining insight into customer decision-making. On the other hand, Zeqiri et al. (2023) revealed that perceived value, perceived convenience and trust affected repurchase intention. Furthermore, Ashiq and Hussain (2024) featured that e-service quality and e-trust offered on e-commerce websites significantly impacted customer e-loyalty. Similarly, Suardhita et al. (2024) revealed that customer trust in the security of online transactions and product quality also plays a key role in building long-term relationships between customers and e-commerce platforms. Besides, Susanto (2024) indicated that customer satisfaction, eservice quality and consumer experience are proven to have a positive effect on consumer trust. However, Ahmed and Siddiqui (2025) founded that most of the people prefers to purchase product using e-retailing website as in present time e-retailers has built trust among the shoppers. In addition, Balli (2025) analyzed result confirm that satisfaction and intention jointly affect consumer loyalty, revealing the multidimensional nature of trust-based consumer behavior on digital platforms.

Moreover, Buba et al. (2025) emphasized that dimensions of online shopping are

Figure 1
Conceptual framework.



Note. Tran and Nguyen (2022).

identified that have effect on consumer satisfaction with the intervention of customer trust. Furthermore, Decatoria-Condino and Caballero (2025) identified consumer experience as the most influential predictor of online purchase decisions, followed by consumer attitude and consumer trust. Likewise, Imtiyaz and Yasin (2025) analyzed factor such as convenience, trust, perceived risk, product variety, and technology acceptance as major determinants of consumer decision-making. Also, Sharma and Pradhan (2025) showed price fairness, delivery speed, product quality, payment method, delivery cost, and perceived usefulness have positive customer satisfaction. On the other hand, Tiwari and Verma (2026) revealed that online shopping has gained widespread acceptance due to convenience, timesaving, wider product choices, and attractive pricing.

Based on the literature review, the study developed the research framework presented in figure 1.

RESEARCH METHODOLOGY

Research design

The study adopted a deductive research approach. Further the study employed positivist research philosophy. This study used a quantitative research design it includes descriptive, relational, and explanatory research design. The descriptive research design was employed to delineate the fundamental properties of the investigated variables (Budhathoki et al., 2025). The relational research design was used to examine the relationship between the antecedent and consequent variables (Budhathoki et al., 2023). Explanatory research design was employed to investigate

the influence of independent variables on dependent variables (Budhathoki & Khadka, 2024).

Population and sample

The targeted population of this study consists of social media users in Kathmandu district especially in Nagarjun municipality who uses social media platforms such as Facebook, Daraz, Hamro bazar and TikTok to online purchase of clothing items. The exact population is unknown, so it is difficult to collect data from the entire population. So, that sample of 402 respondents' is selected for the study. This study uses convenience sampling techniques to select respondents. If the population size is unknown but expected to be large, use statistical formulas to determine the sample size (Cochran, 1977). The Cochran's formula is shown below:

$$n = \frac{(z^2 * p * q)}{e^2}$$

(Where, n = required sample size (384); Z = Z-value (e.g., 1.96 for 95% confidence level); p = estimated proportion (0.5 if unknown); q = 1 – p, e = margin of error (5 %))

The close ended questionnaire is distributed online through social media platforms such as Facebook, Instagram, WhatsApp, and messenger. Respondents were asked to fill out the questionnaire during their free time. Data collection was started from 27th June to July 9th.

Sources of data and analysis tools

This study used primary data collected through structured close ended questionnaire. The questionnaire includes demographics and five-point Likert-scale. The questionnaire was designed based on the findings from the literature study. The measurement items in questionnaire Likert-scale variables for security, privacy, trust and perceived risk on online purchase intention were taken from previous studies (Sharma & Pradhan, 2025; Tiwari & Verma, 2026; Suardhita et al., 2024). The study employed the SPSS software version 32.0.0 was used for data analysis.

Table 1
Reliability test

Variable dimensions	Number of items	Cronbach's Alpha
Security	5	0.814
Privacy	5	0.799
Trust	5	0.789
Perceived risk	5	0.873
Purchase intention	4	0.815

Before the questionnaire was distributed, a pilot study was conducted in which 61 people were given the questionnaire to evaluate its efficacy and reliability. Table 1 shows the estimated Cronbach's alpha coefficients for the main dimensions in this study: security (0.814), privacy (0.799), trust (0.789), perceived risk (0.873), and purchase intention (0.815).

Analytical model

This study used the regression model to examine the cause-and-effect correlations between antecedent and subsequent variables. The model is used in the previous study by Sharma and Pradhan (2025).

$$PI = \beta_0 + \beta_1 PR + \beta_2 P + \beta_3 S + \beta_4 T + e$$

(Where, PI=Purchase intention, PR=Perceived risk, P=Privacy, T=Trust, S=Security, β_1- β_4 = coefficient of predictor, e= Error term, β_0 = constant)

Variable definition

Independent variables

Security: Security refers to consumers' trust that an online shopping platform has enough safeguards in place to protect personal and financial information from unauthorized access, fraud, hacking, and other cyber dangers. Effective security procedures provide a secure online shopping environment, boost consumer confidence, and alleviate concerns about online transactions. When consumers believe an online shop provides excellent security protection, they are more inclined to trust the platform and have a higher intention to buy items or services online (Flavián & Guinaliu, 2006; Kim et al., 2007).

H_1: Security has a significant positive impact on online purchase intention.

Privacy: Privacy relates to consumers' perceptions of how well online retailers acquire, manage, store, and use their personal information. Consumers are more likely to make purchases from online shopping platforms when they are certain that their personal information will be kept secure and not disclosed or misused without their permission. Strong privacy policies assist to alleviate consumer concerns about information exploitation and contribute to a more trustworthy online buying experience (Malhotra et al., 2004; Bansal et al., 2010).

H_2: Privacy has a significant positive effect on online purchase intention.

Trust: Trust is the belief that an online buying platform is reliable, honest, and capable of keeping its promises throughout the purchasing process. It represents customers' trust in the store to deliver products or services as promised, preserve sensitive information, and conduct transactions fairly. Because online purchasing includes uncertainty and minimal physical interaction, trust is critical in reducing perceived risks and persuading customers to make purchases online. As a result, higher levels of consumer trust have a beneficial impact on purchase intention (Gefen, 2000; McKnight et al., 2002).

H_3: Trust has a significant positive impact on online purchase intention.

Perceived risk: Perceived risk refers to a consumer's view of the potential negative effects or uncertainty connected with doing an online transaction. It indicates the chance that consumers may suffer financial loss, product dissatisfaction, or other negative consequences while purchasing goods or services online. Because internet shopping does not include direct physical touch between buyers and sellers, consumers frequently sense higher uncertainty during the purchasing process. Masoud (2013) identified six significant elements of perceived risk in online shopping: financial risk, product risk, time risk, delivery risk, social risk, and security risk. Consumers are less likely to make online transactions when they perceive a higher level of risk (Järvenpää et al., 2000; Masoud, 2013).

H_4: Perceived risk has a positive significant effect on online purchase intention.

Dependent variable

Purchase intention: Purchase intention refers to a consumer's willingness and likelihood of purchasing products or services from an online shopping platform in the future. It shows the consumer's intended purchasing behavior after weighing the available options and making an overall assessment of the online store. Purchase intention is widely regarded as a valid predictor of actual purchase behavior and is frequently used in

e-commerce research to analyze consumers' future purchasing decisions (Dodds et al., 1991; Pavlou, 2003).

FINDINGS AND DISCUSSION

Findings

Demographic responses: Table 2 displays the demographic characteristics of the respondents. In terms of gender, respondents were virtually evenly distributed, with 49.8% (n = 200) females and 49.5% (n = 199) males, while 0.7% (n = 3) classified as others. In terms of age, most respondents (69.9%, n = 281) were between 20 and 40 years old, followed by 17.4% (n = 70) who were under 20 years old and 12.7% (n = 51) who were over 40. Similarly, 39.8% (n =

Table 2
Demographic profile of the respondents

Variables	Categories	Frequency	Percent	Cumulative Percent
Gender	Female	200	49.8	49.8
	Male	199	49.5	99.3
	Others	3	0.7	100
Age group	Below 20	70	17.4	17.4
	20-40	281	69.9	87.3
	Above 40	51	12.7	100
Occupation	student	123	30.6	30.6
	Employed	160	39.8	70.4
	unemployed	73	18.2	88.6
	Business	46	11.4	100
Digital payment method	Mobile banking	172	42.8	42.8
	E-Sewa	136	33.8	76.6
	Khalti	62	15.4	92
	Fone Pay	32	8	100
Frequency of digital payment use	Daily	97	24.1	24.1
	Several time a week	122	30.3	54.5
	Occasionally	141	35.1	89.6
	Rarely	42	10.4	100
How often do you shop online	Daily	31	7.7	7.7
	Several a time a week	62	15.4	23.1
	Occasionally	154	38.3	61.4
	Rarely	155	38.6	100
Mode of shopping	Facebook	38	9.5	9.5
	TikTok	94	23.4	32.8
	Daraz	192	47.8	80.6
	Others	78	19.4	100
	Total	402	100	

Table 3
Descriptive analysis

Statistics/variables	Security	Privacy	Trust	PR	PI
Mean	3.55	2.98	3.40	4.02	2.77
Median	3.4	2.6	3.4	4.2	2.5
Mode	3.4	2.6	3.2	4.4	2
Std. Deviation	0.57	0.76	0.60	0.62	0.81
Variance	0.32	0.59	0.36	0.38	0.67

Table 4
ANOVA-test for equality of mean across age

Variables		Sum of Squares	df	Mean Square	F	Sig.
Security	Between Groups	1.913	2	0.957	2.961	0.053
	Within Groups	128.914	399	0.323		
	Total	130.827	401			
Privacy	Between Groups	1.839	2	0.919	1.564	0.211
	Within Groups	234.558	399	0.588		
	Total	236.396	401			
Trust	Between Groups	0.315	2	0.157	0.435	0.648
	Within Groups	144.44	399	0.362		
	Total	144.755	401			
Perceived risk	Between Groups	0.712	2	0.356	0.917	0.4
	Within Groups	154.807	399	0.388		
	Total	155.519	401			
Purchase intention	Between Groups	0.14	2	0.07	0.104	0.901
	Within Groups	269.156	399	0.675		
	Total	269.296	401			

160) of respondents were employed, making it the largest occupational category. Students made up 30.6% (n = 123) of the sample, followed by unemployed people at 18.2% (n = 73) and company owners at 11.4% (n = 46). Mobile banking was the most popular digital payment method among respondents, accounting for 42.8% (n = 172). This was followed by e-Sewa at 33.8% (n = 136), Khalti at 15.4% (n = 62), and Fone pay at 8.0% (n = 32). In terms of digital payment frequency, 35.1% (n = 141) of respondents reported using it occasionally, 30.3% (n = 122) used it several times per week, 24.1% (n = 97) used it daily, and 10.4% (n = 42) reported using it seldom. However, when it comes to online purchasing frequency, most respondents (38.6%, n = 155) said they shopped online seldom, followed by those who shopped occasionally. Meanwhile, 15.4% (n = 62) shopped many times each week, while just 7.7% (n = 31) reported buying online every day. Finally, Daraz was the most popular online purchasing

Table 5
Multiple comparisons LSD for all variables

Variables	(I) Age	(J) Age	Mean Diff. (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Security	Below 20	20-40	-0.02503	0.07593	0.742	-0.1743	0.1242
		Above 40	0.18532	0.10465	0.077	-0.0204	0.391
	20-40	Below 20	0.02503	0.07593	0.742	-0.1242	0.1743
		Above 40	.21036*	0.08652	0.015	0.0403	0.3804
	Above 40	Below 20	-0.18532	0.10465	0.077	-0.391	0.0204
		20-40	-.21036*	0.08652	0.015	-0.3804	-0.0403
Privacy	Below 20	20-40	0.17267	0.10242	0.093	-0.0287	0.374
		Above 40	0.07686	0.14116	0.586	-0.2006	0.3544
	20-40	Below 20	-0.17267	0.10242	0.093	-0.374	0.0287
		Above 40	-0.09581	0.1167	0.412	-0.3252	0.1336
	Above 40	Below 20	-0.07686	0.14116	0.586	-0.3544	0.2006
		20-40	0.09581	0.1167	0.412	-0.1336	0.3252
Trust	Below 20	20-40	0.02218	0.08037	0.783	-0.1358	0.1802
		Above 40	0.0981	0.11077	0.376	-0.1197	0.3159
	20-40	Below 20	-0.02218	0.08037	0.783	-0.1802	0.1358
		Above 40	0.07592	0.09158	0.408	-0.1041	0.256
	Above 40	Below 20	-0.0981	0.11077	0.376	-0.3159	0.1197
		20-40	-0.07592	0.09158	0.408	-0.256	0.1041
Perceived risk	Below 20	20-40	-0.1084	0.08321	0.193	-0.272	0.0552
		Above 40	-0.05216	0.11467	0.649	-0.2776	0.1733
	20-40	Below 20	0.1084	0.08321	0.193	-0.0552	0.272
		Above 40	0.05624	0.09481	0.553	-0.1301	0.2426
	Above 40	Below 20	0.05216	0.11467	0.649	-0.1733	0.2776
		20-40	-0.05624	0.09481	0.553	-0.2426	0.1301
Purchase intention	Below 20	20-40	0.00905	0.10972	0.934	-0.2066	0.2247
		Above 40	0.06246	0.15121	0.68	-0.2348	0.3597
	20-40	Below 20	-0.00905	0.10972	0.934	-0.2247	0.2066
		Above 40	0.05342	0.12501	0.669	-0.1923	0.2992
	Above 40	Below 20	-0.06246	0.15121	0.68	-0.3597	0.2348
		20-40	-0.05342	0.12501	0.669	-0.2992	0.1923

platform, chosen by 47.8% (n = 192) of respondents. TikTok was the second most popular platform, with 23.4% (n = 94), followed by other platforms (19.4%, n = 78) and Facebook (9.5%, n = 38).

Descriptive analysis: Table 3 shows descriptive statistics of the study. Perceived risk (PR) was found to have the highest mean value (4.02), followed by security and trust. Similarly, privacy has the lowest average

Table 6
Correlation analysis

Variables	Security	Privacy	Trust	PR	PI
Security	1				
Privacy	.565***	1			
	(.001)				
Trust	0.570***	.591***	1		
	(.001)	(.001)			
Perceived risk	0.036	-.209***	0.038	1	
	0.469	(.001)	0.445		
Purchase intention	.477***	.703***	.633***	-.218***	1
	(.001)	(.001)	(.001)	(.001)	

value (2.98), as does purchase intention (Mean 2.77). Security has the lowest standard deviation (0.57), followed by trust, perceived risk, and privacy. Purchase intention had the biggest standard deviation (0.81). Similarly, purchase intention had the greatest variance (0.67), followed by privacy, purchase intention, and trust, while security had the smallest variance (0.32).

ANOVA test: Table 4 ANOVA results reveal that there is no significant difference in security responses across three age groups, with ($p>0.05$). Similarly, there is no significant variation in privacy across age groups (p-value = 0.211). However, there is no significant variation in trust across the three level ages (p-value = 0.648). Furthermore, there is no significant difference in perceived risk across the three age groups, ($P>0.05$). Likewise, there is no significant difference in purchase intention across the three age groups, (p-value =0.901).

Table 5 demonstrates that a multiple comparison analysis was used to compare differences in the research variables across the three age groups (under 20, 20-40, and above 40). The findings show that age differences were only statistically significant for security. A significant difference was seen between respondents aged 20-40 and those over 40 (mean difference = -0.21036, p = 0.015), showing that respondents over 40 expressed higher security perceptions than those aged 20-40. There were no significant differences between age groups for privacy, trust, perceived risk, or purchase intention, since all related p-values were more than 0.05. Except for security, age does not appear to have a substantial influence on these variables.

Correlation analysis: Table 6 shows a positive and significant association between security and purchase intention ($r=0.477$, $p<0.01$). The correlation between privacy and purchase intention has found to be positive and substantial ($r=.703$, $p < 0.01$). Trust is positively correlated with purchasing intention ($r= 0.633$, $p<0.01$). Furthermore, the association between perceived risk and purchase intention is negative and substantial ($r= -0.218$, $p<0.01$).

Regression analysis: As shown in Table 7, the adjusted R squared value of 0.585 represents 58.50 percent of the variation in the four

Table 7
Regression analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.295	0.247		1.195	0.233
Security	0.033	0.061	0.023	0.541	0.589
Privacy	0.478	0.048	0.448	9.959	0.001
Trust	0.492	0.059	0.361	8.316	0.001
Perceived risk	-0.183	0.045	-0.139	-4.085	0.001
Adjusted R square	0.585	F	138.723	Sig	0.001

independent variables with dependent variables. Also, the influence of security is found to be positive and insignificant on purchases intention ($r = 0.033$, $p > 0.05$), rejecting the H_1 hypothesis. Privacy has a positive and significant impact on purchasing intention ($r = 0.478$, $p < 0.01$), which supports H_2 hypothesis. Similarly, trust has a positive and significant effect on purchase intention ($r = 0.492$, $p < 0.01$), supporting the H_3 hypothesis, whereas perceived risk has negative and significant relation with purchase intention ($r = -0.183$, $p < 0.01$), confirming the H_4 hypothesis. The regression model has a statistically significant, as shown by the F-statistic of 138.723 ($p = 0.01$), which is significant at the 1% significance level. The linear regression equation is estimated as follows:

$$PI = 0.295 + 0.033\ S + 0.478\ P + 0.492\ T - 0.183\ PR + e$$

Discussion

The security has a positive but minor impact on online buying intentions. This conclusion contradicts with Mofokeng's (2021); Ashiq and Hussain's (2024) findings that security is a crucial factor influencing online buying intentions. This could be because security is an important feature of online business; though, simple security processes can be used across many platforms. As a result, security may be seen as a basic requirement rather than a significant element in consumer purchase decisions. Similarly, privacy has a positive and significant impact on online purchase intention. The findings are consistent with previous studies by Decatoria-Condino and Caballero (2025). Consumers may be concerned about their personal information being misused or accessed without their permission. Thus, online platforms that provide sufficient privacy protection can instill greater trust and comfort in consumers, boosting their chances of completing an online transaction. Furthermore, trust has a positive and significant impact on online purchasing intentions. The findings are consistent with Abbas et al. (2022); Ashiq and Hussain (2024). When purchasing online, consumers and sellers have hardly anything in the form of personal interaction. As a result, consumer trust in the retailer or online platform may reduce uncertainty and increase confidence in the transaction, leading to a higher purchase intention. However, perceived risk has a negative and considerable impact on online purchasing intentions. The findings are supported by the work of Imtiyaz and Yasin (2025) as well as Tran and Nguyen (2022). Consumers may be

more anxious about a purchase when they perceive a larger risk, such as the risk of losing money, receiving a defective or low-quality goods, delivery issues, or the misuse of personal information. As a result, higher perceived risk may lower buyers' desire to buy products online.

CONCLUSION

The objective of the study was to access the results of different factors like security, privacy, trust and perceived risk that has influence on online purchase intention. Security has positive and insignificant impact on online purchase intention. The findings show that focusing on security is not enough to improve online purchase intention. The privacy and trust have significant and positive effects on purchase intention. This indicates that customer privacy and trust are important factors and that focusing on them can improve purchase intentions. Consumers feel more comfortable buying online if they believe their personal information is secure and the sellers are reliable and trustworthy. Perceived risk significantly and negatively affects purchase intention. This suggests that risk has an direct relation with purchase intention. This finding is significant in relation to the planned theory, which states that an individual's inner beliefs about the consequences of a specific action influence their attitudes toward that behavior. Therefore, providing clear and realistic product detail and images helps consumers evaluate the product before making an online purchase. At the same time, safe transactions, privacy protection, trust building, and risk minimization can result in a happier and more confident online purchasing experience. As a result, increasing privacy protection encourages consumer trust, and lowering perceived risk helps online businesses enhance consumer confidence and buying intention.

IMPLICATIONS

The finding of this study determines the implications for online consumers, e-commerce platforms, government and policy maker. Retailers should focus on protecting customers' personal and financial information and maintaining transparent privacy policies. They should also earn consumer trust through providing accurate product information, reliable delivery services, secure payment options, clear return and refund policies, and responsive customer support. Nepal government authorities and policymakers should improve consumer protection, data privacy and e-commerce regulations and promote awareness of safe online shopping practices. Consumers should also be encouraged to verify the credibility of the online sellers, read the product information and feedback from customers carefully and understand the privacy and return policies before making a purchase decision.

This study was limit with geographical area, longitudinal data, quantitative research approach, convenience sampling methods, limited variables. Future studies should include larger and more diverse samples from urban and rural areas of Nepal. Also incorporate additional factors such as customer satisfaction, product quality, price, delivery service, social media influence, and previous online shopping experience, as well as qualitative methods, interviews, and cross-country comparisons to provide deeper insights into online consumer behavior.

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NCMT JOURNAL OF
MULTIDISCIPLINARY STUDIES (NJMS)

ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Digital Loneliness Despite Hyper Connectivity: *The Mediating Role of Loneliness in the Relationship Between Social Media Use and Well-Being Among Undergraduate IT Students in Baluwatar, Nepal*

Alex Yonjan Lama

National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
la.alexyonjan23@ncmt.edu.np

Received: 18 Aug., 2026 | Revised: 12 Sept., 2026 | Accepted: 8 Oct., 2026

Abstract: *In the online world of today, social media has become an inseparable part of life, offering channels of communication, interaction and connection. However, increased social media use may also be linked to loneliness and change in individual well-being. There are previous studies about social media use, loneliness and wellbeing but limited research has been done on the mediation effect of loneliness in the setting of undergraduate IT students in Baluwatar, Nepal. The present study, therefore, investigated the association between social media use and well-being and whether loneliness mediates this association. The independent variable was social media activities (SMA) and the dependent variable was wellbeing (WB) with loneliness (L) as the mediating variable. The study used Social Comparison Theory. The research design was quantitative research design with descriptive, correlation and explanatory research design. Primary data were collected from undergraduate IT students of Baluwatar using structured questionnaire on five-point Likert scale. The method of convenience sampling was adopted and 397 valid responses were collected. Data were analyzed using SPSS and PROCESS Macro. Descriptive statistics, Pearson correlation, multiple Ordinary Least Square (OLS) regression was used to explore the relationships and effects among the variables of the study. Results indicate significant positive effects of social media activities on loneliness and significant direct and total effects on well-being. Loneliness has an insignificant direct impact on well-being. The indirect effect of social media activities on well-being through loneliness is insignificant. The results suggest that students should balance their online and offline social interactions and use social media in a meaningful way. Educational institutions can organize programs on digital wellness and awareness. Convenience sample, self-report data, and cross-sectional design of the study may limit the generalizability of the findings.*

Keywords: Loneliness, social media activities, well-being

JEL Classification: I31, I19, Z13

Cite as: Lama, A. Y. (2026). Digital loneliness despite hyper connectivity: The mediating role of loneliness in the relationship between social media use and well-being among undergraduate IT students in Baluwatar, Nepal. *NCMT Journal of Multidisciplinary Studies, 1*(1), 103-118.

INTRODUCTION

Loneliness is related with various negative physical and mental health effects (Park et al., 2020). Due to its increasing effect on public health, loneliness has recently been identified as a global health problem. Also, Fear of Missing Out (FoMO) has been identified as a factor that encourages people to spend more time on social media in order to remain informed about the activities and experiences of others (Przybylski et al., 2013). Although, social media connects people but they may also increase social media use and lead to sensations of anxiety and emotional disconnection (Elhai et al., 2021).

The widespread use of social media platforms has changed the way adolescents communicate, build relationships, and view themselves (Boyd, 2014). Although social media helps in connection and social interaction, current research shows that excessive use may have negative effects on mental health, including a higher risk of depressive symptoms among teenagers (Shannon et al., 2022). In today's rapidly changing digital use of social media has been related to higher levels of State-Fear of Missing Out (State-FoMO), as individuals become concerned about missing out on social experiences, information, or activities shared by others (Baker et al., 2016; Chai et al., 2018).

Previous studies have shown that social media use is associated with various psychological outcomes, including loneliness, social anxiety, depressive symptoms, and emotional well-being (Koçak et al., 2025; Hamdan et al., 2025; Saini, 2025; Zhao et al., 2025). Several studies have used different mediating variables, such as loneliness, social anxiety, and depressive symptoms, to explain the relationship between social media use and psychological well-being (Koçak et al., 2025; Hamdan et al., 2025; Saini, 2025; Zhao et al., 2025). In addition, past research has used moderating variables such as adaptive perfectionism (Wan & Zhou, 2025) to better understand this relationship. However, this considers loneliness as the mediating variable and does not include any moderating variable. Furthermore, to the best of the researcher knowledge, no previous study has specifically examined the relationship between social media use and well-being through the mediating role of loneliness on undergraduate IT students in Baluwatar. Therefore, this study was conducted to address this research gap as well as issues and provide evidence in the Nepalese context for the first time.

Research questions

- Is there a significant relationship between social media activities, loneliness, and well-being among undergraduate IT students in Baluwatar?
- Do social media activities significantly influence loneliness among undergraduate IT students in Baluwatar?
- Does loneliness mediate the relationship between social media activities and well-being among undergraduate IT students in Baluwatar?

Objectives

The primary aim of this study was to examine the mediating role of loneliness in the relationship between social media activities

and well-being among undergraduate IT students in Baluwatar. Hence, the specific objectives of this study include the following:

- To analyze the relationship between social media activities, loneliness, and well-being of undergraduate IT students in Baluwatar.
- To examine the effect of social media activities on loneliness, and well-being among undergraduate IT students in Baluwatar.
- To examine the mediating effect of loneliness on the relationship between social media activities and well-being among undergraduate IT students in Baluwatar.

LITERATURE REVIEW

Theoretical review

Social Comparison Theory: Social comparison theory was developed by Festinger (1954), this theory suggests that people are motivated to compare themselves to others to evaluate their own abilities, opinions and self-worth. This theory is significantly relevant to the social media context. In particular, adolescents tend to compare themselves to the often idealized and curated versions of their friends and influencers on platforms like Instagram and TikTok. Such comparisons could lead to negative self-evaluations and feelings of inadequacy, thus exacerbating depressive symptoms (Vogel et al., 2014). Perloff (2014) suggested that social media increases self-comparison as people are always exposed to other people's carefully curated highlight reels that are often filtered and selectively presented. Teenagers are especially susceptible to these comparisons since their sense of self is still forming. Perloff (2014) found significant associations between frequent use of social media and depressive symptoms, body dissatisfaction, and low self-esteem especially among teenage girls. Furthermore, Appel et al. (2016) found significant associations between adverse emotional consequences and upward social comparisons (i.e., comparing oneself to someone perceived as better off) on social media. Adolescents who often see posts about other people achievements, trips and ideal lifestyles may develop a distorted sense of reality which can result in a sense of loneliness.

Empirical review

Social media use and loneliness: Bonsaksen et al. (2023) investigated the associations between social media use and loneliness in a cross-national population: do motives for social media use matter in Norway, UK, USA, and Australia. They found more time spent on social media, associated with more loneliness by the linear regression analysis.

H_1: *SM activities and Loneliness have direct effect on well-being.*

H_2: *SM activities have indirect impact on well-being through loneliness.*

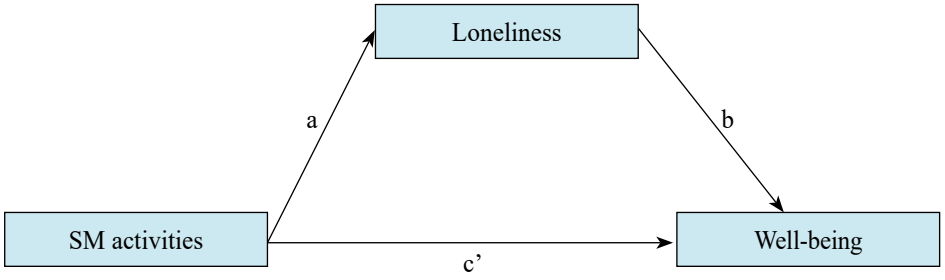
H_3: *SM activities have total influence on well-being.*

Table 1
Summary of previous studies

Author (s)	Year	Country	Methodology	Findings
Gregory et al.	2023	USA	ANOVA and $\chi 2$ statistics	Found that time spent on social media was not significantly associated with loneliness, as no meaningful differences were observed across different usage time groups. However, using Facebook as the primary social media platform was significantly associated with higher loneliness, compared to non-primary Facebook users.
Simmons et al.	2023	USA	Correlation and linear regression analysis	Found negative relations bonding social capital (BSC) and loneliness, and positive relationship between BSC psychological, social and emotional well-being. There is a negative relation between WhatsApp use and loneliness was Found. Social Network Sites (SNS) use has an insignificant relationship with loneliness.
Jia et al.	2024	China	Regression and robustness tests	Found social media usage frequency has positive impact on self-efficacy and loneliness.
Munegowda and Donni	2024	India	Descriptive and correlation analysis	Found time spent on social media use has insignificant relationship with loneliness.
Wang et al.	2024	Northern Taiwan	Descriptive and correlation analysis	Found time spent on Facebook and age has significant relation with loneliness. Loneliness has insignificant relation with shyness tendency.
Alzain et al.	2025	Saudi Arabia	Correlation and linear regression analysis	Found loneliness and fear of missing out have significant relation with social media addiction.
Ayhan and Eroğlu	2025	Kyrgyzstan	Descriptive and correlation analysis	Found social media addiction has significant relation with loneliness.
Grund et al.	2025	USA	Descriptive statistics and linear regression analysis	Found that moderate and high social media use were associated with increased odds of depressive symptoms compared to low social media use. High social media users were significantly more likely to report depressive symptoms than low social media users
Hamdan et al.	2025	Israel	Correlation analysis	Found that loneliness and social media addiction were significantly associated with suicidal ideation among college students during the COVID-19 pandemic

Author (s)	Year	Country	Methodology	Findings
Kim et al.	2025	The Bahamas	Chi-square test (χ^2)	Found that girls reported higher levels of social media use, active and passive social media engagement, cyberbullying experiences, and mental health issues, while boys were more likely to engage in sexting and offline risk behaviors. The study also Found that being female, experiencing sexting or cyberbullying, using X (Twitter), and engaging in risk behaviors were associated with increased suicidal ideation.
Koçak et al.	2025	Turkey	Descriptive and correlation analysis	Found social network addiction has significant relation with loneliness.
Matthews et al.	2025	UK	Descriptive and correlation analysis	Found use of social media platforms has insignificant relation with loneliness.
Saini	2025	South Africa	Descriptive statistics, correlation and linear regression	Investigated the impact of social media shopping activities on well-being focusing on the mediating roles of emotions and loneliness.
Wan and Zhou	2025	China	ANOVA, correlation, hierarchical regression, mediation (bootstrap)	Found that social media use significantly increases state-FoMO, and loneliness is positively associated with both social media use and FoMO. FoMO partially mediates the relationship between loneliness and social media use.
Meynadier et al.	2026	Australia	Pearson correlation and hierarchical regression	Found social media engagement has significant relation with social media action, key psychological and demographic predators.
Schütz et al.	2026	Europe, North America, Germany and Norway	$\chi 2$ statistics and logistic regression	Found online communication: close friends, wider circle of friends, internet friends and Problematic social media use has significant relation with loneliness. Loneliness has insignificant relation with problematic social media use.
Zheng et al.	2026	Australia	Spearman's correlation	Found phone calls and texting reduce the loneliness among middle-aged and older adults.
Zhou et al.	2026	Finland	Latent moderated structural equation modeling (LMS),	Found that excessive internet use (EIU) was positively associated with both loneliness and depressive symptoms, and loneliness was also positively related to depressive symptoms.

Figure 1
Research framework of study



Note. Saini (2025).

Based on the literature review, the study developed the research framework presented in *figure 1*.

METHODOLOGY

Research design

This study used descriptive research design was used to describe the demographic characteristics of the respondents and the key variables included in the study (Budhathoki et al., 2025). The correlational research design was used to examine the relationship between social media activities, loneliness, and well-being. The explanatory research design was used to investigate the effect of social media use on well-being through the mediating role of loneliness. The study consists of one independent variable, social media use; one mediating variable, loneliness; and one dependent variable, well-being.

Population and sample

The target population of this study consists of undergraduate IT students in Baluwatar. Since the exact number of undergraduate IT students in Baluwatar was unknown and continuously changing, the population was considered to be large. Therefore, a sample size of 384 was determined at a 95% confidence level with a 5% margin of error (Cochran, 1977). The sample size was selected using a sample calculator provided by (Qualtrics & Fisher , 2023). The study used a convenience sampling technique to select respondents from the target population. Since the actual number of undergraduate IT students in the study area is unknown but assumed to be large, Cochran's formula was used to determine the required sample size for an unknown or large population. The formula is shown below.

$$n = \frac{Z^2 * P * (1-P)}{e^2}$$

(Where, n = Sample size (384); Z= Z-score (e.g., 1.96 for 95% confidence level); p = estimated proportion (use 0.5 to maximize variability); e = margin of error (5%))

Primary data were collected using a structured, close-ended questionnaire developed through Google Forms. The questionnaire was distributed digitally through platforms like Facebook, Instagram, WhatsApp, and Messenger, allowing respondents to participate voluntarily and complete the survey at their convenience.

Sources of data and analysis tools

This study used primary data collected through a structured questionnaire. The

questionnaire consists of two sections: demographic information and five-point Likert-scale items measuring social media use, loneliness, and well-being. The questionnaire was developed based on the findings and validated measurement scales identified from the literature review. The study used Process Macro (Version 4.3) for SPSS and IBM SPSS Statistics Version 32 to analyze the data. The Process Macro, developed by Hayes (2022), examines the associations between variables using Ordinary Least Squares (OLS) (Budhathoki et al., 2023). The *Table 2* shows the reliability analysis:

Table 2
Reliability test

Variable dimensions	Number of Items	Cronbach's Alpha
Social media activities	5	0.841
Loneliness	5	0.914
Well-being	5	0.852

As shown in Table 2, before starting the crucial data collection, a pilot study of 69 respondents was performed to determine the questionnaire's reliability and feasibility. All alpha values determined were higher than the acceptable level of 0.70, proving that the measuring items were internally consistent and reliable.

Analytical model

In this study, regression determines the relationship between independent, mediating, and dependent. Let's assume X stands for the independent variable, Y is the dependent variable, and M stands for the mediating variable. The study used four multiple OLS regression models with path model's statistics to investigate the cause-and-effect relationship linking the predictor, mediating, and response variables (Budhathoki & Khadka, 2024). According to Hayes (2022), the regression coefficient a_j denotes the effect of the independent variable on the mediating variable, while a_jb represents the indirect effect (IE) of the independent variable on the dependent variable through the mediating variable (i.e., X → M → Y) (Budhathoki & Khadka, 2024). Similarly, the direct effect (DE) of the independent variable on the dependent variable is represented by the regression coefficient a and c′ (i.e., X → M; X/M → Y). The total effect (TE) is calculated as the sum of a_jb and c'_j (i.e., Total Effect = $a_jb + c'_j$). If a × b × c′ is positive, the model indicates complementary mediation, whereas if a × b × c′ is negative, the model indicates competitive mediation. The indirect effect model presents the t-statistics which is calculated by dividing the effect by BootSE. When the t-statistics is greater than 1.96, the indirect effect is considered significant, whereas a t-statistics less than 1.96 indicates that the indirect effect is insignificant. If direct and indirect effects are significant then the model is said to be partial mediation. If direct effect is insignificant and indirect effect is significant then the model is said to be full mediation. Also, if the indirect effect is insignificant and the direct effect is significant, the model is said to be full mediation (Budhathoki et al., 2023). The mediating effect is represented by the following equations:

Model 1 (DE): $L(M) = i_M + ax + e_M$

Model 2 (DE): $WB(Y) = i_Y + c'x + bM + e_Y$

Model 3 (IE): $WB(Y) = i_Y + ab + e_Y$

Model 4 (TE): $WB = i_Y + (c'x + ab) + e_Y$

Where,

L = Loneliness, WB = Well-being, x = Social media activities, M = Mediating variable (i.e. Loneliness), a = regression coefficients representing the effect of the predictor variables on the mediating variable, b = Regression coefficient representing the effect of the mediating variable on the response variable, c = Direct effects of the predictor variables on the response variable after controlling for the mediating variable, i = Intercept, e = Error item.

Definition of variable

Independent variable

Social media activities: Social Media Activities are those behaviors and interactions committed by individuals where individuals can share their information and make various connection with virtual communities through text, video, photos, and other contents. Individuals and businesses share their contents on social media platforms like Facebook, X, LinkedIn, Instagram, TikTok, YouTube, and others (Paljug, 2026).

Mediating variable

Loneliness: Loneliness is a common human experience that occurs when a person feels a lack of social connection. It is a subjective feeling and can be different from every individual. An Individual may feel lonely when their relationship with others is missing or they do not meet their need. Loneliness is a distressing experience which can lead an individual to both depression and low self-esteem (Bekhet et al., 2008).

Dependent variable

Well-being: Well-being is defined as "the state of being well" (Kitayama & Markus, 2000). Wellbeing refers to a positive state of life in which individuals feel good about themselves and their circumstances. It includes having self-worth, maintaining social connections with others, achieving accomplishments, and having a sense of purpose in life. Wellbeing also involves being satisfied with one's current situation while maintaining an optimistic outlook toward the future (Netemeyer et al., 2018).

FINDINGS AND DISCUSSION

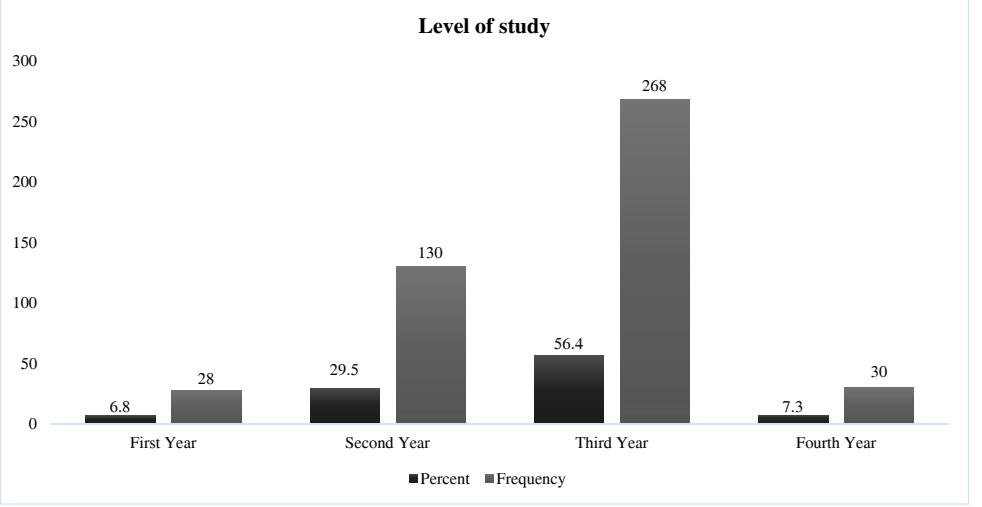
Findings

Demographics responses: Table 3 results show that the majority of the respondents used more than 4 hours/day on social media (87.7%, n = 348), followed by 2–4 hours (10.8%, n = 43) and only a few respondents used less than 2 hours/day (1.5%, n = 6). The age distribution

Table 3
Demographic description of respondents

		Frequency	Percent	Cumulative Percent
Average daily time spent on social media	Less than 2 hours	6	1.5	1.5
	2-4 hours	43	10.8	12.3
	More than 4 hours	348	87.7	100
Age group	Below 20	131	33	33
	20-24	249	62.7	95.7
	Above 24	17	4.3	100
	Total	397	100	

Figure 2
Distribution of respondents by level of study

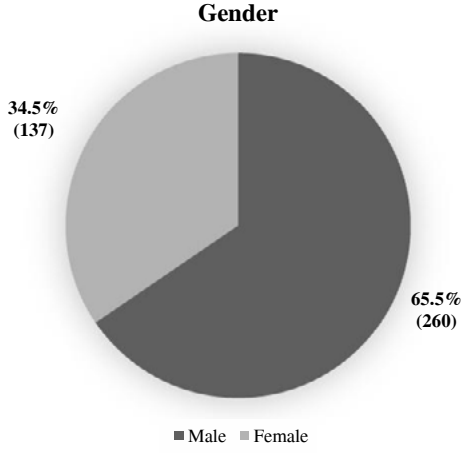


of respondents was dominated by the 20–24 years age group (62.7%, n = 249), followed by those below 20 years (33.0%, n = 131) and only 4.3% (n = 17) were above 24 years of age. Sample size was 397 (100%). Figure 2 shows the distribution of respondents by level of study.

In Figure 2, Most of the respondents were third year students, comprising 56.4% (n=268) of the total respondents. Second year students were next with 29.5% (n = 130) of the respondents. A smaller percentage, 7.3% (n = 30), were in their fourth year. The respondents were 6.8% (n = 28) first-year students. This distribution gives an idea of the representation of the levels of study of the undergraduates surveyed.

Figure 3 shows the chart was divided into two segments representing male and female respondents. The largest segment corresponds to male respondents, comprising 65.5% of the total sample, while female respondents account for 34.5%. This visual representation provides a clear overview of the gender composition of the surveyed population, with male respondents representing the majority of the participants.

Figure 3
Distribution of respondents by gender



Descriptive analysis: In Table 4, the average social media activities score is 4.6035, with

Table 4
Descriptive statistics

Statistics	Social media activities	Loneliness	Well-being
N	397	397	397
Mean	4.60	4.43	3.89
Median	5	4.6	4.2
Mode	5	5	5
Std. Deviation	0.73	0.92	1.19
Variance	0.53	0.83	1.43

Table 5
Correlational analysis

Variable		SMA	L	WB
Social media activities	Pearson Correlation	1		
	Sig. (2-tailed)			
Loneliness	Pearson Correlation	0.641***	1	
	Sig. (2-tailed)	(0.001)		
Well-being	Pearson Correlation	0.276***	0.181***	1
	Sig. (2-tailed)	(0.001)	(0.001)	

*** *Correlation is significant at the 0.001 level (2-tailed).*

a median and mode of 5. The standard deviation is 0.72967 and the variance is 0.532. This shows that respondents reported high social media activities in general. The mean loneliness score is 4.4322, the median is 4.6 and the mode is 5. Standard deviation is 0.91252. Variance is 0.833. This indicates a relatively high level of loneliness was reported by respondents in general. Well-being also has a mean of 3.8922, a median of 4.2 and a mode of 5. The standard deviation is 1.19733 and the variance is 1.434. Thus, participants reported a moderate-to-high level of well-being, but responses were more variable than for social media activities and loneliness. Generally, the mean values of the three study variables ranged between 3.8922 and 4.6035 on the five-point Likert scale. The highest mean was found for social media activities (4.6035) followed by loneliness (4.4322) whereas the lowest mean was for well-being (3.8922).

Correlations analysis: As shown in Table 5, social media activities (SMA) and loneliness (L) were positively correlated and statistically significant ($r = 0.641$, $p < .01$). So, more social media users are more likely to report more loneliness. Social media activities were also positively correlated with well-being (WB) ($r = 0.276$, $p < .01$). Loneliness was also positively correlated with well-being ($r = 0.181$, $p < .01$).

Regression analysis: The result of Table 6 present that the model 1 is statistically significant ($F = 276.0571$, $p < .01$) and accounts for 41.14% of the variance in

Table 6
Direct effect of the social media activities on loneliness

Variables	Coefficient	Se	T	P	LLCI	ULCI
Constant	0.7397	0.225	3.2872	0.0011	0.2973	1.182
SMA	0.8021	0.0483	16.615	(0.001)	0.7072	0.897
F-statistics	276.0571	R=0.6414	R^2=0.4114	df_1=1.0000	df_2=395.000	
P value	(0.001)	MSE=0.4914				

Table 7
Direct effect of the independent and mediating variables on well-being

Variables	Coefficient	Se	T	P	LLCI	ULCI
Constant	1.8015	0.3754	4.7991	(0.001)	1.0635	2.5395
SMA	0.4451	0.1036	4.2972	(0.001)	0.2414	0.6487
L	0.0094	0.0828	0.114	0.9093	-0.1534	0.1723
F-statistics	16.2306	R=0.2759	R^2=0.0761	df_1=2.0000	df_2=394.000	
P value	(0.001)	MSE=1.3312				

loneliness (R^2 = 0.4114). Thus, social media activities (SMA) make up a significant proportion of the differences in respondents' loneliness. The study found that social media activities have a positive and statistically significant effect on loneliness (a = 0.8021, p < .01). *Table 7* shows the direct effects of the independent variable and loneliness on well-being.

In Table 7, the model 2 is statistically significant (F = 16.2306, p < .01), and (R^2 = 0.0761) explains 7.61% of the variance in well-being. The social media activities (SMA) positively and significantly impact well-being (c' = 0.4451, p < .01). However, loneliness (L) does insignificantly impact well-being (b = 0.0094, p = .9093). Table 8 shows the total effect model of independent variable on well-being

In Table 8, the results showed the whole model 4 is statistically significant (F = 32.5296, p <.01) and (R^2 = 0.0761) accounted for 7.61% of the variance of well-being. Total effect of social media activities (SMA) on well-being was positive and statistically significant (r = 0.4526, p <.01). *Table 9* presents the indirect effect model.

Table 9 shows the indirect effect of social media activities (SMA) on well-being (WB) through loneliness (L) had an insignificant effect (effect = 0.0076, t = 0.1009). Table 10 presents the direct, total, and indirect effects of independent variable on well-being through loneliness.

Table 10 shows the results show that social media activities (SMA) have a significant direct effect on well-being (WB) which supports H_1. The indirect effect of social media activities on well-being via loneliness (L) was also insignificant. The indirect effect was not significant and so the H_2 hypothesis was rejected. But the total effect of social media activities on well-being is significant which supports H_3. So, there was the

Table 8
Total effect model

Variables	Coefficient	Se	T	P	LLCI	ULCI
Constant	1.8085	0.3699	4.8892	(0.001)	1.0813	2.5357
SMA	0.4526	0.0794	5.7073	(0.001)	0.2966	0.6087
F-statistics	32.5296	R= 0.2758	R^2= 0.0761	df_1=1.0000	df_2=395.000	
P value	(0.001)	MSE= 1.3279				

Table 9
Indirect effect model

Independent variables	Mediating variable	Effect	BootSE	BootLLCI	BootULCI	t-statistics
SMA	L	0.0076	0.0753	-0.1638	0.1357	0.1009

Table 10
Mediation analysis summary

Variables effect	Direct effect	Total effect	Indirect effect	Relationship	Conf. Interval		t-statistics	Conclusion
					Lower Bound	Upper Bound		
SMA→ WB	0.4451 (0.001)	0.4526 (0.001)	0.0076	SMA→L→ WB	-0.164	0.136	0.1009	Full mediation

insignificant and significant effect of direct, total and indirect effect which represents full mediation.

Discussion

Social media activities (SMA) have significant positive effect on loneliness. This is similar with findings of Jia et al. (2024); Alzain et al. (2025); Ayhan and Eroğlu (2025); Koçak et al. (2025); Wan and Zhou (2025) but contradicts with Gregory et al. (2023); Munegowda & Donni (2024); Simmons et al. (2023); Matthews et al. (2025) who found insignificant relation. Furthermore, the positive effect of social media activities on well-being was significant. In addition, loneliness had an insignificant effect on well-being, which is opposite to the findings of Saini (2025); Wan and Zhou (2025). Finally, the mediating effect of loneliness between social media activities and well-being is insignificant, which was different from the results of Wan and Zhou (2025) that found a significant partial mediating effect.

CONCLUSION

The present study was conducted to examine the relationship between social media activities and well-being and the mediating role of loneliness among undergraduate IT students in Baluwatar. Results showed that social media activities had a significant direct and total effect on well-being. Furthermore, social media activities had a significant effect on loneliness, whereas loneliness had an insignificant effect on well-being. The findings suggest that an increase in social media activities is associated with

an increase in loneliness, while social media activities also have a significant relationship with well-being. This implies that loneliness has an insignificant mediating effect on the relationship between social media activities and well-being. The results provide support for Social Comparison Theory, which explains how individuals may evaluate themselves by comparing their lives, experiences, and social status with others, particularly through social media. In real life, frequent engagement with social media may expose undergraduate IT students to continuous social comparisons, which may contribute to increased feelings of loneliness and influence their well-being. Thus, developing awareness of social comparison and maintaining balanced social media use may help reduce feelings of loneliness and contribute toward better well-being.

IMPLICATIONS

The findings indicate that undergraduate IT students, educational institutions and social media users need to be more aware of the impact of social media activities on social and emotional experiences. Therefore, the study recommends that students should balance their online and offline social contacts and engage in meaningful social media use, given the significant association between higher social media activity and loneliness. Colleges could undertake digital wellness campaigns to promote positive social media behavior. Social media users also need to be aware of how their online behavior can contribute to sensations of loneliness. Other factors such as social comparison and fear of missing out, social support, self-esteem and quality of online interactions should be considered.

However, this research has some limitations. The study had a geographical limitation, as the sample was collected from a limited geographical area. Therefore, the findings may not fully represent the undergraduate IT students or the general population of Nepal, and may have limited generalizability to other geographical areas, institutions, or student groups. There may have been selection bias because of the study's convenience sampling. Secondly, the study only examined social media behaviors, loneliness and well-being, and other variables such as social anxiety, depression, fear of missing out, self-esteem, social comparison, and academic stress may also influence the relationship between these variables. Also, Loneliness, however, did not appear to serve as a relevant mediator of the association between social media activities and well-being. The study was also based on self-report data which might be influenced by perception and recall of the respondents. Finally, the cross-sectional design does not permit to study changes over time in social media activities, loneliness and well-being, or strong causal relations. Future research should consider employing larger and more diverse samples, probability sampling, longitudinal designs, and additional variables to further clarify these relationships.

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ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Sleep pattern and academic performance: *Examining the role of sleep quality, duration, bedtime, and wake-up time in undergraduate IT students in Kathmandu*

Sampanna Barakoti
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
ba.sampanna23@ncmt.edu.np

Received: 18 Aug., 2026 | Revised: 12 Sept., 2026 | Accepted: 8 Oct., 2026

Abstract: *The purpose of the study was to see the effect of independent variables of sleep quality, sleep length, bed & wake-up time on dependent variable of academic performance of undergraduate Information Technology (IT) students in Kathmandu. Irregular sleep patterns and sleep deprivation are on the rise among university students; however, sleep is critical to students' cognitive performance, ability to learn, attention, and overall academic achievement. The work was based on the Sleep-Wake Regulation Theory. The study tested alternative hypotheses to examine the effects of sleep quality, sleep duration, and bed & wake-up time on academic performance among undergraduate IT students. Descriptive, correlational and relational research designs were used in the quantitative research method. The target population was undergraduate IT students of Kathmandu and primary data was collected from 403 respondents using the convenience sample technique. Primary data was collected with a standardized questionnaire, administered directly through Google Forms. Data analysis was performed by SPSS including descriptive statistic, Pearson correlation analysis and linear regression analysis. The results showed that academic achievement was positively related to sleep quality, sleep duration, bed & wake-up time. In addition, sleep duration, bed & wake-up time were found to have a significant positive effect on academic performance whereas sleep quality was not found to have a significant effect. The findings suggest that adequate sleep and a consistent sleep routine may help students perform better in their academics. This highlights the need to encourage good sleep hygiene among university students. The study was limited to undergraduate IT students, convenience sampling and self-reported data were used in the study. Other characteristics such as stress, mental health or study habits which may influence academic performance were not considered.*

Keywords: Academic performance, bed & wake-up time, sleep duration, sleep quality

JEL Classification: II23, I21, I10, J24

Cite as: Barakoti, S. (2026). Sleep pattern and academic performance: Examining the role of sleep quality, duration, bedtime, and wake-up time in undergraduate IT students in Kathmandu. *NCMT Journal of Multidisciplinary Studies, 1*(1), 119-136.

INTRODUCTION

Sleep is the natural biological process that every individual must undergo for their psychological, emotional, and physical well-being as well as in the performance of certain cognitive functions, such as remembering things or making decisions. Quality of sleep can be measured both quantitatively and qualitatively (Giri et al., 2013). Sleep is necessary for the processes of recovery, functioning of the brain, controlling one's emotions, etc. Nowadays, problems connected with sleep are considered one of the most significant problems in terms of public health among the adolescent population. When it comes to the effective usage of sleep, it is stated that adolescence (10-24 years old) is the period full of various changes that condition significant alterations connected with sleeping patterns. Among the high school students, only some of them sleep the recommended 8-10 hours (Zhang et al., 2021). The late beginning of classes at school, pressure in schools, and use of different gadgets before bedtime foster the occurrence of sleeping problems.

Students who don't get enough sleep often report common mental health problems, which many will likely need assistance to successfully address. Poor quality of sleep has an impact on various areas of behavior, including executive function, hormone balance, emotional regulation, and attentiveness. A variety of distinct anomalies were found in numerous investigations that tried depriving small groups of healthy people of all sleep for one or two nights (Sutton, 2014). University students frequently struggle with poor sleep quality, which negatively impacts their academic performance (Lemma et al., 2013). Poor sleep quality was twice as common among university students as it was in the general population. Most research looking at the impacts of sleep quality and duration with bed time and wake-up time on academic performance have connected longer and better quality sleep with better academic performance such as school grades and study effort. Similarly, sleep irregularity plays a part in academic achievement. Sleep inconsistency (social jet lag) is defined by inconsistency in sleep pattern and/or duration from day to day. It is generally observed in the form of sleep debt during weekdays followed by oversleep on weekends. Adolescents and young adults who stay up late but have rigid morning schedules are more likely to experience sleep irregularities. Adolescents who have greater sleep irregularity perform worse in school (Lee et al., 2015).

A large number of students experience irregular sleep patterns, inadequate sleep, poor sleep quality and irregular sleep and wake times due to academic and lifestyle pressures. These sleep variables can have a profound impact on students' concentration, memory and academic performance. Thus, this study aims to investigate the association between sleep pattern, sleep quality, sleep duration, bedtime, wake-up time and academic performance of students.

Previous studies examining the relationship between sleep quality, sleep duration, bedtime, wake-up time, and academic performance have primarily focused on medical students and other health-related student populations (BaHammam et al. 2012; Siraj et al., 2014; Siddiqui et al., 2016). However, limited research has been conducted among Information Technology (IT) students, despite the unique academic demands and technology-driven lifestyles associated with this field. Furthermore, most prior studies have been carried out in

countries outside Nepal, resulting in a lack of context-specific evidence regarding the sleep behaviors and academic performance of Nepalese students. In addition, many previous studies have employed qualitative research approaches whereas this study used quantitative approach on this topic. Nonetheless, no study has comprehensively examined the relationship between sleep quality, sleep duration, bedtime, wake-up time, and academic performance among IT students in Nepal using a quantitative approach, making this one of the inaugural studies to investigate this specific context. Therefore, this study was conducted to address this research gap.

Research questions

- Is there any relationship between sleep quality, sleep duration, bedtime & wake-up time, and academic performance?
- Do sleep quality, sleep duration, bedtime & wake-up time affect academic performance?

Objectives

The main objective of this research is to investigate the factors like sleep quality, sleep duration, wake-up & bedtime, influencing academic performance among undergraduate IT students in Kathmandu. Furthermore, the particular aims are outlined as follows:

- To examine the relationship between sleep quality, sleep duration, bedtime & wake-up time, and academic performance.
- To analyze the effect of sleep quality, sleep duration, bedtime & wake-up time on academic performance.

LITERATURE REVIEW

Theoretical review

Sleep-Wake Regulation Theory: Sleep-wake regulation theory was developed by Borbely (1982). The two processes model of sleep regulation indicates that there are two processes that regulate sleep: one is "sleep pressure" and the other is "circadian rhythm". The sleep-wake regulation theory states that to attain adequate sleep duration, good sleep quality and an established sleep and wake schedule for the body and brain to achieve proper recovery and rest. The sleep-wake regulation theory theorizes that sleeping is governed by the interplay of an individual's circadian rhythm and their body's sleep drive (Nakie et al., 2024). Thus, maintaining an adequate quantity of sleep, a good quality of sleep, and consistent bedtimes and rise times contributes to appropriate recovery/rest from sleep for both brain and body. When students consistently sleep with enough quality, quantity, and regularity, they experience improvements in their attention, memory, concentration, and information processing abilities (cognitive functioning), which in turn correlates to improved learning outcomes and overall better academic performance (Hosokawa et al., 2022). In contrast, poor-quality sleep, insufficient quantity of sleep, having irregular bedtimes, and having irregular morning wake times has a negative impact on the sleep/wake cycle causing a reduction in cognitive functioning therefore negatively impacting their academic success.

Empirical review

Sleep quality and academic performance: Siddiqui et al. (2016) evaluated sleep patterns and predictors of poor sleep quality among medical students in King Khalid University in Saudi Arabia. ANOVA and independent sample t-test identified sleep

Table 1
Summary of prior studies

Author (s)	Year	Country	Methodology	Findings
Seun-Fadipe and Mosaku	2017	Nigerian	Correlation study	Revealed the academic performance of students with good sleep quality was significantly better than those with poor sleep quality
Lawson et al.	2019	Ghana	Chi square test/ Correlation study	Found sleep quality during lectures were statistical significantly related with academic performance scores
Maheshwari and Shaukat	2019	Pakistan	Correlation survey	Encountered lower GPA had very bad subjective sleep quality.
Okano et al.	2019	USA	Correlation survey	Noticed sleep quality is significantly related with academic performance scores.
Alfonsi et al.	2020	Italy	Longitudinal measures	Observed quality was not significantly related to academic performance.
Jalali Khazaei et al.	2020	Iran	Correlation test	Reported Subjective sleep quality was not significantly related with academic outcomes among the students.
Rodrigue et al.	2020	Ecuador	Logistic regression	Reported significant statistical differences in sleep quality according to academic performance.
Toscano-Hermoso et al.	2020	Spain	Independent sample t test	Devised Sleep quality was statistical significantly related with academic performance scores.
Gallego-Gómez et al.	2021	Spain	Logistic regression	Found sleep quality was statistical significantly related with academic performance scores
Kalbacher and Randler	2024	Germany	Correlations survey	Showed the sleep quality was statistical significantly related with academic performance scores.
Nakie et al.	2024	Dominican Republic, Egypt, Guyana, India, Mexico, Pakistan, and Sudan	Egger's test	Found poor sleep quality is significantly related to academic performance of university student of Africa.
Razaq et al.	2024	Pakistan	Correlation study	Showed that there was high frequency of stress and poor sleep quality with significant association study

Author (s)	Year	Country	Methodology	Findings
Khaled et al.	2025	Saudi Arabia	Multivariate regression	Reported insufficient sleep quality was not significantly affected by factors like gender, different age groups, number of courses per semester, daytime sleeping, and students with varying Grade Point Averages.
Xu et al.	2025	China	Correlation analysis	Identified effect of sleep quality on learning engagement is significant.
Nzamwita et al.	2026	Rwanda	Linear regression analysis	Observed the sleep quality was negative and statistical significantly related with reduced academic performance scores

duration, sleep quality, sleep efficiency, sleep latency are significantly related with academic performance scores.

H_1: *Sleep quality has a positive or negative and significant effect on academic performance.*

Sleep duration and academic performance: BaHammam et al. (2012) examined relationship between sleep and wake habits and academic performance in medical students: A cross-sectional study in Saudi Arabia. The regression analysis result found that sleep duration has significant relation with academic performance scores.

H_2: *Sleep duration has a significant impact on academic performance.*

Bedtime & wake-up time and academic performance: BaHammam et al. (2012) examined relationship between sleep and wake habits and academic performance in medical students: A cross-sectional study in Saudi Arabia. The regression analysis result found that bed & wake-up time have significant relation with academic performance scores.

H_3: *Bedtime & wake-up time has a significant influence on academic performance.*

Based on the literature review, the study developed the conceptual framework presented on *figure 1*

METHODOLOGY

Research design

The study employed a deductive research approach. The research philosophy applied for the study was positivist. The study adopted quantitative research design. The study combined explanatory, relational and descriptive research methods. A descriptive research design was used to describe the basic characteristics of the variables under study (Budhathoki et al., 2024). The relationship between antecedent and consequent factors was examined as a research design by employing the relational research design (Budhathoki et al., 2023). The study used an explanatory research design, to investigate the effect of independent variables on dependent variables (Budhathoki et al., 2025).

Table 2
Summary of previous studies

Author (s)	Year	Country	Methodology	Findings
Siraj et al.	2014	Malaysia	ANOVA	Discovered sleep duration is statistical significantly related with academic performance.
Kabrita and Hajjar-Muça	2016	Lebanon	Correlation survey	Showed sleep duration was significantly related to academic performance.
Siddiqui et al.	2016	Saudi Arabia	ANOVA and independent sample t-test	Identified sleep duration is significantly related with academic performance scores.
Maheshwari and Shaukat	2019	Pakistan	Correlation survey	Encountered lower GPA had very bad subjective sleep duration
Okano et al.	2019	USA	Correlation survey	Noticed sleep duration is significantly related with academic performance scores.
Alfonsi et al.	2020	Italy	Longitudinal measures	Observed total sleep time was not significantly related to academic performance.
Rodrigue et al.	2020	Ecuador	Logistic regression	Reported significant statistical differences in sleep duration according to academic performance.
Toscano-Hermoso et al.	2020	Spain	Independent sample t-test	Devised sleep duration was statistical significantly related with academic performance scores.
Gallego-Gómez et al.	2021	Spain	Logistic regression	Found sleep duration was statistical significantly related with academic performance scores
Kalbacher and Randler	2024	Germany	Correlation survey	Showed the sleep duration was statistical significantly related with academic performance scores.
Xu et al.	2025	China	Correlation analysis	Identified effect of sleep duration on learning engagement is significant.
Nzamwita et al.	2026	Rwanda	Linear regression analysis	Observed the sleep duration was negative and statistical significantly related with reduced academic performance scores
Saha et al.	2026	Bangladesh	Chi-square test	Spotted the sleep duration was statistical significantly related with academic performance scores.

Table 3
Summary of earlier studies

Author (s)	Year	Country	Methodology	Findings
Kabrita and Hajjar-Muça	2016	Lebanon	Correlation survey	Showed bedtime & wake-up time was significantly related to academic performance.
Lawson et al.	2019	Ghana	Chi-square test/ Correlation study	Spotted bedtime & wake-up time during lectures were statistical significantly related with academic performance scores
Okano et al.	2019	USA	Correlation survey	Noticed bedtime & wake-up time is significantly related with academic performance scores.
Alfonsi et al.	2020	Italy	Longitudinal measures	Observed total bedtime & wake-up time was not significantly related to academic performance.
Jalali Khazaei et al.	2020	Iran	Correlation test	Reported Subjective bedtime & wake-up time was not significantly related with academic outcomes among the students.
Xu et al.	2025	China	Correlation analysis	Identified effect of bedtime & wake-up time on learning engagement is significant.
Saha et al.	2026	Bangladesh	Chi-square test	Spotted the bedtime & wake-up time was statistical significantly related with academic performance scores.

Population and sample

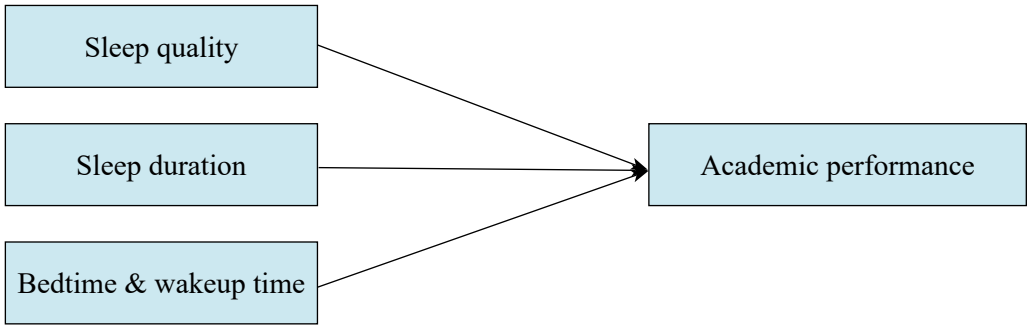
The study's target population was the undergraduate students enrolled in the IT Faculty in Kathmandu, taking different IT courses. The population was considered to be infinite because the exact number of IT students in the study region was not known and was constantly changing. Therefore, the convenience sampling method was used to select 403 respondents who were required to be Kathmandu-based IT faculty students. Cochran's methods were used to compute the sample size when the population size was unknown but expected to be large (Cochran, 1977). The following is the Cochran's formula:

$$n = \frac{z^2 * p * q}{e^2}$$

(Where, n = required sample size (384), Z = Z-value (e.g., 1.96 for 95% confidence level), p = estimated proportion (0.5 if unknown), q = 1 – p, e = margin of error (5%))

Using Google Forms, a structured survey with closed-ended questions was created and disseminated via Facebook, Instagram, WhatsApp, Messenger, and other social media sites from July 24 to August 5, 2026.

Figure 1
Conceptual framework



Note. Okano et al. (2019); Alfonsi et al. (2020); Xu et al. (2025).

Table 4
Reliability test

Variable Dimension	Number of Items	Cronbach's Alpha
Sleep quality	5	0.843
Sleep duration	5	0.866
Bedtime & wake-up time	5	0.908
Academic performance	5	0.803

Sources of data and analysis tools

Primary data were collected mainly through a structured questionnaire with closed-ended questions. The data were collected using a questionnaire on Google Forms which was then distributed to the intended respondents through several social media platforms. The measurement items on the questionnaire were measured on a five-point Likert scale. Primary data were analyzed using the Statistical Package for the Social Sciences (SPSS program, IBM SPSS Statistics Version 32.0.0.0 (134).

Table 4 shows the reliability test of the respondent. A pilot study was conducted on fifty students by using a Google Form questionnaire to test its reliability and effectiveness. The Cronbach's alpha coefficients of the constructs of the study (sleep quality, 0.843; sleep duration, 0.866; bed & wake-up time, 0.908; academic performance, 0.803) were calculated and presented. The computed alpha values were all greater than the usual threshold of 0.7, indicating a high degree of internal consistency among the variables measuring each construct.

Analytical model

The cause-and-effect correlations between antecedent and succeeding variables were assessed in this study using the regression model. The model was used in the previous study by (Budhathoki et al., 2025).

$$Y = i + a_1x_1 + a_2x_2 + a_3x_3 + e$$

(Where, a_1-a_3 = Coeficient of antecedent variable, x_1 = Sleep quality, x_2 = Sleep

duration, x_3 = Bedtime & wake-up time, e = Error term, i = Constant, Y= Academic performance of students).

Definition of variable

Independent variable

Sleep quality: According to Vijayan et al. (2025), sleep quality refers to one's personal contentment with every dimension of the sleep process. Sleep quality entails different aspects, such sleep latency (which is the amount of time it takes a person to fall asleep), sleeping time (the amount of time one is asleep in total), sleep stability (the ability to remain sleeping through the whole night), and sleep depth (the feeling of being rested and fresh upon waking up from sleep) (Vijayan et al., 2025). The definition of sleep quality is the extent to which the sleep one gets is recuperative and brings one back to life. It's not only about the amount of sleep a person gets but also about how efficiently the body and the brain go through the natural sleep cycles with no major interruptions. High sleep quality implies that a person manages to sleep without interruptions and get restorative sleep, whereas low sleep quality situation may involve trouble falling asleep, frequent night awakenings, or waking up in a tired state. Sleep quality is viewed as an important factor influencing physical health, emotional state, mental activity, and success in studies given that it influences attention, concentration, memory, and learning abilities.

Sleep duration: Sleep duration generally refers to the total amount of sleep obtained either during the nocturnal sleep episode or over the 24-h period (Kline, 2013). Sleep duration is the amount of time a person sleeps (Lee et al., 2023). There are several factors that can influence the duration of sleep. They are: Age, Lifestyle habit, Stress, mental health, work, environment and Social Obligation. Getting enough sleep helps the body and brain recover from daily activities, aids in memory consolidation, improves cognitive functioning, and helps regulate emotions. In contrast, inadequate sleep duration can result in tiredness, lack of focus, poor decision-making, and lower academic achievement. Adequate sleep is especially important for students because learning, information processing, and academic success are highly dependent on adequate rest.

Bedtime & wakeup time: Bedtime (also known as putting to bed or tucking in) is a parenting ritual that helps children feel more secure, and also to get used to a more rigid sleep schedule than they might otherwise prefer (Scoresby, 2000). Regular bedtimes maintain the body's internal biological clock, the circadian rhythm, which controls sleep and wakefulness. As a rule, going to bed early and at the same time is connected with better quality and longer sleep, while going to bed late or at irregular times can disturb the normal pattern of sleep and lessen its quality. Bedtime among students can be affected by academic workload, social activities, technology use, and lifestyle factors, and can impact academic performance.

The wake-up time determines when one wakes up. Waking up early makes our brain fresh, resulting in better performance in the studying process. The wake-up time is an essential part of the sleep-wake cycle and has an important effect on the regulation of the circadian cycle. Waking up at the same time guarantees the establishment of sleep patterns and good quality of sleep; whereas, waking up on an irregular basis can be a reason for sleeping problems during the night as well as fatigue during the day. The

wake-up time may influence not only the total duration of sleep but also the level of alertness, concentration, and effectiveness during the whole day.

Dependent variable

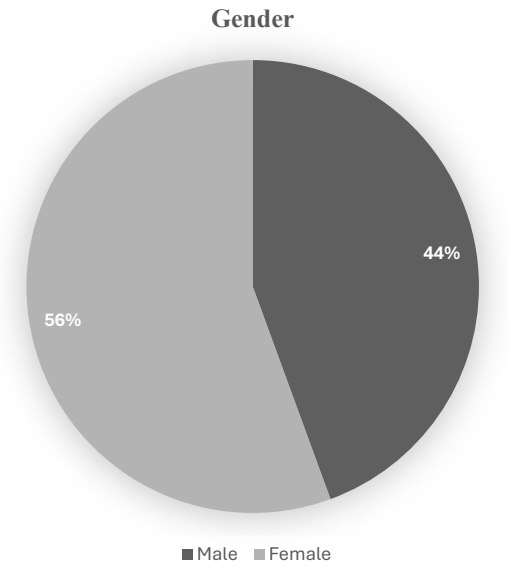
Academic performance: Academic performance refers to the measure of student achievement in academic subjects. Typically, teachers and education officials use classroom performance, graduation rates and results of standardized tests to assess achievement (Surbano, 2020). Academic performance is the measure of students' progress and success in their studies, which can be evaluated by self-reported metrics or objective indicators such as graduation marks and time to graduation (Souto-Otero et al., 2023). Academic performance is the ability of a student to acquire knowledge, understand concepts, apply learning and meet educational requirements (Singh et al., 2012). There are a number of factors such as study habits, motivation, learning environment, and health issues such as sleep that affect academic performance. The dependent variable in this study is academic performance and it is studied against sleep quality, sleep duration, bedtime and wake-up time.

FINDINGS AND DISCUSSION

Findings

Demographics responses: The distribution of gender of participants is represented in *Figure 2*. Among 403 respondents, 224 respondents (55.6%) were female respondents and 179 respondents (44.4%) were male. The outcome shows that the majority of the respondents were females, because male respondents were in lesser number than female counters in the sample. The distribution of genders is more or less equal and results in readiness of the survey to produce details to find out the impact of sleep patterns on academic performance.

Figure 2
Gender of the respondents



The distribution of semester of participants is represented in Figure 3. The fourth semester has the highest number of the sample with 93 (23.1%) of the total respondents. Next was the sixth semester, with 65 responders (16.1%). In contrast, 64 respondents (15.9%) were from the fifth semester, 55 respondents (13.6%) were from the first semester, 53 respondents (13.2%) were from the second semester, 52 respondents (12.9%) were from the seventh semester, 17 respondents (4.2%) were from the third semester and 4 respondents (1%) were from the eighth semester.

The distribution of age of participants is represented in *Figure 4*. The majority of respondents, 186 (46.2%), belonged to the 21-23 years age group, making it the largest segment of the sample. This was followed by 136 respondents (33.7%) aged 18-20 years. Meanwhile, 81 respondents (20.1%) were

Figure 3
Semester of the respondents

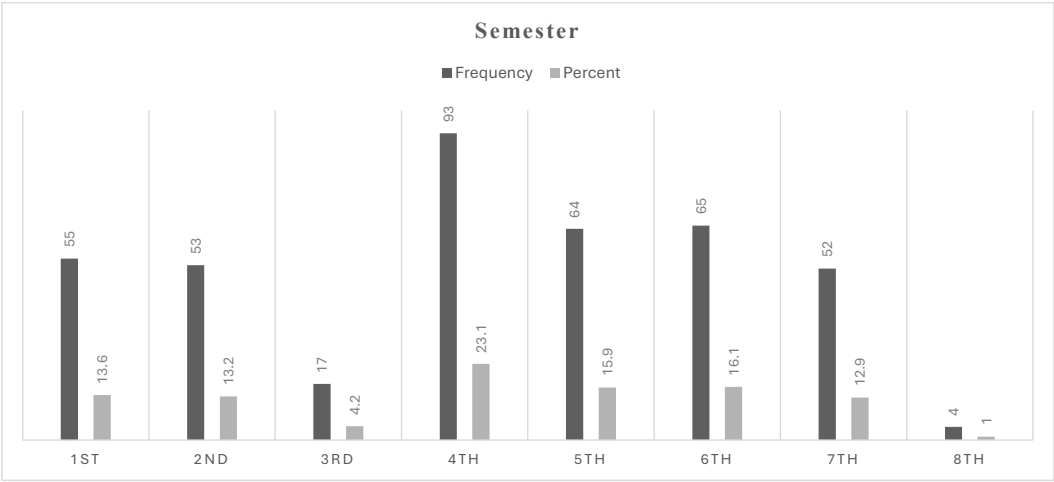
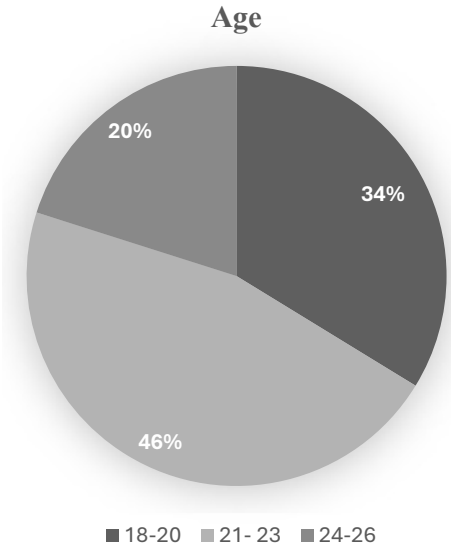


Figure 4
Age of the respondents



between 24–26 years, while no age group of respondents were above 26.

The distribution of current living arrangement of the respondents is represented in *Table 5*. The majority of respondents, 140 (34.7%), lives with family, making it the largest segment of the sample. This was followed by 114 respondents (28.3%) living in rent room. Meanwhile, 89 respondents (22.1%) lives with relatives, while 60 respondent (14.9%) lives in hostel.

The findings in *Table 6* show the descriptive analysis of 403 respondents shows that most of the students (57.8%) sleep for 5–6 hours a night while 39.7% sleep for 7–8 hours. The majority of the respondents (66.0%) usually wake-up from 5:00 AM to 6:00 AM, showing the early waking pattern. As far as academic performance is concerned majority (76.7%) have CGPA between 3.2 and 3.6, 17.1% have CGPA more than 3.6. Pre-sleep electronic device use was very common, with 57.1% of the participants reporting always and 39.7% often use of devices before sleeping. More than half of the respondents (51.6%) spend 4–6 hours daily on electronic devices for non-academic purposes.

Descriptive analysis: *Table 7* shows mean scores indicate sleep duration has the highest mean score of 3.02, while bedtime & wake-up

Table 5
Current living arrangement of the respondents

Current Living Arrangement	Frequency	Percent	Cumulative Percent
With family	140	34.7	34.7
Hostel	60	14.9	49.6
Rent room	114	28.3	77.9
With relatives	89	22.1	100
Total	403	100	

Table 6
Basic information of the respondents

		Frequency	Percent	Cumulative percent
On average, how many hours do you sleep per night?	Less than 5 hours	6	1.5	1.5
	5–6 hours	233	57.8	59.3
	7–8 hours	160	39.7	99
	More than 8 hours	4	1	100
What time do you usually wake up?	Before 5:00 AM	3	0.7	0.7
	5AM – 6 AM	266	66	66.7
	6 AM – 7 AM	121	30	96.8
	After 7:00 AM	13	3.2	100
What is your current CGPA/GPA?	Below 2.7	5	1.2	1.2
	2.7 – 3.2	20	5	6.2
	3.2 – 3.6	309	76.7	82.9
	Above 3.6	69	17.1	100
How often do you use electronic devices (phone, laptop, tablet) before sleeping?	Never	3	0.7	0.7
	Rarely	3	0.7	1.5
	Sometimes	7	1.7	3.2
	Often	160	39.7	42.9
	Always	230	57.1	100
How many hours per day do you spend using electronic devices outside of academic purposes?	Less than 1 Hour	1	0.2	0.2
	2-4 Hours	109	27	27.3
	4-6 Hours	208	51.6	78.9
	6-8 Hours	71	17.6	96.5
	More than 8 Hours	14	3.5	100

time had the lowest score of 2.72. The median figures show a range of 2.60-3.0 for all variables. The mode was found to be equal to 3 for all items which means the most common category for responses was 3. Further analysis of standard deviation revealed that it ranged from 0.499 to 0.796, indicating a moderate level of variability in the responses given.

Correlation analysis: As shown in the *Table 8*, a positive and significant correlation is observed between sleep quality and academic performance ($r = 0.263$, $p < 0.01$). This shows that the better the quality of sleep, the better the academic performance. Similarly, the relationship between sleep duration and academic performance is

Table 7
Descriptive statistics

Statistics/variables	SQ	SD	BWT	AP
N	403	403	403	403
Mean	2.79	3.02	2.72	2.9
Median	2.8	2.8	2.6	3
Mode	3	3	3	3
Std. deviation	0.796	0.499	0.543	0.568
Variance	0.634	0.249	0.295	0.322

Table 8
Correlation analysis

Variables		SQ	SD	BWT	AP
Sleep quality	Pearson Correlation	1			
	Sig. (2-tailed)				
Sleep duration	Pearson Correlation	.375***	1		
	Sig. (2-tailed)	(.001)			
Bedtime and wake-up time	Pearson Correlation	.172***	.559***	1	
	Sig. (2-tailed)	(.001)	(.001)		
Academic performance	Pearson Correlation	.263***	.720***	.535***	1
	Sig. (2-tailed)	(.001)	(.001)	(.001)	

*** *Correlation is significant at the 0.001 level (2-tailed).*

found to be positive and significant ($r = 0.720$, $p < 0.01$). indicating strong positive relationship between sleep duration and academic performance. Correlation between bedtime and wake-up time and academic performance is positive and significant ($r = 0.535$, $p < 0.01$). It demonstrates that regularity in bedtimes and wake times is positively associated with academic achievement.

Regression analysis: *Table 9* shows the impact of independent variable on dependent variable. The impact of sleep quality was found to be statistically insignificant ($r = 0$, $p = 0.991$), rejecting the alternative hypothesis (H_1). The coefficient of sleep quality ($B = 0.000$) indicates that sleep quality has no significant effect on academic performance among the respondents. Although sleep quality showed a positive and significant correlation with academic performance, it was found to have no significant effect in the regression analysis. Sleep-related variables, especially duration, may share variation and multicollinearity, explaining this disparity. Thus, sleep quality is connected with academic achievement at the bivariate level, but its contribution is insignificant when other variables are examined.

The impact of sleep duration is found to be positive and highly significant ($r = 0.696$, $p < 0.01$), accepting the alternative hypothesis (H_2). Similarly, bedtime and wake-up time have a positive and significant impact on academic performance ($r = 0.202$, $p < 0.01$),

Table 9
Regression analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.249	0.126		1.969	0.05
Sleep quality	0	0.026	0	0.011	0.991
Sleep duration	0.696	0.049	0.612	14.112	.001
Bedtime and wake-up time	0.202	0.043	0.193	4.738	.001
Adjusted R	0.541	F	158.885	Sig.	.001

accepting the alternative hypothesis (H_3). The overall regression model is statistically significant ($F = 158.885$, $p < 0.01$), indicating the model was fitted. The adjusted R^2 value of 0.541 shows that 54.1 percent of the variation in academic performance is explained by independent variables, while the remaining 45.9 percent is explained by other factors not included in the model. The linear equation is estimated as follow:

$$Y = 0.249 + 0X_1 + 0.696X_2 + 0.202X_3 + e$$

Discussion

Regression results show that sleep quality has insignificantly impact on academic performance. The result was inconsistent with Seun-Fadipe and Mosaku (2017); Lawson et al. (2019); Maheshwari and Shaukat (2019); Okano et al. (2019); Rodrigue et al. (2020); Toscano-Hermoso et al. (2020); Gallego-Gómez et al. (2021); Kalbacher and Randler (2024); Nakie et al. (2024); Razaq et al. (2024); Xu et al. (2025); and Nzamwita et al. (2026); who found a significant relationship between sleep quality and academic performance. However, the results are consistent with the findings of Alfonsi et al. (2020); Jalali Khazaei et al. (2020); and Khaled et al. (2025). And, The study found the sleep duration have a positive and statistically significant impact on academic performance among undergraduate IT students which was consistent with Siraj et al. (2014); Kabrita and Hajjar-Muça (2016); Siddiqui et al. (2016); Okano et al. (2019); Toscano-Hermoso et al. (2020); Gallego-Gómez et al. (2021); Kalbacher and Randler (2024); Xu et al. (2025); BaHammam et al. (2012) and Saha et al. (2026). However, the results are inconsistent with the findings of Alfonsi et al. (2020) who found no significant association between sleep duration and academic performance, and Nzamwita et al. (2026) who found a negative association between sleep duration and academic performance.

Findings indicate a positive and statistically significant impact of bedtime and wake-up time on academic performance. The findings suggest that students who keep a regular bedtime and wake-up schedule tend to do better academically. The results are consistent with the studies of BaHammam et al. (2012); Kabrita and Hajjar-Muça (2016); Lawson et al. (2019); Okano et al. (2019); Xu et al. (2025) and Saha et al. (2026). Students maintain healthy circadian rhythms, become more alert, and learn more efficiently with consistent sleep schedules. However, the results are contrasted with those of Alfonsi et al. (2020) and Jalali Khazaei et al. (2020) who found no significant association

between bedtime and wake-up time and academic performance.

CONCLUSION

This study was designed to investigate the association of sleep quality, sleep duration, sleeping and waking times with academic performance of undergraduate IT students of Kathmandu. The results revealed that sleep duration and bedtime and wake-up time has a significant positive influence on academic performance. Sleep duration emerged as the strongest predictor, indicating that students who obtained adequate sleep were more likely to achieve better academic outcomes. Similarly, maintaining appropriate bedtime and wake-up schedules was found to contribute positively to academic performance. However, sleep quality did not show a statistically significant effect on academic performance when analyzed alongside the other sleep-related variables. Overall, the findings suggest that the quantity and timing of sleep play a more important role in influencing academic performance than perceived sleep quality among the students in this study. Therefore, promoting healthy sleep duration and consistent sleep schedules may help improve students' academic achievement.

The sleep-related factors affect academic performance and reinforce the existing evidence that healthy sleep habits are necessary for students' cognitive functioning and academic achievement. Adequate sleep and a consistent sleep schedule help to improve concentration, memory, learning and overall academic performance. Therefore, the present study emphasizes on the need of promoting healthy sleep behaviors among university students via awareness programs, academic work load management and the guidance to maintain proper sleep routines. In general, the study reveals that changing sleep habits may be a powerful and effective strategy for increasing students' academic performance.

IMPLICATIONS

The outcomes of this research emphasize the importance of sleeping patterns and habits regarding the students' success in their studies. The findings about the sleep duration and the time when the students go to bed or wake-up are of great importance as they show that students should sleep sufficiently and have stable sleeping hours which can boost their studying and overall achievement. Moreover, this research is helpful not only for the students but also for the educational institutions which can implement sleep education programs as well as among parents and policymakers. The results of this research add to the already existing knowledge base related to sleep and success in the academia in the context of Nepal.

There are also some shortcomings of this research that must be taken into account when analyzing the findings. First of all, the research was held only among undergraduate students of Information Technology in some colleges in Kathmandu Valley, and therefore, it was not possible to say whether this research can be generalized to other faculties of study such as Engineering, Management, Humanities, Medicine, and Education or not. Second, the sample represents convenience sampling that does not guarantee sample representativeness. Third, the research is based on the self-reported statistics of students regarding their academic performance and sleep patterns that can be affected by social desirability bias, recall

bias, and wrong answers by the participants. The study employed a cross-sectional research design, collecting data at a single point in time. Therefore, it is not possible to establish cause-and-effect relationships between sleep-related factors and academic performance. Future studies may adopt longitudinal research designs to examine how changes in sleep patterns influence academic performance over time. The focus of the research was solely on the quality of sleep, duration of sleep, and time of going to bed and waking up, without mentioning any other important factors affecting academic knowledge like stress, psychological well-being, studying behavior, physical activity, nutrition, social and economic status, family atmosphere, and involvement in studies.

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ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

Unrealistic beauty ideals: *Examining the Effects of Body Image, Social Media Use, and AI-generated Images on Self-esteem Among Female Social Media Users in Tarakeshwor Municipality*

Easter Tamang
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
ta.easter23@ncmt.edu.np

Received: 18 Aug., 2026 | Revised: 12 Sept., 2026 | Accepted: 8 Oct., 2026

Abstract: *The growth of social media and AI-generated images has contributed to the normalization of unrealistic beauty standards and digitally enhanced appearances, which may influence perceptions of beauty and self-esteem. Therefore, this study examined the effects of body image, social media use, and AI-generated images on self-esteem among female social media users in Tarkeshwor Municipality, Kathmandu, Nepal. Body image, social media use, and AI-generated images were considered independent variables, while self-esteem was the dependent variable. Age group was considered as a moderating variable. The study was guided by Social Comparison Theory and Objectification Theory. A quantitative approach was adopted using descriptive, relational, and explanatory research designs. The target population comprised female social media users in Tarkeshwor Municipality, and 451 respondents were selected through convenience sampling. Primary data were collected using a structured questionnaire and analyzed using Pearson correlation and linear regression analysis. The findings revealed that body image has a positive but insignificant effect on self-esteem, whereas social media use has a significant negative effect. In contrast, AI-generated images had a significant positive effect on self-esteem. These findings highlight the importance of responsible social media use, digital and AI literacy, and critical awareness of appearance-related and digitally enhanced appearances. The study has several limitations, including its geographical focus on a single urban area, which may limit the generalizability of the findings to other populations and geographical settings in Nepal. Furthermore, the cross-sectional design limits the ability to establish causal relationships and assess changes in self-esteem over time. The study also focused exclusively on female social media users, although beauty-related content and AI-generated images may also influence male social media users. Future research could address these limitations by including larger and more diverse samples, broader geographical settings, and longitudinal research designs.*

Keywords: AI-generated images, body image, digital well-being, self-esteem, social media use

JEL Classification: I31, D91, J16

Cite as: Tamang, E. (2026). Unrealistic beauty ideals: Examining the effects of body image, social media use, and AI-generated images on self-esteem among female social media users in Tarakeshwor Municipality. *NCMT Journal of Multidisciplinary Studies, 1*(1), 137-152.

INTRODUCTION

In the past two decades, social media has become an essential part of everyday life, influencing how people communicate, express themselves, and perceive their own value. Platforms such as Instagram and TikTok frequently expose users to content related to beauty, success, and lifestyle. While these platforms provide opportunities for connection and self-expression, they may also shape users' perceptions of themselves. Research has shown that social media use can influence self-esteem through social comparison, as individuals often evaluate their appearance, achievements, and lifestyles against those of others encountered online (Vogel et al., 2014; Wang et al., 2017; Rüther et al., 2023).

Social media has become a powerful source of beauty-related content that influences young women's perceptions of attractiveness and appearance. Constant exposure to idealized beauty images on social media platforms can promote appearance-based comparisons and shape users' perceptions of beauty (Perloff, 2014). Research has found that young women who are exposed to idealized images on social media report higher levels of body dissatisfaction and a greater desire to change their appearance (Fardouly et al., 2015). Furthermore, young women are especially susceptible to the negative effects of beauty standards promoted through social media, which may adversely affect their body image and appearance-related perceptions (Brown & Tiggemann, 2016).

Artificial intelligence has introduced a new form of digital influence through AI-generated faces and virtual influencers. Unlike human influencers, virtual influencers are computer-generated characters designed to portray flawless appearances and idealized lifestyles. Exposure to digitally altered and idealized images may negatively affect body image and self-perception among users (Kleemans et al., 2018). Moreover, virtual influencers often present highly idealized appearances, which may contribute to appearance anxiety and unrealistic beauty expectations among social media users (Deng & Jiang, 2023). Although individuals are aware that virtual influencers are not real, they may still engage in social comparison with them, which can negatively affect their well-being, self-perception, and self-esteem (Nasr et al., 2025).

Previous studies have examined the impact of social media, virtual influencers, and AI-generated content on body image and psychological well-being using mediating variables such as social comparison, internalization of beauty standards, self-objectification, and recognition of AI-generated influencers (Kushwaha, 2024; Çınaroğlu & Yilmazer, 2025; Forrai et al., 2026). In addition, several qualitative studies have explored how social media and beauty ideals shape women's perceptions and experiences (Jaiswal et al., 2023; Shukla et al., 2023; Özkan, 2023). Although previous research has provided valuable insights into the psychological effects of social media and AI-generated content, existing studies have primarily focused on specific relationships among body image, social media use, AI-generated content, and psychological outcomes (Tufail et al., 2024; Ahmed et al., 2025; Yeo et al., 2025). However, limited quantitative research has investigated the combined influence of body image, social media use, and AI-generated images on self-esteem among female social media users. Furthermore, most existing studies have been conducted in international contexts (Terry et al., 2026; Husnain et al., 2026; Bennett et

al., 2026). To the best of the researcher's knowledge, empirical evidence regarding this issue within the Nepalese context remains limited. Therefore, this study aims to address these gaps by examining the effects of body image, social media use, and AI-generated images on self-esteem among female social media users in Tarkeshwor Municipality.

Research questions

- Is there a significant relationship between body image, social media use, AI-generated images, and self-esteem among female social media users?
- What is the effect of body image, social media use, and AI-generated images on female self-esteem?

Objectives of the study

The major objective of this study is to examine the effects of body image, social media use, and AI-generated images on self-esteem among female social media users in Tarkeshwor Municipality. Hence, the specific objectives of the study include the following:

- To examine the relationship between body image, social media use, AI-generated images, and self-esteem among female social media users.
- To determine the effects of body image, social media use, and AI-generated images on self-esteem.

LITERATURE REVIEW

Theoretical review

Social Comparison Theory: Social Comparison Theory was developed by Festinger (1954). The theory suggested that individuals evaluated themselves by comparing their abilities, achievements, and appearances with those of others. With the widespread use of social media platforms such as TikTok, Instagram, and YouTube, users were frequently exposed to idealized representations of beauty, wealth, and happiness. These portrayals often encouraged individuals to compare themselves with others, which could lead to feelings of inadequacy and lower self-esteem. Therefore, the theory explained how exposure to idealized social media content could negatively influence individuals' perceptions of their appearance and self-worth.

Objectification Theory: Objectification Theory was proposed by Fredrickson and Roberts (1997). The theory explained that repeated exposure to idealized beauty standards could cause individuals to evaluate themselves primarily based on their physical appearance. With the advancement of artificial intelligence, various AI tools and filters were increasingly used to enhance facial features and appearance on digital platforms. These technologies often promoted unrealistic beauty standards by emphasizing features such as flawless skin, facial symmetry, and idealized attractiveness. As a result, individuals could develop unrealistic expectations regarding their appearance, which might negatively affect their self-esteem, self-worth, and overall self-perception.

Empirical review

According to the previous research, Ji et al. (2022) argued that virtual influencers promote unattainable beauty ideals and idealized body images, which may contribute to body image concerns and negative self-perceptions among female audiences. Similarly, Khalil et al. (2022) found that the internalization of beauty standards was positively associated with self-objectification

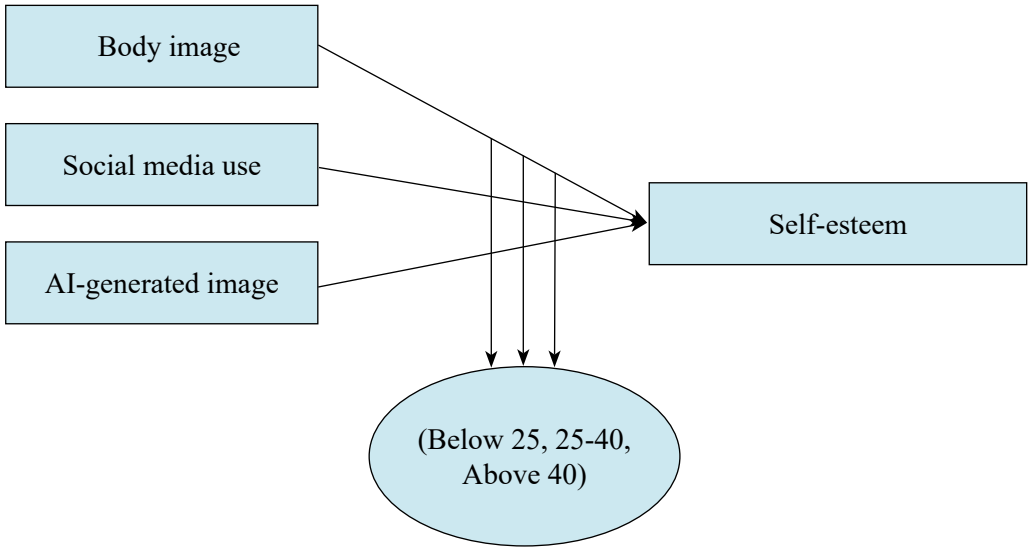
and body image dissatisfaction, highlighting the potential psychological consequences of appearance-based social comparison. In addition, Jaiswal et al. (2023) found that influencers on social media can significantly affect young women's perceptions of beauty. Likewise, Shukla et al. (2023) reported that social media exposure influences body image and self-esteem among teenage girls, suggesting that digital platforms can shape how young women perceive themselves and their appearance. Additionally, Kushwaha (2024) highlighted that exposure to unrealistic beauty ideals on social media can negatively affect women's body image, self-perception, and self-esteem.

Based on prior research, Tufail et al. (2024) found that exposure to AI-generated content had a significant negative impact on self-esteem and body image. Similarly, Ahmed et al. (2025) reported a positive relationship between media influence and body surveillance, suggesting that exposure to idealized beauty portrayals contributes to self-objectification and body image concerns among women. In addition, Babu et al. (2025) reported that body image and self-perception were significant positive predictors of identity development, with body image exerting the strongest influence. However, social comparison was not found to have a significant effect on identity development. Moreover, Çınaroğlu and Yilmazer (2025) showed that self-objectification significantly mediated the relationship between problematic social media use and body image disturbance. Likewise, Miglani (2025) found that increased social media use was associated with greater self-objectification and body consciousness, highlighting the role of digital media in shaping women's self-perception and appearance-related concerns.

Resha and Izzaty (2025) indicated that self-esteem and social comparison had a positive and statistically significant influence on body image among adolescent girls. In a similar vein, Shabeer et al. (2025) examined a significant positive relationship between social media use and the internalization of contemporary beauty standards. However, the direct relationship between social media use and self-esteem was not statistically significant. Correspondingly, Yeo et al. (2025) found that while virtual influencers did not significantly affect women's body appreciation, perceived similarity to the influencer positively influenced body perceptions, highlighting the importance of identification in shaping self-perception. By contrast, Adan (2026) showed that exposure to virtual influencers significantly and negatively influenced self-esteem and lifestyle satisfaction. Additionally, Arvanitidou (2026) highlighted that AI-generated beauty technologies and virtual influencers promote unrealistic beauty ideals, encouraging self-surveillance and social comparison that may negatively affect women's self-perception and self-image.

Likewise, Bennett et al. (2026) found that exposure to AI-generated images negatively affected body satisfaction in both informed and uninformed groups. Nevertheless, participants who were aware that the images were AI-generated reported a more pronounced reduction in trust toward technology. Furthermore, Bharti (2026) highlighted that unrealistic beauty ideals amplified through social media and AI-enhanced content contribute to body dissatisfaction, self-objectification, and reduced self-esteem by encouraging appearance-based social comparison. On a related note, Forrai et al. (2026) recognized AI-generated influencers did not reduce harmful social comparisons,

Figure 1
Research framework of study



but greater knowledge about them was linked to better well-being. Similarly, Husnain et al. (2026) revealed that AI filters significantly enhance perceived beauty and confidence, but also negatively affect self-esteem and mental well-being. Ultimately, Terry et al. (2026) revealed that the AI influencer's physical and mental humanlikeness had a significant relationship with the perceived authenticity of the AI influencer.

Based on the literature review, the study developed the research framework presented in *figure1*.

METHODOLOGY

Research design

The study adopted a deductive research approach and was grounded in a positivist research philosophy. A quantitative research design was employed, incorporating descriptive, relational, and explanatory research designs. The descriptive research design was utilized to describe the demographic characteristics of the respondents and the key variables of the study (Budhathoki et al., 2025). The relational research design was used to examine the relationships among independent and dependent variables. Furthermore, the explanatory research design was employed to investigate the influence of body image, social media use, and AI-generated images on self-esteem among female social media users.

Population and sample

The study targeted population comprised female social media users in Tarakeshwor Municipality, Kathmandu, who actively engage with platforms such as Instagram, TikTok, Snapchat, and Facebook. Due to the unknown size of the population, it was not feasible to collect data from all members. The minimum required sample size was 384 respondents based on Cochran's formula.

The sample size was determined using Cochran's formula (Cochran, 1977), which

was appropriate for large or unspecified populations:

$$n = \frac{Z^2 * P * (1-P)}{e^2}$$

(Where, n = sample size (384); Z = Z-score at a 95% confidence level (1.96); p = estimated proportion (0.5); e = margin of error (5%))

Primary data were collected through a structured close-ended questionnaire distributed online via social media platforms, including Instagram, WhatsApp, Messenger, Gmail, Viber, and TikTok. Participation was voluntary, and respondents completed the questionnaire at their convenience.

Sources of data and analysis tools

The questionnaire consists of two sections: demographic information and a series of statements measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was developed based on a review of the relevant literature on AI-generated faces, virtual influencers, self-perception, and self-esteem, with measurement items adapted from established studies. The collected data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 26. Descriptive statistics, reliability analysis, correlation analysis, and regression analysis were employed to examine the relationships among variables.

Table 1
Reliability test

Variable Dimension	Number of Items	Cronbach's Alpha
Body image	4	0.762
Social media uses	5	0.866
AI generated images	5	0.897
Self-esteem	5	0.809

A pilot study was conducted prior to the distribution of the questionnaire, and the questionnaire was distributed to 54 respondents to assess its reliability and effectiveness. In this research, the computed Cronbach's alpha values for the variables were 0.762 for body image, 0.866 for social media use, 0.897 for AI-generated images, and 0.809 for self-esteem, as presented in *Table 1*. All the computed alpha values exceeded the standard criterion of 0.70, indicating an acceptable level of internal consistency among the items used to measure each construct.

Analytical model

The influence of body image, social media use, and AI-generated images on self-esteem among female social media users was examined using a linear regression model. The model was adapted from the study conducted by Resha et al. (2025) and was employed to assess the effect of the independent variables on self-esteem.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

Where, (Y = Self-esteem, β_0 = Constant (intercept), β_1, β_2, β_3 = Regression coefficients of the independent variables, X_1 = Body image, X_2 = Social media use, X_3 = AI-generated images, ϵ = Error term).

Definition of variables

Independent variables

Body image: Body image refers to the way individuals perceive, think about, and feel toward their physical appearance (Babu et al., 2025). A positive body image involves acceptance, appreciation, and satisfaction with one's appearance, whereas a negative body image is characterized by dissatisfaction and insecurity. With the increasing prevalence of artificial

intelligence-generated content on social media, concerns regarding body image have grown. Continuous exposure to idealized and digitally edited images of beauty may lead individuals to compare themselves with unrealistic standards, potentially affecting their body satisfaction and self-perception (Rahmadiansyah et al., 2022).

H_1: *Body image has a significant influence on female self-esteem.*

Social media use: Social media use refers to the use of social networking platforms such as Instagram, TikTok, and Facebook for communication, information sharing, and social interaction. These platforms have become an important part of daily life and may influence how individuals perceive themselves through exposure to others' lives, appearances, and experiences (Soh et al., 2024). According to Festinger's Social Comparison Theory, individuals often compare their abilities, achievements, and appearance with others. Such comparisons, particularly with those perceived as more attractive or successful, may contribute to feelings of inadequacy, body dissatisfaction, and lower self-esteem (Martí et al., 2024).

H_2**:** *Social media use has a significant effect on the self-esteem of female social media users.*

AI-generated images: AI-generated images are visual representations created with the aid of artificial intelligence rather than through traditional photography or manual editing. Recent advances in artificial intelligence technology have made it possible to generate highly realistic images that are often difficult to distinguish from actual photographs (Elgammal et al., 2017). As these images become more common on social media, they play an important role in shaping perceptions of beauty and appearance. Exposure to idealized and digitally generated images may promote unrealistic beauty standards and negatively affect body image, self-perception, and self-esteem (Kleemans et al., 2018).

H_3: *Exposure to AI-generated images significantly influences self-esteem.*

Dependent variables

Self-esteem: Self-esteem is a global sense of personal worth and value. It is affected by a range of factors such as individual accomplishments, social connections, and self-view. People with high self-esteem tend to see themselves in a positive light and are more resilient when faced with difficulties. In contrast, low self-esteem is more likely to lead to feelings of inadequacy, insecurity, and self-doubt (Orth et al., 2012). Exposure to unrealistic beauty ideals on social media may negatively influence self-esteem by encouraging unfavorable self-comparisons.

FINDINGS AND DISCUSSION

Findings

Demographics responses: Table 2 presents the background information of the 451 respondents who participated in the study. Almost half of the respondents, 222 (49.2%), were below 25 years old. Another 163 (36.1%) were between 25 and 40 years, while 66 (14.6%) were above 40 years. Thus, most of the respondents were relatively young. In terms of education, the majority, 308 respondents (68.3%), had a bachelor's degree. This was followed by 76 (16.9%) with a master's degree, 52 (11.5%) with higher secondary education, and 15 (3.3%) with secondary education.Among the social media platforms, TikTok was the

Table 2
Demographic responses

		Frequency	Percent	Cumulative Percent
Age	Below 25	222	49.2	49.2
	25-40	163	36.1	85.4
	Above 40	66	14.6	100
Education level	Secondary level	15	3.3	3.3
	Higher secondary level	52	11.5	14.9
	Bachelor's degree	308	68.3	83.1
	Master's degree	76	16.9	100
Social media platforms	Instagram	101	22.4	22.4
	TikTok	200	44.3	66.7
	Facebook	134	29.7	96.5
	Snapchat	16	3.5	100
Time Spent	1-2 hours	179	39.7	39.7
	3-4 hours	69	15.3	55
	More than 5 hours	203	45	100
Exposure to AI-generated image	Never	31	6.9	6.9
	Rarely	83	18.4	25.3
	Sometimes	159	35.3	60.5
	Often	35	7.8	68.3
	Very often	143	31.7	100
	Total	451	100	

most commonly used platform, with 200 respondents (44.3%), followed by Facebook (29.7%), Instagram (22.4%), and Snapchat (3.5%).Regarding daily social media use, 203 respondents (45.0%) reported spending more than five hours per day on social media. Another 179 (39.7%) spent one to two hours, while 69 (15.3%) spent three to four hours. In terms of exposure to AI-generated images, 159 respondents (35.3%) reported seeing them sometimes, 143 (31.7%) very often, 83 (18.4%) rarely, 35 (7.8%) often, and 31 (6.9%) never.

Table 3 presents the respondents basic general knowledge about engagement of social media. Out of 451 respondents, 437 (96.9%) regularly used social media platforms such as Instagram, TikTok, and Facebook, while 14 (3.1%) did not. For AI-generated images, 355 (78.7%) respondents were aware that some social media images were AI-generated, while 96 (21.3%) were not. Similarly, 403 (89.4%) had seen AI-generated faces or virtual influencers on social media, whereas 48 (10.6%) had not. In terms of appearance comparison, 141 (31.3%) respondents had compared their appearance with AI-generated faces or virtual influencers, while 310 (68.7%) had not. However, 281 (62.3%) believed that AI-generated faces and virtual influencers influence people's perceptions of beauty and self-worth, while 170 (37.7%) did not.

Descriptive analysis: Table 4 results show that self-esteem has the highest mean score (M = 3.847), followed by AI-generated images (M = 3.739), social media use (M

Table 3
Basic information of respondents

Questions	Responses				Total	
	Yes	Percent	No	Percent	Count	Percent
Do you regularly use social media platforms like Instagram, TikTok, Facebook ?	437	96.9	14	3.1	451	100
Were you aware that some social media images are AI-generated?	355	78.7	96	21.3	451	100
Have you ever seen AI-generated faces or virtual influencers on social media?	403	89.4	48	10.6	451	100
Have you ever compared your appearance with AI-generated faces or virtual influencers?	141	31.3	310	68.7	451	100
Do you believe AI-generated faces and virtual influencers influence people's perception of beauty and self-worth?	281	62.3	170	37.7	451	100

Table 4
Descriptive statistics

Statistics/Variables	BI	SMU	AIG	SE
N	451	451	451	451
Mean	3.51	3.588	3.739	3.847
Median	3.5	3.6	4	3.8
Mode	3.5	3.6	4	4.4
Std. Deviation	0.7245	0.806	0.7343	0.6969
Variance	0.525	0.65	0.539	0.484

= 3.588), and body image (M = 3.510). The relatively higher mean score of self-esteem suggests that respondents generally report a high level of self-esteem. In contrast, body image has the lowest mean score, indicating that respondents report relatively lower levels of positive body image. This may suggest greater concerns or mixed perceptions regarding their physical appearance. AI-generated images have the highest median (Md = 4.00), while body image has the lowest median (Md = 3.50). Similarly, self-esteem has the highest mode (Mo = 4.40), indicating that a relatively high level of self-esteem is the most common response. In contrast, body image has the lowest mode (Mo = 3.50). Overall, the mean, median, and mode values suggest that the responses are generally distributed around the moderate-to-high level across the study variables. In terms of variability, social media use has the highest standard deviation (SD = 0.806) and variance (0.650), indicating that respondents differ the most in their social media use. This variation could be due to differences in the frequency and intensity of social media use among respondents. In contrast, self-esteem has the lowest standard deviation (SD = 0.6969) and variance (0.484), indicating that respondents' scores on self-esteem are relatively more consistent.

Table 5
ANOVA-test for equality of means across age

Variables		Sum of Squares	df	Mean Square	F	Sig.
Body image	Between Groups	87.903	2	43.952	132.772	0.001
	Within Groups	148.302	448	0.331		
	Total	236.205	450			
Social media uses	Between Groups	81.524	2	40.762	86.626	0.001
	Within Groups	210.807	448	0.471		
	Total	292.33	450			
AI generated images	Between Groups	25.23	2	12.615	25.998	0.001
	Within Groups	217.386	448	0.485		
	Total	242.615	450			
Self-esteem	Between Groups	2.284	2	1.142	2.373	0.094
	Within Groups	215.621	448	0.481		
	Total	217.905	450			

ANOVA Test

The *Table 5* reveals that there is a significant difference in body image across the three age groups, as the p-value is 0.001, which is less than 0.05. Likewise, there is a significant difference in social media use across the age groups, as the p-value is 0.001, which is less than 0.05. Similarly, there is a significant difference in AI-generated images across the age groups, with a p-value of 0.001, which is less than 0.05. However, there is no significant difference in self-esteem across the three age groups, as the p-value is 0.094, which is greater than 0.05. In order to further determine which specific age groups, differ significantly, a multiple comparison LSD test is performed.

As seen from *Table 6*, there are significant mean differences in body image among all three age groups. The mean differences between Below 25 and 25–40 ($p = 0.006$), Below 25 and Above 40 ($p = 0.001$), and 25–40 and Above 40 ($p = 0.001$) are statistically significant, as all the p-values are less than 0.05. This implies that body image differs significantly across all three age groups. Similarly, there are significant mean differences between Below 25 and 25–40 ($p = 0.001$) and between 25–40 and Above 40 ($p = 0.001$) in terms of social media use. However, the mean difference between Below 25 and Above 40 is not significant ($p = 0.553$), as the p-value is greater than 0.05. This indicates that social media use differs significantly between some age groups, while there is no significant difference between respondents below 25 and those above 40. Significant mean differences are also observed for AI-generated images between Below 25 and 25–40 ($p = 0.001$) and between Below 25 and Above 40 ($p = 0.001$). However, the difference between 25–40 and Above 40 is not significant ($p = 0.517$), as the p-value is greater than 0.05. Therefore, respondents below 25 differ significantly from both older age groups in their responses to AI-generated images, while there is no statistically significant difference between the 25–40 and Above

Table 6
Multiple comparisons LSD for all variables

Variables	(I) Age group	(J) Age group	Mean Diff. (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Body image	Below 25	25-40	.16511*	0.05935	0.006	0.0485	0.2817
		Above 40	-1.16083*	0.08066	0.001	-1.3194	-1.0023
	25-40	Below 25	-.16511*	0.05935	0.006	-0.2817	-0.0485
		Above 40	-1.32594*	0.08394	0.001	-1.4909	-1.161
	Above 40	Below 25	1.16083*	0.08066	0.001	1.0023	1.3194
		25-40	1.32594*	0.08394	0.001	1.161	1.4909
Social media uses	Below 25	25-40	-.8972*	0.0708	0.001	-1.036	-0.758
		Above 40	-0.0572	0.0962	0.553	-0.246	0.132
	25-40	Below 25	.8972*	0.0708	0.001	0.758	1.036
		Above 40	.8400*	0.1001	0.001	0.643	1.037
	Above 40	Below 25	0.0572	0.0962	0.553	-0.132	0.246
		25-40	-.8400*	0.1001	0.001	-1.037	-0.643
AI generated images	Below 25	25-40	-.4902*	0.0719	0.001	-0.631	-0.349
		Above 40	-.4242*	0.0977	0.001	-0.616	-0.232
	25-40	Below 25	.4902*	0.0719	0.001	0.349	0.631
		Above 40	0.0659	0.1016	0.517	-0.134	0.266
	Above 40	Below 25	.4242*	0.0977	0.001	0.232	0.616
		25-40	-0.0659	0.1016	0.517	-0.266	0.134
Self-esteem	Below 25	25-40	-0.0071	0.0716	0.921	-0.148	0.134
		Above 40	.1981*	0.0973	0.042	0.007	0.389
	25-40	Below 25	0.0071	0.0716	0.921	-0.134	0.148
		Above 40	.2052*	0.1012	0.043	0.006	0.404
	Above 40	Below 25	-.1981*	0.0973	0.042	-0.389	-0.007
		25-40	-.2052*	0.1012	0.043	-0.404	-0.006

** The mean difference is significant at the 0.05 level.*

40 age groups. For self-esteem, there is no significant mean difference between Below 25 and 25–40 ($p = 0.921$), as the p-value is greater than 0.05. However, significant mean differences are observed between Below 25 and Above 40 ($p = 0.042$) and between 25–40 and Above 40 ($p = 0.043$), as both p-values are less than 0.05. This indicates that the Above 40 age group differs significantly in self-esteem from both younger age groups, while there is no significant difference between the Below 25 and 25–40 age groups.

Correlation analysis: *Table 7* shows the correlation analysis between body image, social media use, AI-generated images, and self-esteem among 451 respondents. The results indicate that the study variables have positive and significant relationships with self-esteem at the 0.01 level. Regarding self-esteem, the results reveal a positive and significant association with AI-generated images ($r = 0.523$, $p < 0.01$), indicating that higher responses to AI-generated images are associated with higher levels of self-esteem. Among the variables studied, AI-generated

Table 7
Correlation analysis

Variable		BI	SMU	AIG	SE
Body image	Pearson Correlation	1			
	Sig. (2-tailed)				
Social media use	Pearson Correlation	.191**	1		
	Sig. (2-tailed)	0.001			
AI generated images	Pearson Correlation	.394**	.573**	1	
	Sig. (2-tailed)	0.001	0.001		
Self-esteem	Pearson Correlation	.229**	.225**	.523**	1
	Sig. (2-tailed)	0.001	0.001	0.001	

** *Correlation is significant at the 0.01 level (2-tailed).*

Table 8
Impact on variables for all samples

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.065	0.177		11.632	0.001
Body image	0.022	0.042	0.023	0.521	0.603
Social media use	-0.094	0.042	-0.109	-2.234	0.026
AI generated images	0.547	0.05	0.577	11.042	0.001
Adjusted R square	0.278	F	58.684	Sig.	0.001

images have the strongest positive association with self-esteem. Similarly, body image is positively and significantly correlated with self-esteem ($r = 0.229$, $p < 0.01$), indicating that more positive body image is associated with higher self-esteem. Furthermore, social media use has a positive and significant relationship with self-esteem ($r = 0.225$, $p < 0.01$), indicating that higher social media use is associated with higher levels of self-esteem.

Regression analysis: *Table 8* shows that body image has a positive but insignificant effect on self-esteem ($B = 0.022$, $p = 0.603$). H1 is rejected as the p-value is greater than 0.05. This indicates that body image does not have a significant influence on female self-esteem. Conversely, social media use has a significant negative effect on self-esteem ($B = -0.094$, $p = 0.026$). Since the p-value is less than 0.05, H2 is accepted, indicating that social media use has a significant effect on the self-esteem of female social media users. Likewise, AI-generated images have a positive and significant effect on self-esteem ($B = 0.547$, $p = 0.001$). Since the p-value is less than 0.05, H3 is accepted, indicating that exposure to AI-generated images significantly influences self-esteem. Among the three independent variables, AI-generated images have the strongest effect on self-esteem, as indicated by the highest standardized coefficient ($\beta = 0.577$). The adjusted R-square value of 0.278 shows that body image, social media use, and AI-generated images together explain

27.8% of the variation in self-esteem. The regression model is statistically significant, as indicated by the F-value of 58.684 ($p = 0.001$), showing that the independent variables collectively have a significant effect on self-esteem.

Discussion

The coefficient of body image (BI) on self-esteem is positive but statistically insignificant. This result is contrary to Babu and Ghafar (2025); and Resha et al. (2025); who found significant relationships between body image, self-perception, and self-esteem. Similarly, social media use (SMU) has a significant negative effect on self-esteem. This finding is consistent with Vogel et al. (2014); Fardouly et al. (2015); Shukla et al. (2023); and Miglani (2025). Furthermore, artificial intelligence-generated images (AIGI) have a positive and significant effect on self-esteem. This finding is contrary to Tufail et al. (2024); Adan (2026); and Bennet et al. (2026); who reported negative effects of AI-generated or digitally manipulated content on self-esteem and body satisfaction.Bottom of Form

CONCLUSION

Body image has a positive but statistically insignificant effect on self-esteem. This suggests that body image alone may not be sufficient to influence self-esteem when social media use and AI-generated images are considered together. Social media use has a significant negative effect on self-esteem, indicating that greater social media use may be associated with lower self-esteem. This may be related to frequent exposure to appearance-related content and comparisons with others. In contrast, AI-generated images have a significant positive effect on self-esteem and are the strongest predictor among the three variables. This suggests that respondents may perceive AI-generated images not only as unrealistic beauty ideals but also as creative, entertaining, or aspirational content. Social Comparison Theory suggests that comparing one's appearance with others on social media may negatively influence self-esteem, while Objectification Theory suggests that repeated exposure to appearance-related ideals may lead individuals to place greater importance on their physical appearance when evaluating themselves. Therefore, the study concludes that digital content may have different relationships with self-esteem depending on how users perceive and interact with it. This highlights the importance of responsible social media use, awareness of appearance-related content, and a critical understanding of AI-generated images.

IMPLICATIONS

The findings of this study have important implications for social media users, social media platforms, content creators, educators, and organizations concerned with digital well-being. Social media users should be encouraged to practice responsible digital use and remain aware of appearance-related comparisons. Social media platforms and content creators should promote authentic, inclusive, and responsible beauty content while clearly labelling AI-generated and digitally altered images. Educational institutions and digital well-being organizations can promote digital and AI literacy, helping users critically evaluate online content and develop a balanced understanding of beauty standards. AI-generated images may be viewed as unrealistic beauty ideals, but they may also be perceived as creative, entertaining, or inspirational content. Therefore, greater

awareness of AI-generated content can help users engage with it more thoughtfully and responsibly, contributing to a healthier digital environment.

There are some limitations that should be considered when interpreting the findings. The study was conducted only among female social media users in Tarkeshwor Municipality, Nepal which may limit the generalizability of the results to other populations and locations. Convenience sampling may have affected the representativeness of the sample, while self-reported responses may have been influenced by recall, interpretation, or social desirability bias. The cross-sectional design does not allow causal relationships to be established or changes in self-esteem over time to be examined. Future research can address these limitations by using larger and more diverse samples, probability-based sampling, and longitudinal or mixed-method research designs. Further studies can also examine factors such as social comparison, psychological well-being, family and peer influence, media literacy, and exposure to online beauty content to provide a more comprehensive understanding of self-esteem in the digital environment.

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ISSN XXXX | Volume 1 | Issue 1 | Sept. 2026

The effect of AI service quality and trust in AI on customer loyalty: *The mediating role of customer satisfaction at Hotel Robot, Samakhusi, Kathmandu*

Pranish Ratna Gubhaju
National College of Management and Technical Science, Kathmandu, Nepal
Lincoln University College, Malaysia
gu.pranishratna23@ncmt.edu.np

Received: 18 Aug., 2026 | Revised: 12 Sept., 2026 | Accepted: 8 Oct., 2026

Abstract: *The increased usage of artificial intelligence-enabled services in the hospitality industry has led to a better understanding of how AI-related factors affect customer experiences and loyalty. This study focuses on the impact of AI service quality and on customer satisfaction and loyalty in Nepal's AI-enabled hospitality industry. AI service quality and trust in AI were considered independent variables, customer loyalty was the dependent variable, and customer satisfaction acted as a mediating variable. The study is based on the Technology Acceptance Model (TAM) and employs a quantitative research approach with descriptive, correlation, and Ordinary Least Squares (OLS) regression models. The target population consisted of Hotel Robot clients from Samakhusi, Kathmandu, who had previously used AI-enabled services. The population size was unknown, so a non-probability convenience sample technique was used, with data collected from 390 respondents using a structured questionnaire. Primary data was collected using Google responses. The regression results revealed that AI service quality and trust in AI have a significant effect on customer satisfaction and loyalty, whereas customer satisfaction has a significant effect on customer loyalty. According to the study, AI service quality and trust in AI have significant impacts on increasing customer satisfaction and loyalty, with customer satisfaction acting as an important path through which AI-related characteristics contribute to customer loyalty. The study was limited by its focus on customers of a single hospitality service in Samakhusi, Kathmandu, its cross-sectional design, and its non-probability convenience sampling technique, which may limit the findings' application to other hospitality environments and locations.*

Keywords: AI service quality, artificial intelligence, customer loyalty, customer satisfaction, trust in AI.

JEL Classification: M31, L83, O33

Cite as: Gubhaju, P. R. (2026). The effect of AI service quality and trust in AI on customer loyalty: The mediating role of customer satisfaction at Hotel Robot, Samakhusi, Kathmandu. *NCMT Journal of Multidisciplinary Studies, 1*(1), 153-169.

INTRODUCTION

Artificial intelligence and robots have applications in a various organizations and businesses (Yang et al., 2020). Furthermore, artificial intelligence has emerged as one of the most crucial technical developments that is revolutionizing the global service sectors. Whether or not these firms survive is determined by their ability to adapt to macroeconomic conditions, financial prosperity, and the ability to create and adjust their services to meet the needs of their clients (Wikhamn, 2019). Hotels have been using current technology such as artificial intelligence and robotics to improve the customer experience and service quality. According to Lee et al. (2021), an individual's object-oriented attitude, as measured by their satisfaction with the quality of services, is closely related to the quality of those services.

Furthermore, artificial intelligence, which has the ability to learn, interact, and adapt, is increasingly being used in the service sector and is quickly becoming a crucial aspect in service innovation (Huang & Rust, 2020). The recent advancements in the field of artificial intelligence and service robots have resulted in the application of AI technology in services, and the future direction of services is shifting toward AI and robotics (Belanche et al., 2020). These scientific and technological breakthroughs are translated into incredibly resourceful customer service methods, which are used to improve the customer experience and happiness, resulting in customer loyalty (Goel et al., 2022).

Similarly, the use of artificial intelligence in service quality results in increased positive impact in customer satisfaction and loyalty in the hospitality industry (Kervenoael et al., 2020). While analyzing the use of AI within the hotel industry, Prentice et al. (2020) found that both AI and human services significantly influence customer satisfaction. Even though technology has been widely used in the service industry as well as in the hospitality industry specifically, finding the right balance between digital and human contact is quite a difficult task. While the question about increasing individual guest experiences remains questionable, it becomes more and more relevant in regard to service quality for creating a competitive advantage when using AI service quality, robots, and service automation (Naumov, 2019).

Previous research on the application of artificial intelligence in the hospitality industry has mostly taken place in foreign countries (Roy et al., 2020; Al-Araj et al., 2022; Sharma et al., 2023) but there is no empirical evidence that the study found regarding the study of the association between artificial intelligence service quality, artificial intelligence trust, customer satisfaction, and customer loyalty in the case of Nepal. Previous studies used as mediating variables such as perceived personalization, satisfaction and customer trust (Mufaddhal, 2025; Sharma et al., 2023; Sumarto et al., 2026). Furthermore, prior studies used moderating variables such as restaurant image (Meeprom & Suttikun, 2024). Unlike these studies, the present research examines the mediating role of customer satisfaction without incorporating a moderating variable. Therefore, this study was conducted to address this research gap.

Research question

- Is there any relationship between AI quality service, trust in AI, customer satisfaction and customer loyalty?

- What is the effect of AI quality service and trust in AI on customer satisfaction?
- Do the AI quality service and trust in AI have an impact on customer loyalty?
- Does customer satisfaction play a mediating role between AI service quality, trust in AI and customer loyalty?

Objective

The main purpose of this research is to examine the effects of AI service quality and trust in AI on customer satisfaction and loyalty in the hospitality industry in Nepal. Thus, the objectives of the study include the following:

- To analyze the relationship among AI service quality, trust in AI, customer satisfaction, and customer loyalty.
- To examine the effects of AI service quality and trust in AI on customer satisfaction.
- To examine the impact of AI service quality and trust in AI on customer loyalty.
- To examine the mediating role of customer satisfaction in the relationship between AI service quality, trust in AI, and customer loyalty.

LITERATURE REVIEW

Theoretical review

Technology Acceptance Model (TAM): Technology acceptance is influenced by an individual's perception of the usefulness and ease of using a technology (Davis, 1989). The Technology Acceptance Model (TAM) explains that individuals are more likely to accept and use a technology when they perceive it as useful and easy to use. Perceived usefulness refers to the extent to which an individual believes that using a particular technology will improve their performance, while perceived ease of use refers to the extent to which an individual believes that using the technology will require little effort (Davis, 1989). TAM has been extensively used by researchers in studies of AI adoption (Sharma et al., 2023). Usually, customers want AI solutions that are useful, simple to use, and can improve their service experience (Davis, 1989). Hospitality customers' acceptance of AI-powered chatbots, service robots, and virtual concierges increases when they perceive them as efficient, reliable, and beneficial. Such positive perceptions can boost customer satisfaction, trust in AI, and loyalty (Singh & Singh, 2024). The potential of TAM in AI-enabled services was demonstrated by Sharma et al. (2023), who found that perceived usefulness, enjoyment, novelty, and speed contribute to customer satisfaction. The study also found that satisfied customers are more likely to trust AI-powered services, which can boost customer loyalty. Therefore, TAM offers a suitable theoretical basis for explaining the impact of AI service quality and trust in AI on customer satisfaction and loyalty in the hospitality industry.

Empirical review

AI service quality and customer satisfaction & loyalty: Roy et al. (2020) examined the customer acceptance of AI in hospitality services: A perspective from the Indian sector. The correlation analysis result found that both AI (performance expectancy and effort expectancy) have a relationship with customers' emotions, which then affect their acceptance or rejection of AI in hospitality services.

H_1: *AI service quality has a significant direct effect on customer loyalty.*

H_2: *AI service quality has a significant indirect impact on customer loyalty through customer satisfaction.*

H_3: *AI service quality has a significant total influence on customer loyalty*

Trust in AI and customer satisfaction & loyalty: Ameen et al. (2021) discovered customer experiences in the age of artificial intelligence through a global survey. The qualitative study indicated that AI (trust and perceived sacrifice) played a significant role in moderating the effects of perceived convenience, personalization, and AI-enabled service quality. The findings

Table 1
Summary of previous studies

Author(s)	Year	Country	Methodology	Finding
Ameen et al.	2021	Global survey	Regression analysis	Revealed the significant effect of relationship commitment on AI-enabled customer experience.
Al-Araj et al.	2022	Jordan	Correlation analysis	Found that AI service quality has a significant relationship with customer satisfaction.
Costa et al.	2022	Brazil	Meta-analysis	Identified that consumer satisfaction in the provision of services is significantly correlated to the adoption of artificial intelligence.
Borghi and Mariani	2023	Global survey	Regression analysis	Highlighted robot performance have an impact on customer satisfaction
Ifekanandu et al.	2023	Nigeria	Regression analysis	Discovered that artificial intelligence yields positive and significant influence on customer experience, customer loyalty, and personalization.
Ivanov and Webster	2023	Global survey	Regression analysis	Indicated that artificial intelligence has direct effect of the appropriateness of robots on the effectiveness and advantage of the robots over human counterparts.
Kim et al.	2024	Global survey	Qualitative conceptual review	Found that artificial intelligence technology is evolving fast in the tourism and hospitality sector.
Li et al.	2023	China	Regression analysis	Demonstrated that AI usage positively impacts CRM performance and that CRM capabilities positively mediate their relationship.
Molinillo et al.	2023	Spain	Regression analysis	Reported that robot-operated restaurants were significantly influenced by positive attitudes toward service robots and objections to their use.

Author(s)	Year	Country	Methodology	Finding
Sharma et al.	2023	India	Regression analysis	Showed that AI in perceived enjoyment, speed, and novelty significantly improved customer satisfaction for service robots in restaurant settings, whereas perceived usefulness did not have any significant impact.
Sardesai et al.	2024	India	Regression analysis	Suggested that AI-powered services significantly enhance customer satisfaction.
Singh and Singh	2024	India	Regression analysis	Confirmed that AI-powered customer service significantly improves customer satisfaction and customer loyalty.
Beyari	2025	Saudi Arabia	Correlational analysis	Verified that artificial intelligence significantly affects customer loyalty.
Hussain et al.	2025	India	Regression analysis	Evidenced that AI perceived efficiency significantly increases customer loyalty.
Mufaddhal	2025	China	Regression analysis	Revealed AI service quality significantly enhances guest loyalty intentions.

also show that relationship commitment has a substantial impact on the AI-enabled consumer experience. Similarly, Meeprom and Suttikun (2024) investigated the relationship between customer perceptions of AI and employee service ratings and customer loyalty during the COVID-19 outbreak in Thailand. The regression analysis results demonstrated that the value of AI service performance, faith in AI technologies, and service assistance offered by workers all had a significant impact on customer engagement. However, client involvement with AI technologies has a negative influence on customer loyalty. Al-Oraini (2025) discovered chatbot dynamics in trust, social presence, and consumer happiness in AI-powered services in Saudi Arabia. The regression study revealed that social-oriented communication, perceptions of competence and warmth, trust, and subjective norms all significantly increased customer satisfaction with chatbots. Furthermore, Sumarto et al. (2026) investigated how AI-based tailored marketing influences customer trust and online repurchase intention in Indonesian e-commerce. The regression model results demonstrated that AI-based tailored marketing has a favorable and significant impact on customer trust and online repurchase intention.

H_4: *Trust in AI has a significant direct effect on customer loyalty.*

H_5: *Trust in AI has a significant indirect impact on customer loyalty through customer satisfaction.*

H_6: *Trust in AI has a significant total influence on customer loyalty*

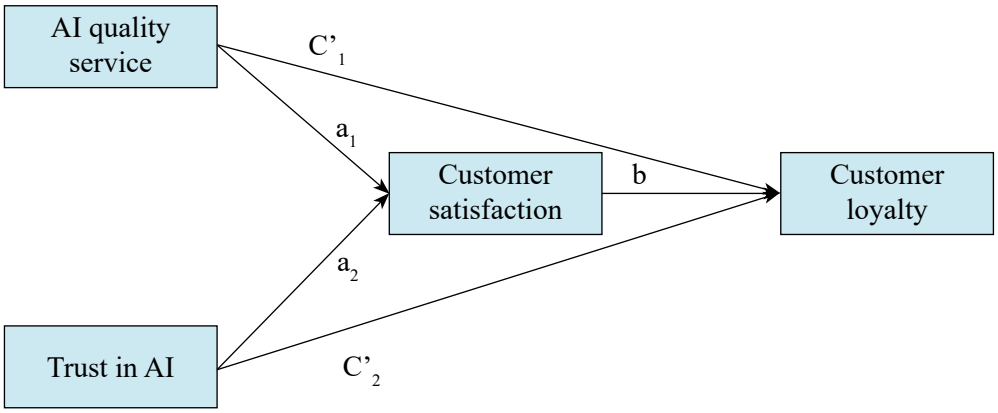
METHODOLOGY

Research design

The research approach used in the study was deductive. Additionally, positivist research philosophy was used in the investigation. This study employs a quantitative research

Figure 1

Research framework



Note. Ameen et al. (2021); Sardesai et al. (2024).

design that combines descriptive, relational, and explanatory research methods. The basic characteristics of the variables under investigation were outlined using the descriptive study approach (Budhathoki et al., 2025). The relationship between the antecedent and consequent factors was investigated using the relational research design (Budhathoki et al., 2023). The impact of independent variables on dependent variables was examined using an explanatory study approach.

Population and sample

The target population of this study consists of customers of Hotel Robot, located in Samakhusi, Kathmandu, who have experienced the Hotel Robot services. Since the exact number of customers is unknown, it was not feasible to collect data from the entire population. The Cochran, (1977) formula is shown below

$$n = \frac{z^2 * p * q}{e^2}$$

(Where, n = required sample size (384); Z = Z-value (e.g., 1.96 for 95% confidence level); p = estimated proportion (0.5 if unknown); q = 1 – p; *e* = margin of error (5 %))

Accordingly, a sample size of 384 respondents is considered adequate for the study. A non-probability convenience sampling technique is employed to select respondents because it allows data to be collected efficiently from customers who are available and willing to participate after experiencing the AI-enabled services at Hotel Robot.

Sources of data and analysis tools

The primary data used in this investigation was gathered through a structured questionnaire. The questionnaire includes a five-point Likert scale and demographic information. Primary data were gathered using google form on July 28th to Aug 5th 2026. The Likert-scale questionnaire's sources are still available. The SPSS program was used in the study to analyze the necessary data.

Table 2 shows that, Pilot study with 50 participants was conducted to ensure its

Table 2
Reliability test

Variable dimensions	Number of items	Cronbach's Alpha
AI service quality	5	0.879
Trust in AI	5	0.826
Customer satisfaction	5	0.872
Customer loyalty	5	0.864

reliability and utility, and if the calculation was above 0.7, additional data collection commenced. Cronbach's alpha coefficients are shown in *Table 2* for AI service quality (0.879), trust in AI (0.826), customer satisfaction (0.872), and customer loyalty (0.864).

Analytical model

In this study, regression analysis was used to determine the relationships among AI service quality, trust in AI, customer satisfaction, and customer loyalty. The study employed four multiple Ordinary Least Squares (OLS) regression models with path model statistics to examine the direct, indirect, and total effects among the independent variables, the mediating variable, and the dependent variable (Budhathoki & Khadka, 2024). According to Hayes (2022), the regression coefficients a_1b and a_2b represent the indirect effects (IE) of the independent variables on the dependent variable through the mediating variable ($X \rightarrow M \rightarrow Y$). Similarly, the direct effects (DE) of the independent variables on the dependent variable are measured by the regression coefficients a_1, a_2, c'_1, and c'_2 (i.e., $X \rightarrow M$ and $X, M \rightarrow Y$). The total effect (TE) is measured by the sum of the indirect effect (a_ib) and the direct effect (c'_i) and Total Effect = ($a_ib + c'_i$). If $a \times b \times c'$ is positive, the mediation model indicates complementary mediation, whereas if $a \times b \times c'$ is negative, the mediation model indicates competitive mediation (Hayes, 2022). If both the direct and indirect effects are significant, the mediation is considered partial mediation. In the Indirect effect model, t-statistics are used, where t-statistics can be determined by dividing the indirect effect estimate by its BootSE. Indirect effect is deemed to be statistically significant if the value of the t-statistics is greater than 1.96 at 5% significance level. On the other hand, if the t-statistics value is less than 1.96, it means that the mediating effect is insignificant. If the indirect effect is significant while the direct effect becomes insignificant after introducing the mediator, the mediation is considered full mediation (Budhathoki et al., 2023).

Model 1 (DE): $CS\ (M) = i_M + a_1X_1 + a_2X_2 + e_M$

Model 2 (DE): $CL\ (Y) = i_Y + c'_1X_1 + c'_2X_2 + b_M + e_Y$

Model 3 (IE): $CL\ (Y) = i_Y + a_1b + a_2b + e_Y$

Model 4 (TE): $CL\ (Y) = i_Y + (c'_1X_1 + a_1b) + (c'_2X_2 + a_2b) + e_Y$

Where, M = customer satisfaction (CS); (Y) = customer loyalty (CL); X_1 = AI service quality; X_2 = Trust in AI, a_1 = Coefficient of the service quality; a_2 = Coefficient effect trust in AI; b = Coefficient of customer satisfaction, c'_1 = Direct effect of AI service quality on CL; and c'_2 = Direct effect of trust in AI on CL; i = Intercept (constant), and e = Error term.

Definition of variable

Independent variable

AI service quality: AI service quality refers to how clients perceive the quality of AI-powered services such as chatbots, service robots, and virtual concierges (Sardesai et al., 2024). It is determined by the extent to which AI technologies provide accurate, dependable, responsive, and relevant services that suit the expectations of customers (Al-Araj et al., 2022). Unlike traditional service quality, which stresses human interactions during service delivery, AI service quality is concerned with the technology capabilities and performance of AI-enabled services. The hospitality industry associates AI service quality to customer satisfaction and loyalty (Sardesai et al., 2024). The importance of service quality in determining customer satisfaction and loyalty has been well documented in hotel research (Ali et al., 2016; Nguyen & Malik, 2022). Customers regard high-quality AI interactions as personalized, efficient, and capable of understanding their demands. This, in turn, increases client trust, satisfaction, and loyalty by improving service quality (Gursoy et al., 2023).

Trust in AI: Trust in AI refers to consumers' faith in artificial intelligence technology based on their dependability, security, competency, and ability to deliver reliable services. Glikson and Woolley (2020) described trust in AI as an individual's ability to place their faith in artificial intelligence systems based on their perceived reliability, competency, and ability to do tasks successfully. Consumers feel trust in adopting AI technology in the context of a service because of their dependability, effectiveness, and transparency in dealing with consumer needs. Trust is a crucial aspect that determines how customers view their experience with AI-enabled services since it mitigates the impact of AI-enabled service quality on customer experience (Ameen et al., 2021).

Mediating variable

Customer satisfaction: Customer Satisfaction is defined as individual's readiness to depend on artificial intelligence systems due to their reliability and competence and whether it meets or exceed the expectation of the user. According to Oliver (1980), customer satisfaction is an emotional reaction that takes place when there is an evaluation of actual performance against prior expectations. In the hospitality industry, according to Sardesai et al. (2024) the quality of AI services and human services has a significant effect on customer satisfaction. Customer Satisfaction shows guest overall evaluation of customer service experience such as Artificial intelligence technology like chatbots and bots. A customer that feels that artificial intelligence services are reliable, reactive, and customized is bound to feel satisfied, thereby affecting his future behavioral intentions and loyalty (Ali et al., 2016)

Dependent variable

Customer loyalty: Customer loyalty refers to a customer's unwavering commitment to acquiring and using a product or service on a regular basis despite the availability of other options. Oliver (1999) described a customer as someone who has a strong desire to make future purchases or patronize their favorite brand. In the AI-enabled hotel business, customer loyalty can be defined as customers' intentions to return to AI services or products, suggest them to others, and create a connection with the service provider. Customers who perceive AI services as dependable, efficient, and

personalized are more likely to create trust and contentment, which strengthens their commitment to hospitality companies (Ali et al., 2016; Sardesai et al., 2024)

FINDINGS AND DISCUSSION

Findings

Demographics responses: *Table 3* shows the gender distribution of the study's participants. A total of 390 people answered the questionnaire, among them, 217 (55.6%) were male and 173 (44.4%) were female.

Table 3
Gender of respondents

Gender	Frequency	Percent	Cumulative Percent
Male	217	55.6	55.6
Female	173	44.4	100
Total	390	100	

Figure 2 represents the age distribution of the respondents. A total of 390 people answered the questionnaire. Among them, 235 respondents (60.3%) were under the age of 30, 135 (34.6%) were between the ages of 30 and 60, and 20 respondents (5.1%) were 60 years or older. The cumulative figures show that 94.9% of responders were under the age of 60, with only 5.1% being 60 or older.

Figure 3
Visit frequency

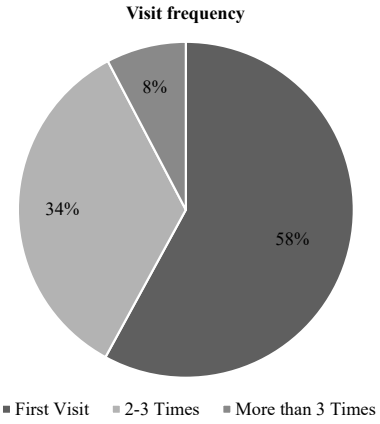


Figure 2
Age group of respondent

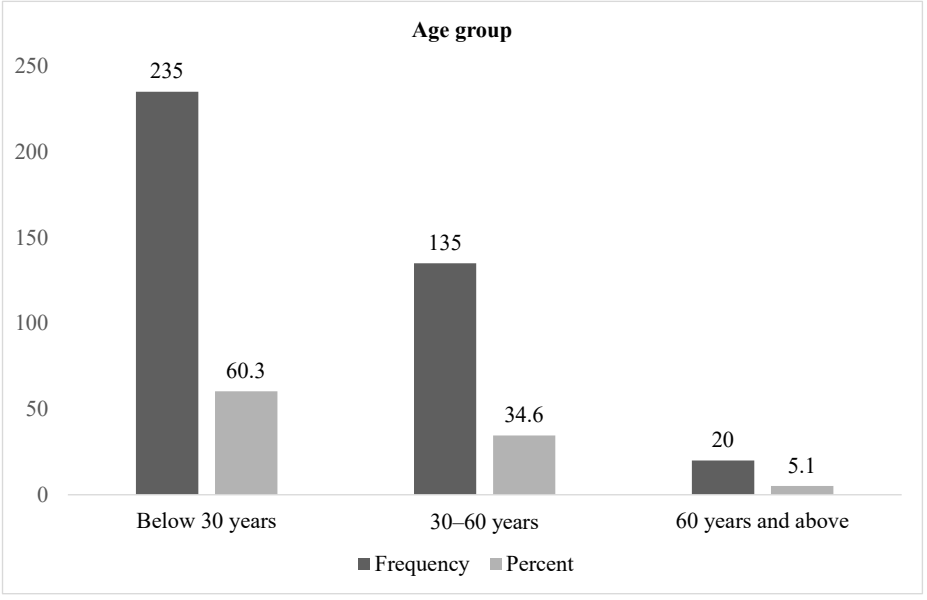


Figure 3 displays the frequency of visits by research participants. Of the 390 respondents, 226 (57.9%) were first-time guests, 134 (34.4%) has visited the Hotel Robot 2-3 times, and 30 (7.7%) has gone more than three times. The cumulative percentages show that 92.3% of respondents were either first-time visitors or has visited Hotel Robot 2-3 times, with only 7.7% having visited more than three times.

Table 4 shows that 80% of respondents has previously utilized AI-enabled services at hotel robots, while 20% had never used such services.

Descriptive analysis: Based on *Table 5* Customer satisfaction was reported to have the highest mean value (4.14) followed by Trust in AI (4.09), AI Service Quality (4.08) and Customer Loyalty (4.07). Similarly, the highest standard deviation values were for AI Service Quality and Customer Loyalty (0.67) followed by Customer Satisfaction (0.62) whereas lowest standard deviation value was for Trust in AI (0.58). Customer

Table 4
Basic information of respondents

Question	Responses				Total	
	Yes	Percent	No	Percent	Count	Percent
Have you previously used AI-enabled services at Hotel Robot?	312	80	78	20	390	100

Table 5
Descriptive statistics

Variable	Mean	Median	Mode	Std. Deviation	Variance
AI service quality	4.08	4.2	4.4	0.67	0.451
Trust in AI	4.09	4.2	4	0.58	0.344
Customer satisfaction	4.14	4.2	4	0.62	0.39
Customer loyalty	4.07	4.2	4	0.67	0.457

Table 6
Correlation analysis

Variable		AISQ	TAI	CS	CL
AI service quality	Pearson Correlation	1			
	Sig. (2-tailed)				
Trust in AI	Pearson Correlation	.437***	1		
	Sig. (2-tailed)	(.001)			
Customer satisfaction	Pearson Correlation	.485***	.406***	1	
	Sig. (2-tailed)	(.001)	(.001)		
Customer loyalty	Pearson Correlation	.467***	.382***	.522***	1
	Sig. (2-tailed)	(.001)	(.001)	(.001)	

****. Correlation is significant at the 0.001 level (2-tailed).*

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	Sig. (2-tailed)	(.001)	(.001)		
Customer loyalty	Pearson Correlation	.467***	.382***	.522***	1
	Sig. (2-tailed)	(.001)	(.001)	(.001)	

Table 7
Direct effect of the antecedent variables on customer satisfaction

Variables	Coefficient	SE	t	P	LLCI	ULCI
Constant	1.653	0.210	7.868	0.001	1.240	2.066
AISQ	0.353	0.044	7.944	0.001	0.265	0.440
TAI	0.255	0.051	5.022	0.001	0.155	0.356
F-statistics	76.0842	R = 0.5313	$R^2 = 0.2822$	$df_1 = 2$	$df_2 = 387$	
P value	(0.001)	MSE = 0.2811				

Loyalty was the variable with the highest variance (0.457), followed by AI Service Quality (0.451), Customer Satisfaction (0.390), and Trust in AI with the lowest variance (0.344). Median values for the four variables were identical (4.2) with mode values ranging from 4.0 to 4.4.

Correlation analysis: Table 6 shows that AI service quality has a positive and significant correlation with customer loyalty ($r = 0.467$, $p < 0.01$). Similarly, trust in AI is also positively and significantly correlated with customer loyalty ($r = 0.382$, $p < 0.01$). Furthermore, customer satisfaction has the strongest positive and significant correlation with customer loyalty ($r = 0.522$, $p < 0.01$).

Regression analysis: Table 7 shows the model 1 statistically significant ($F = 76.0842$, $p < .01$) and ($R^2 = .2822$) explains 28.22% of the variance in customer satisfaction. The results show that AI service quality has a positive and significant effect on customer satisfaction ($a_1 = .3533$, $p < .01$). Similarly, trust in AI has a positive and significant effect on CS ($a_2 = .2559$, $p < .01$). It means higher level of AI service quality and trust in AI have higher level of customer satisfaction.

According to Table 8, the regression model 2 is statistically significant ($F = 68.0422$, $p < .01$) and ($R^2 = .3459$) explains 34.59% of the variance in customer loyalty. The results show that AI service quality has a positive and significant direct effect on customer loyalty ($c'_1 = .2390$, $p < .01$). Similarly, trust in AI has a positive and significant direct effect on customer loyalty ($c'_2 = .1564$, $p<0.01$). Among the three variables, customer satisfaction has the strongest effect on customer loyalty ($b = .3806$, $p < .01$).

Table 8
Direct effect of the antecedent and mediating variables on customer loyalty

Variables	Coefficient	SE	t	P	LLCI	ULCI
Constant	0.878	0.234	3.746	0.002	0.417	1.339
AISQ	0.239	0.049	4.811	0.001	0.141	0.336
TAI	0.156	0.054	2.870	0.004	0.049	0.263
CS	0.380	0.052	7.230	0.001	0.277	0.484
F-statistics	68.0422	R = 0.5881	R^2 = 0.3459	df_1 = 3	df_2 = 386	
P value	(0.001)	MSE = 0.3015				

Table 9
Total effect model

Variables	Coefficient	SE	t	P	LLCI	ULCI
Constant	1.5076	0.2316	6.5097	0.001	1.0523	1.9629
AISQ	0.3735	0.049	7.6193	0.001	0.2771	0.4698
TAI	0.2538	0.0562	4.5189	0.001	0.1434	0.3642
F-statistics	67.0415	R = 0.5073	R^2 = 0.2573	df_1 = 2	df_2 = 387	
P value	(0.001)	MSE = 0.3414				

Table 10
Indirect effect model

Antecedent variables	Mediator	Effect	BootSE	BootLLCI	BootULCI	t-statistics
AI service quality	CS	0.1345	0.0336	0.0732	0.2029	4.003
Trust in AI	CS	0.0974	0.0453	0.0235	0.2003	2.15

Table 11
Mediation analysis summary

Variables	Direct effect	Total effect	Indirect effect	Relationship	Con. Interval (CI)		t-statistics	Conclusion
					Lower	Upper Bound		
AISQ → CL	0.2390 (0.000)	0.3735 (0.000)	0.135	AISQ → CS → CL	0.073	0.203	4.003	Partial mediation
TAI → CL	0.1564 (0.0043)	0.2538 (0.000)	0.097	TAI → CS → CL	0.024	0.2	2.15	Partial mediation

According to Table 9, the model is statistically significant (F = 67.0415, p < .01) and (R^2 = .2573) explains 25.73% of the variance in customer loyalty. AI service quality has a positive and significant total effect on customer loyalty (coefficient = .3735, p < .01). Similarly, trust in AI has a positive and significant total effect on customer loyalty (coefficient = .2538, p < .01).

According to Table 10, the results show that the indirect effect of AI service quality

on customer loyalty through customer satisfaction is significant (effect = 0.1345, t = 4.003). Furthermore, trust in AI also has a significant indirect effect on customer loyalty through customer satisfaction (effect = 0.0974; t = 2.15).

According to Table 11, the results show that all variables have direct, total and indirect significant effect on customer loyalty. Therefore, all six hypotheses are accepted. It presents partial mediation.

Discussion

AI service quality significantly and positively affected customer satisfaction. This is consistent with the findings of Mufaddhal (2025); Sardesai et al. (2024); Al-Araj et al. (2022); Costa et al. (2022). Similarly, trust in AI significantly and positively affected customer satisfaction, which is consistent with Ameen et al. (2021); Al-Oraini (2025). Moreover, AI service quality and trust in AI significantly and positively affected customer loyalty. These findings are consistent with Mufaddhal (2025); Sardesai et al. (2024); Singh and Singh (2024). Also, customer satisfaction significantly and positively affected customer loyalty, supporting the findings of Sardesai et al. (2024); Sharma et al. (2023). Finally, the mediating role of customer satisfaction is consistent with the result of Sardesai et al. (2024); Li et al. (2023).

CONCLUSION

AI service quality and trust in AI have a strong positive effect on customer satisfaction. According to the findings, improving the quality of AI-enabled services and increasing customer trust in AI boosts customer satisfaction. Similarly, the study discovered that AI service quality and trust in AI had a significant positive impact on customer loyalty. Customers are typically loyal to hospitality services when they believe AI enabled services are dependable, efficient, and trustworthy. Furthermore, the findings showed that customer satisfaction has a considerable positive impact on customer loyalty, meaning that the more satisfied consumers are, the more likely they are to develop a stronger commitment to AI enabled hospitality services. The mediation study's findings revealed that customer satisfaction partially mediates the relationship between AI service quality and customer loyalty, as well as trust in AI and customer loyalty. This shows that AI service quality and trust in AI have both direct and indirect impact on customer loyalty through customer satisfaction. These findings are consistent with the Technology Acceptance Model (TAM), which emphasizes how users' attitudes toward technology influence their adoption and subsequent behavioral responses. Thus, improving the quality, efficiency, reliability, and trustworthiness of AI-enabled hospitality services might result in higher customer satisfaction and loyalty. Hospitality companies may earn customers' trust by providing effective and dependable AI services that improve overall customer satisfaction and create long-term loyalty.

IMPLICATIONS OF THE STUDY

The study has key implication for hospitality service providers, managers, business owners and government. Since AI service quality and trust in AI has great impact on customer satisfaction and loyalty AI enabled services should focus on providing reliable, efficient, accurate,co and trustworthy AI-enabled services. Hospitality businesses

should regularly evaluate and improve the performance of their AI systems, ensure accurate service delivery, protect customer information, and provide transparent interactions with customers. Businesses should also ensure that AI services are easy to use and able to respond effectively to customer needs. Government should develop clear guidelines and policies for the responsible use of AI in the hospitality sector, particularly regarding customer data protection, transparency, service reliability, and consumer rights. The government can also support AI adoption by improving digital infrastructure and providing training and awareness programs for hospitality businesses.

There are certain limitations to this study, it was conducted among Hotel Robot customers in Samakhusi, Kathmandu, which may limit the findings applicability to other places and hospitality settings. Because the study used a cross-sectional methodology, it was impossible to investigate changes in customer perceptions over time. Furthermore, the study only looked at AI service quality, AI trust, customer satisfaction, and customer loyalty, despite the fact that other factors such as personalization and perceived risk may have an impact on these variables. Future research could involve larger and more diverse samples, other AI related characteristics, and a variety of geographical places and hospitality environment.

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ISSN XXXX-XXXX
9 771234 567003