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RELIANCE ON GENERATIVE AI-GENERATED INFORMATION AND INFORMATION-VERIFICATION PRACTICES AMONG UNDERGRADUATE MASS COMMUNICATION STUDENTS IN PAKISTAN

A QUANTITATIVE CORRELATIONAL STUDY

Ayesha Fatima

ayeshafatimalcwu@gmail.com

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Ayesha Fatima

Abstract

Generative artificial intelligence (GenAI) is increasingly used by university students to obtain information, summarise material, develop ideas, and support written work. These uses are relevant to mass communication education because students in this field are expected to evaluate sources and verify factual claims before information is reproduced or disseminated. This study examined the relationship between reliance on GenAI-generated information and information-verification practices among undergraduate mass communication students in Pakistan. A quantitative, cross-sectional, correlational design was used. The sample comprised 200 students from two public and two private universities. A 20-item questionnaire measured reliance and verification on five-point scales. The reliance and verification measures demonstrated good internal consistency, with Cronbach's alpha values of .866 and .872, respectively, and principal component analysis supported one composite score for each construct. Pearson correlation showed a statistically significant negative relationship between reliance and verification, $r = -.387$, $p < .001$. A consistent result was obtained through Spearman correlation, $\rho = -.377$, $p < .001$. Simple linear regression was significant and indicated that reliance accounted for 15.0% of the variance in verification scores, $R^2 = .150$. The results suggest that students who reported greater reliance on GenAI-generated information also reported less frequent verification. Journalism and mass communication curricula should therefore teach AI use together with practical verification routines, source tracing, citation checking, and evidence-based fact-checking.

INTRODUCTION

Generative artificial intelligence (AI) technologies are becoming increasingly integrated into educational and professional sectors, which has presented challenges and opportunities for media, journalism, and communication students (Rudolph et al., 2024). As news outlets increasingly rely on and integrate artificial intelligence, it is inevitable that students are educated about the ethical and professional use of these technologies (McGrath et al., 2025; Pavlik, 2023). It is also important to understand that the transformation of the educational landscape through generative AI

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requires an essential understanding of how it is affecting the learning process and professional skill development in education (Chen & Cheung, 2025; Daniel et al., 2025).

Recent research has shown that students use GenAI not only for content generation, but also to obtain knowledge, summarise information, support research, and receive assistance with academic tasks (Stojanov et al., 2024).In media and communication education, AI tools have also been incorporated into data analysis, data processing, and content-verification activities, with research highlighting their potential to support the development of analytical skills among students (Gomez-Diago, 2022; Wenger et al., 2025). Researchers have emphasised that the use of AI in education may alter student engagement with learning material, critical thinking, memory, and professional skill development, depending on the nature and intensity of use (Abbas et al., 2024; Tian & Zhang, 2025).

Recent research developments have also reflected the limited availability of guidance for AI integration in journalism education. This requires an in-depth understanding of how journalism students use AI and how curricula and institutional policies can support ethical, critical, and professionally responsible use (Jiang & Rafeeq, 2019; Pavlik, 2023). Reviews of the wider higher education literature similarly show that empirical work has developed quickly, but common theoretical foundations and consistent guidance for learning remain limited (McGrath et al., 2025).

This study, in order to understand the use of AI-generated information by students, intends to explore the relationship between reliance on generative AI and information-verification practices among Pakistani students. The focus is placed specifically on undergraduate mass communication students because the professional expectations associated with journalism and media work make source evaluation, factual accuracy, and verification important parts of their academic preparation (Deuze, 2006; Reyes-de-Cózar et al., 2022).

The ability of GenAI systems to produce fluent and organised responses can make generated information appear authoritative even when it contains unsupported claims or incorrect references. Research has documented fabricated bibliographic citations and substantive citation errors in outputs generated by widely used language models, which means that the surface quality of a response cannot be treated as evidence of its accuracy (Walters & Wilder, 2023). Verification is therefore not an optional activity added after the use of AI. It is part of the process through which a user decides whether an AI-generated claim, quotation, statistic, or source can be used responsibly (Holzmann et al., 2025).

This concern is especially relevant to journalism and mass communication. Journalistic work involves the selection, interpretation, and public distribution of information, and errors may be reproduced rapidly when material is copied from an AI system without checking the original source. Digital journalism education has already been required to respond to changes in news production, audience behaviour, and professional technologies (Jiang & Rafeeq, 2019). GenAI adds another requirement: students must learn to use a productive tool without transferring professional judgement and evidentiary responsibility to the tool itself (Pavlik, 2023).

Evidence from Pakistan suggests that university students generally recognise the usefulness of ChatGPT, while also expressing concerns about inaccurate information, academic integrity, over-reliance, and reduced deep thinking (Alghazo et al., 2025). Research conducted with university students has also linked extensive ChatGPT use with outcomes such as procrastination and memory loss, although the relationship between AI use and learning remains dependent on the way the tool is used and the context in which it is introduced (Abbas et al., 2024). These studies are valuable, but they do not directly establish whether students who rely more heavily on AI-generated information also engage less frequently in information verification.

The present study addresses this gap by examining reliance and verification as related but distinct behaviours. Reliance represents the degree to which students depend on GenAI-

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generated information for academic and information-related tasks. Verification represents the extent to which they check sources, citations, quotations, statistics, dates, names, and factual claims before accepting or using generated information. Studying these constructs together provides a direct way to examine whether greater dependence on AI is accompanied by weaker oversight of its outputs.

Research Question and Hypothesis

RQ1. What is the relationship between reliance on information generated by generative AI and information-verification practices among undergraduate mass communication students in Pakistan?

H1. Reliance on generative AI-generated information is negatively associated with information-verification practices among undergraduate mass communication students in Pakistan.

H0. There is no association between reliance on generative AI-generated information and information-verification practices among undergraduate mass communication students in Pakistan.

Literature Review

Generative AI Use and Reliance in Higher Education

Research shows that university students rely on ChatGPT to obtain knowledge and summaries and to support different aspects of assignment preparation (Stojanov et al., 2024). This reliance is not uniform. In a latent profile analysis of university students, Stojanov et al. (2024) identified low reliers, knowledge seekers, proactive learners, all-rounders, and assignment delegators. The profiles differed in the tasks for which ChatGPT was used, demonstrating that reliance is better understood as a pattern of dependence across activities rather than only as frequency of use.

The difference between use and reliance is important. A student may use GenAI regularly while still treating its output as a draft, comparing it with course readings, and taking responsibility for the final judgement. Another student may use it less frequently but delegate a complete assignment or accept a response without checking it. Reviews of GenAI in higher education identify both supportive uses, such as explanation, feedback, brainstorming, and personalised assistance, and risks related to accuracy, academic integrity, and reduced cognitive engagement (Lo, 2023; McGrath et al., 2025; Tlili et al., 2023). These mixed findings indicate that the educational value of AI depends on how it is used and how much intellectual responsibility remains with the learner.

Empirical evidence also shows that the demands placed on students can encourage greater use. Abbas et al. (2024) found that academic workload and time pressure were associated with ChatGPT use, and frequent use was related to procrastination, memory loss, and lower academic performance in their study. Their findings do not imply that every use of GenAI is harmful, but they show why reliance should be examined as a behavioural construct. When AI becomes a routine substitute for effort rather than a support for effort, the learner may complete a task while engaging less fully with its reasoning requirements.

At the same time, research does not show that using AI always has a negative effect on learning. When GenAI is used in well-planned learning activities, it can support academic performance, critical thinking, motivation, and student engagement. It can also give students quick and personalized support during learning (Deng et al., 2025; Heung & Chiu, 2025). In journalism and media education, AI is being used for tasks such as news gathering and data analysis. Research also shows the importance of helping students develop AI literacy, practical skills, critical thinking, and ethical awareness (Imran, 2025; Wenger et al., 2025). However, some journalism students use these tools without fully understanding how they produce information, which shows the need to teach students how to question and check AI-generated content (Veenstra et al., 2025). Therefore, the main issue is not simply whether students should use GenAI, but how it should be used in ways that support learning while still encouraging critical

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thinking, reflection, and independent judgement.

Generative AI in Journalism and Mass Communication Education

Journalism education has long been required to respond to technological change. Digital platforms have transformed newsgathering, production, distribution, and audience interaction, which has increased the importance of digital competencies in journalism programmes (Jiang & Rafeeq, 2019; Reyes-de-Cózar et al., 2022). Professional preparation must therefore combine technical fluency with the enduring responsibilities of accuracy, source evaluation, ethical reasoning, and public accountability (Deuze, 2006).

GenAI extends this challenge because it can participate directly in tasks that resemble journalistic work. It can propose angles, summarise reports, draft questions, translate material, reorganise text, and produce apparently complete explanations. Pavlik (2023) argued that these tools have important implications for journalism and media education because they demonstrate both considerable productive capacity and clear limitations. A curriculum that teaches only the operational use of AI may produce efficient users, but it may not produce journalists who can recognise unsupported claims, missing context, or unreliable sourcing.

Recent studies show that AI can have some benefits for learning. Irfan et al. (2023) found that using AI literacy activities and ChatGPT in journalism education helped students improve their critical thinking and journalistic writing skills. Baptista et al. (2025) asked journalism students to compare AI-generated news with human-written news and judge features such as readability, information quality, and writing style. In both studies, students used AI as part of clear learning activities. This is important because using AI for guided tasks is different from simply accepting an AI-generated answer without checking or thinking about it.

The literature therefore presents two related requirements for journalism programmes. First, students need practical familiarity with technologies that are changing newsroom work. Second, the same students need stronger capacity to interrogate AI outputs. The first requirement supports employability and professional adaptation, while the second protects the standards that make journalistic information credible. These requirements should not be treated as opposites. The educational task is to integrate AI in a way that preserves verification as a visible and assessable part of the work process.

Information Verification and Responsible GenAI Use

Information verification is therefore a central component of responsible GenAI use. Verification can include checking whether cited references exist, consulting the original source of a quotation, confirming statistics against authoritative databases, comparing factual claims with independent sources, checking dates and names, and cross-referencing news or media-related information. A study of university students' attitudes toward ChatGPT incorporated information verification and responsible use into the examination of students' academic adoption of the technology, indicating that verification has become an important dimension of AI-mediated academic behaviour (Acosta-Enriquez et al., 2024).

Holzmann et al. (2025) showed that verification can be an important part of critical thinking when using AI. In their ChatGPT Fact-Check activity, students checked AI-generated sources and compared AI-generated claims with evidence from research articles. They then decided whether the available evidence supported or rejected the claims. This shows that verification is a practical activity in which students actively check the accuracy of AI-generated information rather than simply trusting it

The need for verification is reinforced by evidence about generated citations. Walters and Wilder (2023) found that AI-generated literature reviews could contain fabricated sources as well

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as errors in real citations. The problem is educationally significant because invented references often appear plausible. Students who do not search for the publication, open the original source, and compare its content with the generated claim may unintentionally reproduce information that cannot be defended. Verification also requires more than locating a matching title. A source may exist but fail to support the claim for which it is cited. Quotations may be altered, statistics may lose their population or time frame, and summaries may omit qualifications. For this reason, effective verification involves source existence, source relevance, claim accuracy, and contextual consistency. These practices correspond with established accounts of media literacy that emphasise the ability to access, interpret, evaluate, and use mediated information critically (Livingstone, 2004).

In journalism education, verification should be applied to both scholarly and public information. Students may need to trace a citation in an academic assignment, verify a statement attributed to a public figure, identify the original dataset behind a statistic, or compare an AI-generated account with multiple news and documentary sources. The professional value of these practices is that they make the reasoning behind a claim visible. The student is not simply reporting that an AI tool produced the information, but demonstrating why the information can be trusted.

Reliance, Cognitive Offloading, and Automation Bias

Cognitive offloading provides one explanation for why reliance may be associated with lower verification. Cognitive offloading occurs when a person uses an external action or tool to reduce the information-processing demands of a task (Risko & Gilbert, 2016). Search engines, reminders, calculators, and written notes can all support performance through offloading. GenAI extends this possibility because it can externalise not only memory, but also summarisation, organisation, drafting, and parts of reasoning.

Offloading is not automatically detrimental. It can release cognitive resources for interpretation and higher-level decision-making when the user remains actively involved. The risk emerges when the external system replaces the monitoring process that should accompany the delegated task. Research on human interaction with automation distinguishes appropriate use from misuse, with misuse including over-reliance that produces failures of monitoring or biased decisions (Parasuraman & Riley, 1997). In an AI-supported academic task, a comparable failure occurs when a fluent output is accepted because it appears complete rather than because its evidence has been checked.

The tendency to rely on easily accessible external information has earlier parallels in research on digital memory. Sparrow et al. (2011) showed that expectations of future access to online information can influence what people remember. Generative AI makes this process different because it does not simply provide a source; it creates and combines information into an answer. Because the answer is presented so conveniently, users may be less likely to think about where the information came from or check the original sources.

Recent research has directly connected AI dependence with critical thinking. Tian and Zhang (2025) found that greater AI dependence was associated with lower critical thinking, They also found that mental tiredness was one possible reason for this, while information literacy could affect the relationship (Tian & Zhang, 2025) . Similarly, Abbas et al. (2024) raised concerns about the effects of using ChatGPT too much. These studies suggest that heavy reliance on AI may be linked to weaker verification practices. However, they also show that students' information literacy and how they use AI can influence these effects.

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Research on online credibility shows that people often use simple shortcuts when deciding whether information is trustworthy. They may judge information based on how clear it sounds, how familiar it feels, how well it is presented, or whether it appears to come from an expert (Metzger & Flanagin, 2013). GenAI-generated answers can also have these features, which may make them seem trustworthy. Verification is therefore important because it encourages users to go beyond simply accepting information that sounds believable and instead check the evidence behind it.

Pakistani Context and Research Gap

The Pakistani higher education context has begun to receive empirical attention. Alghazo et al. (2025) found that university students generally perceived ChatGPT as useful, particularly for research and information gathering, but also reported concerns about unreliable information, false references, academic integrity, dependency, and reduced deep thinking. Their findings show that students are aware of both benefits and risks, although awareness does not necessarily indicate consistent verification behaviour.

Abbas et al. (2024) also studied university students and demonstrated that the consequences of ChatGPT use may be connected with workload, time pressure, and the intensity of use. Together, these studies establish that GenAI is relevant to Pakistani university learning and that over-reliance is a recognised concern. However, the available evidence is mostly focused on general student populations, perceptions, adoption, or broad academic outcomes.

A more specific gap remains in relation to mass communication students. These students are preparing for fields in which unverifiable information can affect public understanding and institutional credibility. Existing journalism education research emphasises digital adaptation and professional competence, while recent AI research demonstrates potential benefits of guided integration (Jiang & Rafeeq, 2019). Less is known about the behavioural relationship between dependence on AI-generated information and students' own verification practices in Pakistan.

The present study therefore tests whether reliance and verification move in opposite directions. A negative association would suggest that students who depend more heavily on generated information may be less likely to undertake independent checking. A weak or absent association would suggest that reliance can coexist with verification. Either result would be educationally useful because it would clarify whether AI-use instruction should concentrate primarily on access and technique or place stronger emphasis on oversight and evidence checking.

Theoretical and Conceptual Framework

The conceptual framework combines together three main ideas: cognitive offloading, reliance on automation, and media literacy. Cognitive offloading explains why students may depend on GenAI to make information-related tasks easier and reduce their effort or workload (Risko & Gilbert, 2016). Research on automation explains that a helpful tool can also lead to problems when people trust and rely on it more than they should (Parasuraman & Riley, 1997). Media literacy, on the other hand, helps users evaluate information, check its sources, compare different claims, and take responsibility for their own judgement (Livingstone, 2004).

Within this framework, reliance does not simply mean using or being exposed to AI. Instead, it refers to how much students depend on GenAI-generated information when completing academic and other information-related tasks. Verification refers to the steps students take to check whether the information is accurate, can be traced to reliable sources, and is suitable to use. A student can rely on AI while still checking important information. However, the proposed negative relationship suggests that as students become more dependent on AI-generated information, they may be less likely to check it independently because the information is readily available.

The framework also recognises that using AI is not necessarily harmful. When used in a guided way, AI can support student engagement and

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help develop analytical skills. For example, students can be asked to explain their prompts, compare different AI responses, check sources, and revise their conclusions (Heung & Chiu, 2025; Holzmann et al., 2025). Therefore, the expected negative relationship does not suggest that AI should not be used in education. Instead, it examines whether greater dependence on GenAI-generated information is associated with weaker verification practices among the students in this study.

The cross-sectional design permits the study to estimate association and statistical prediction, but it does not establish that reliance causes weaker verification. Lower verification may encourage reliance, reliance may reduce verification, or both may be influenced by other factors such as AI literacy, time pressure, task difficulty, confidence, or institutional guidance. The conceptual framework is consequently used to interpret the direction of the observed relationship without making a causal claim.

Methods

Research Design

The study used a quantitative, cross-sectional, correlational design to examine the association between reliance on information generated by generative artificial intelligence and information-verification practices among undergraduate mass communication students in Pakistan. Cross-sectional correlational designs are appropriate for examining relationships among measured variables at one point in time when no experimental manipulation is introduced (Creswell & Creswell, 2018; Setia, 2016). The variables were measured without experimental manipulation; consequently, the analyses estimate association and statistical prediction rather than causation.

Participants and Study Context

For recruitment, initially 238 candidates were reached out through convenience sampling, however, only 201 candidates gave consent to participate. One response provided neutral, neither agree or nor disagree, responses for all the questions in the survey. So, that survey was discarded. Therefore, the study included responses from 200 undergraduate mass communication students recruited in person from two public and two private universities in Pakistan. The survey collection for this study took place from 15th December, 2025 to 15th January 2026. The surveys were collected under supervised in-person administration to ensure the responses are completely filled without any missing information. All participants were provided with informed consent forms before data collection. The identities of the participating universities and participants are withheld to preserve institutional confidentiality, and to maintain anonymity of personally identifying information of individual participants. The sample was relatively balanced by gender, with 51.0% female, 47.5% male, and 1.5% preferring not to disclose gender. Participants were aged 18 to 24 years, with a mean age of 20.14 years (SD = 1.37) and a median age of 20 years. Third-year students formed the largest group (32.0%), followed by fourth-year students (25.0%), while first- and second-year students each represented 21.5% of the sample. Most participants were enrolled in public universities (63.0%), whereas 37.0% attended private universities.

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Gender

Table 1: Gender wise representation of study participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	95	47.5	47.5	47.5
	Female	102	51.0	51.0	98.5
	Prefer not to say	3	1.5	1.5	100.0
	Total	200	100.0	100.0	

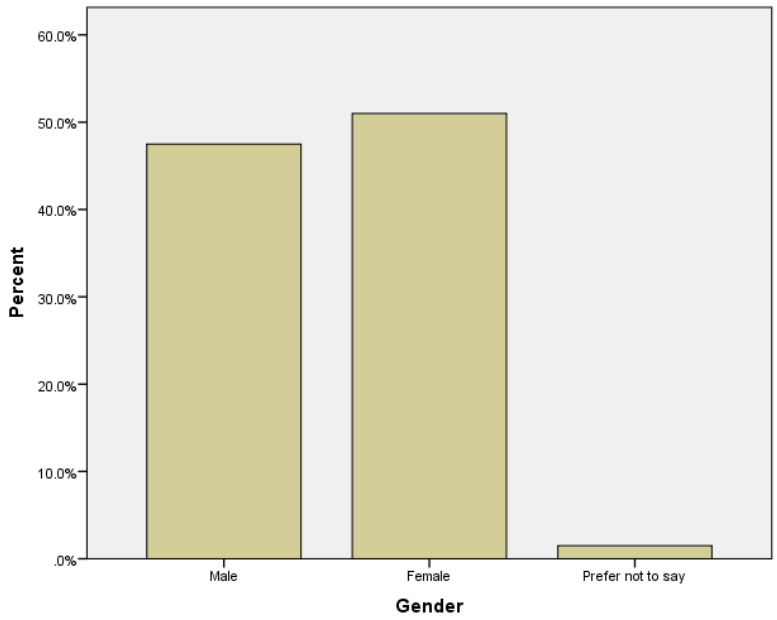

Figure 1: Graphical representation of gender wise study participants

Table 2: Age wise representation of study participants

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18	28	14.0	14.0	14.0
	19	39	19.5	19.5	33.5
	20	52	26.0	26.0	59.5
	21	49	24.5	24.5	84.0
	22	25	12.5	12.5	96.5
	23	5	2.5	2.5	99.0
	24	2	1.0	1.0	100.0

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Total	200	100.0	100.0	

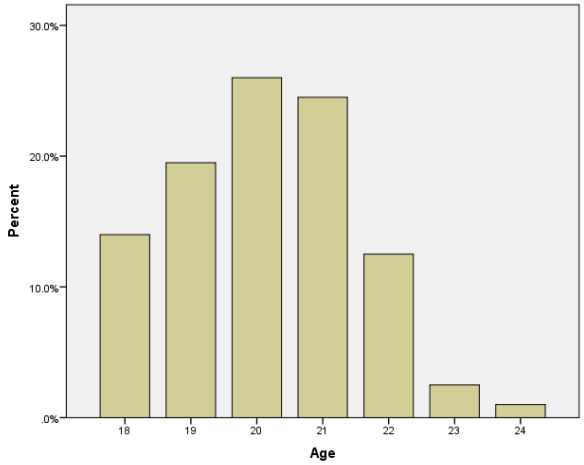

Figure 2: Graphical representation of age wise study participants

Table 3: Year of study wise representation of study participants

Year_of_Study

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	First Year	43	21.5	21.5	21.5
	Second Year	43	21.5	21.5	43.0
	Third Year	64	32.0	32.0	75.0
	Fourth Year	50	25.0	25.0	100.0
	Total	200	100.0	100.0	

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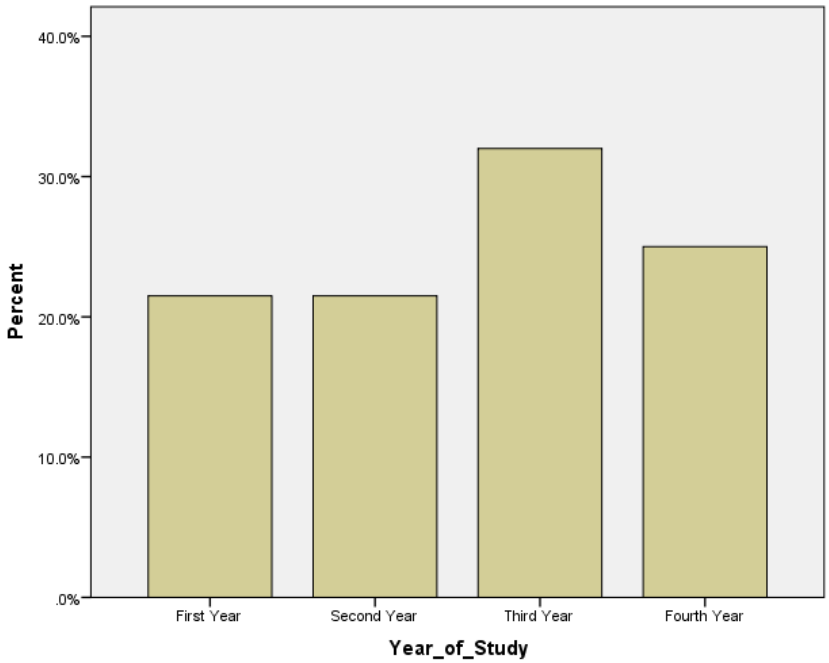

Figure 3: Graphical representation of year of study wise research participants

Table 4: University sector wise representation of study Participants

University_Sector

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Public	126	63.0	63.0	63.0
	Private	74	37.0	37.0	100.0
	Total	200	100.0	100.0	

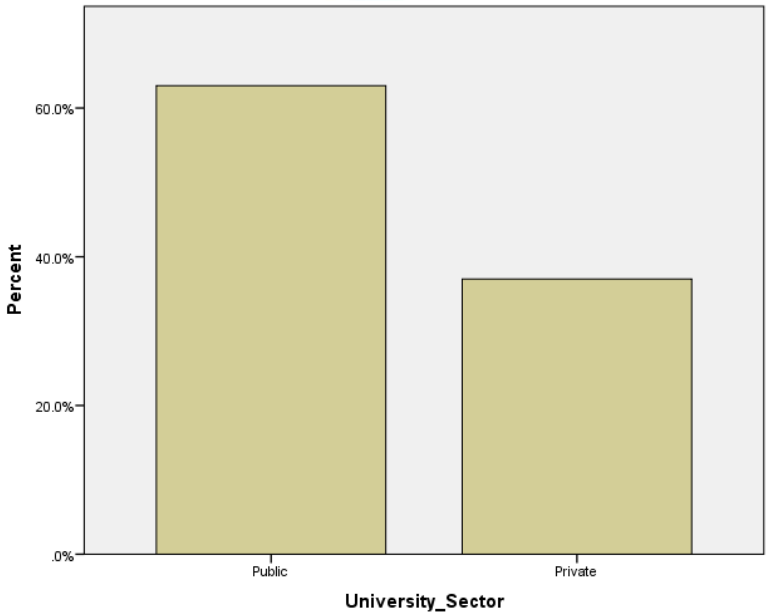

Figure 4: Graphical representation of public versus private university sector-wise study participants

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Measures

The questionnaire included 20 main items. Ten items (R1–R10) measured how much participants relied on information generated by Gen AI, while the other ten items (V1–V10) measured their information-verification practices. Responses were recorded on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The Likert scale is commonly used to measure different levels of agreement and can be used to create a combined score when several items measure the same concept (Norman, 2010). The questionnaire included researcher-developed items on reliance on Gen AI-generated information and verification items, based on existing literature, Some verification items were included to capture context-specific practices such as checking citations, statistics, quotations, factual claims, and media information.

Data Screening and Score Construction

The dataset was screened for the number of cases, valid response coding, missing data, and exact duplicate response profiles. Frequencies were inspected for all 20 substantive items as part of a structured data-screening process (Field, 2018). Composite scores were then calculated as the mean of all ten items within each construct using the SPSS MEAN.10 function, which required a valid response on every item.

Reliability and Component Structure

Internal consistency was assessed separately for the ten reliance items and the ten verification items using Cronbach's alpha, a coefficient used to evaluate the consistency of multi-item scores (Cronbach, 1951; Tavakol & Dennick, 2011). Corrected item-total correlations and alpha-if-item-deleted statistics were inspected to evaluate individual item performance, while recognising that alpha should be interpreted with the item content and dimensional structure rather than as a stand-alone proof of validity (Taber, 2018). The dimensional structure of each item set was examined using principal component analysis based on the correlation matrix (Jolliffe & Cadima, 2016). Sampling adequacy was evaluated using the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity (Bartlett, 1954; Kaiser, 1974). The analyses used the eigenvalue-greater-than-one criterion and no rotation because one component was retained for each measure.

Statistical Analysis

Descriptive statistics were calculated for the questionnaire items and the two composite scores. Distributional suitability was examined using skewness, kurtosis, histograms, normal probability plots, boxplots, and Shapiro-Wilk tests (Ghasemi & Zahediasl, 2012; Shapiro & Wilk, 1965). Pearson's two-tailed correlation was the primary test of the relationship between reliance and verification, consistent with its use for assessing the direction and strength of a linear association between continuous variables (Schober et al., 2018). Spearman's rho was used to check whether the results were consistent. A simple linear regression was also conducted to examine whether Reliance Mean could predict Verification Mean. To check the reliability of the regression results, standardized predicted values and residuals, the Durbin-Watson statistic, residual plots, Cook's distance, leverage, and residual normality were examined (Field, 2018). All analyses were conducted using SPSS.

Results

Data Screening and Participant Characteristics

The dataset included 200 participants. All the R1–R10 and V1–V10 questions had complete responses. All responses were also within the expected 1-to-5 range. The exact-profile duplicate check classified all 200 records as primary cases, indicating that no duplicate 20-item response profiles were identified. The recomputed composite scores matched the imported composites exactly.

Participants ranged from 18 to 24 years of age (M = 20.14, SD = 1.37). The sample included 102 women (51.0%), 95 men (47.5%), and three participants who preferred not to state their gender (1.5%). First- and second-year students each accounted for 21.5% of the sample (n = 43 each), third-year students accounted for 32.0% (n = 64), and fourth-year students accounted for 25.0% (n = 50). A total of 126 participants

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(63.0%) attended public-sector universities and 74 (37.0%) attended private-sector universities.

Reliability and Component Structure

The reliance measure demonstrated good internal consistency (Cronbach's alpha = .866). Corrected item-total correlations ranged from .481 to .698, and the alpha-if-item-deleted values ranged from .844 to .861, all below the full-scale alpha. The verification measure also demonstrated good internal consistency (Cronbach's alpha = .872). Its corrected item-total correlations ranged from .531 to .676, while alpha-if-item-deleted values ranged from .852 to .864. These results did not identify an item whose removal would improve the reliability of either complete ten-item measure.

Table 5. Reliability Statistics: Reliance on GenAI-Generated Information

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.866	.866	10

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Table 6. Item-Total Statistics: Reliance on GenAI-Generated Information

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
R1	27.71	51.624	.634	.435	.849
R2	27.70	52.344	.625	.422	.850
R3	27.87	52.811	.549	.318	.856
R4	27.79	52.207	.587	.360	.853
R5	27.72	52.022	.593	.377	.853
R6	27.88	54.850	.481	.259	.861
R7	27.90	52.989	.548	.334	.856
R8	27.85	52.524	.585	.366	.853
R9	27.64	51.227	.698	.519	.844
R10	27.84	54.480	.502	.281	.860

Table 7. Reliability Statistics: Information-Verification Practices

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.872	.872	10

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Table 8. Item-Total Statistics: Information-Verification Practices

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
V1	28.32	53.616	.537	.302	.864
V2	28.26	53.799	.574	.343	.861
V3	28.43	52.086	.628	.421	.856
V4	28.18	54.145	.581	.371	.860
V5	28.26	52.824	.603	.415	.858
V6	28.49	53.507	.578	.340	.860
V7	28.54	53.486	.592	.376	.859
V8	28.51	51.387	.676	.487	.852
V9	28.48	52.572	.603	.390	.858
V10	28.37	53.641	.531	.300	.864

For the reliance items, the Kaiser-Meyer-Olkin measure was .918 and Bartlett's test of sphericity was significant, $\chi^2(45) = 639.466$, $p < .001$. One component had an eigenvalue above 1 (4.570), explained 45.702% of the variance, and had loadings ranging from .574 to .782. For the verification items, the Kaiser-Meyer-Olkin value was .921 and Bartlett's test was significant, $\chi^2(45) = 654.489$, $p < .001$. The retained component had an eigenvalue of 4.657, explained 46.572% of the variance, and produced loadings from .623 to .761. The principal component results therefore supported the use of one composite score for each item set in this sample.

Table 9 . KMO and Bartlett's Test: Reliance on GenAI-Generated Information

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.918
Bartlett's Test of Sphericity	Approx. Chi-Square	639.466
	df	45
	Sig.	.000

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Table 10. Total Variance Explained: Reliance on GenAI-Generated Information

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.570	45.702	45.702	4.570	45.702	45.702
2	.832	8.319	54.021			
3	.759	7.587	61.608			
4	.679	6.786	68.394			
5	.655	6.546	74.940			
6	.606	6.063	81.003			
7	.576	5.764	86.767			
8	.494	4.940	91.707			
9	.462	4.615	96.322			
10	.368	3.678	100.000			

Extraction Method: Principal Component Analysis.

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Table 11. SPSS Component Matrix: Reliance on GenAI-Generated Information

Component Matrix[a]

	Component
	1
R9	.782
R1	.725
R2	.718
R5	.686
R8	.681
R4	.679
R3	.646
R7	.646
R10	.597
R6	.574

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

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Table 12. KMO and Bartlett's Test: Information-Verification Practices

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.921
Bartlett's Test of Sphericity	Approx. Chi-Square	654.489
	df	45
	Sig.	.000

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Table 13. Total Variance Explained: Information-Verification Practices

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.657	46.572	46.572	4.657	46.572	46.572
2	.752	7.522	54.094			
3	.719	7.193	61.288			
4	.685	6.848	68.136			
5	.655	6.545	74.681			
6	.614	6.136	80.817			
7	.574	5.743	86.560			
8	.534	5.335	91.896			
9	.428	4.280	96.176			
10	.382	3.824	100.000			

Extraction Method: Principal Component Analysis.

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Table 14. Component Matrix: Information-Verification Practices

Component Matrix[a]

	Component
	1
V8	.761
V3	.718
V5	.694
V9	.694
V7	.684
V4	.675
V6	.671
V2	.664
V1	.631
V10	.623

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Composite Descriptive Statistics and Distributional Checks

The mean reliance score was 3.0875 (SD = 0.80075; range = 1.20-4.70), and the mean verification score was 3.1535 (SD = 0.80400; range = 1.10-4.90). Reliance had skewness of -0.087 and kurtosis of -0.597; verification had skewness of -0.197 and kurtosis of -0.379. Shapiro-Wilk tests were not significant for reliance (W = .987, p = .066) or verification (W = .988, p = .106). The results showed that both composite scores were reasonably close to a normal distribution.

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Table 15. Descriptive Statistics for the Composite Scores

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
Reliance_Mean	200	1.20	4.70	3.0875	.80075	-.087	.172
Varification_Mean	200	1.10	4.90	3.1535	.80400	-.197	.172
Valid N (listwise)	200						

Descriptive Statistics

	Kurtosis	
	Statistic	Std. Error
Reliance_Mean	-.597	.342
Varification_Mean	-.379	.342
Valid N (listwise)		

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Table 16. Tests of Normality for the Composite Scores

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Reliance_Mean	.046	200	.200*	.987	200	.066
Varification_Mean	.053	200	.200*	.988	200	.106

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

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Relationship Between Reliance and Verification

Pearson's correlation showed a clear negative relationship between relying on GenAI for information and verification practices. In simple terms, participants who relied more on GenAI were less likely to verify the information they received. This relationship was statistically significant ($r = -.387$, $p < .001$, $N = 200$). The Spearman correlation showed a similar negative and statistically significant result ($\rho = -.377$, $p < .001$), which further supports this finding.

Table 17. Pearson Correlations Table

Correlations

		Reliance_Mean	Varification_Mean
Reliance_Mean	Pearson Correlation	1	-.387**
	Sig. (2-tailed)		.000
	N	200	200
Varification_Mean	Pearson Correlation	-.387**	1
	Sig. (2-tailed)	.000	
	N	200	200

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

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Table 18. Spearman Correlations Table

Correlations

			Reliance_Mean	Varification_Mean
Spearman's rho	Reliance_Mean	Correlation Coefficient	1.000	-.377**
		Sig. (2-tailed)	.	.000
		N	200	200
	Varification_Mean	Correlation Coefficient	-.377**	1.000
		Sig. (2-tailed)	.000	.
		N	200	200

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

Simple Linear Regression

The simple regression model was statistically significant, $F(1, 198) = 34.919$, $p < .001$. The model accounted for 15.0% of the variance in verification scores ($R = .387$, $R^2 = .150$, adjusted $R^2 = .146$). The unstandardized coefficient for reliance was negative, $B = -0.389$, $SE = 0.066$, $\beta = -.387$, $t = -5.909$, $p < .001$, 95% CI [-0.519, -0.259]. Thus, a one-unit increase in reliance was associated with an estimated 0.389-unit decrease in verification. However, this relationship is based on cross-sectional data, so it shows an association rather than a causal effect.

Table 19. Regression Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.387[a]	.150	.146	.74316	1.883

a. Predictors: (Constant), Reliance_Mean

b. Dependent Variable: Varification_Mean

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Table 20. Regression ANOVA Table

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.285	1	19.285	34.919	.000[b]
	Residual	109.352	198	.552		
	Total	128.638	199			

a. Dependent Variable: Varification_Mean

b. Predictors: (Constant), Reliance_Mean

Table 21. Regression Coefficients and Confidence Intervals

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4.354	.210		20.751	.000	3.940	4.768
	Reliance_Mean	-.389	.066	-.387	-5.909	.000	-.519	-.259

a. Dependent Variable: Verification_Mean

The Durbin-Watson statistic was 1.883. Standardized residuals ranged from -2.697 to 2.371, the maximum Cook's distance was 0.039, and the maximum centered leverage value was 0.028. The standardized residuals were approximately normally distributed (Shapiro-Wilk $W = .993$, $p = .468$), and the residual plots did not show a marked pattern that would invalidate the fitted linear model.

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Table 22. Residuals Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.5266	3.8873	3.1535	.31131	200
Std. Predicted Value	-2.014	2.357	.000	1.000	200
Standard Error of Predicted Value	.053	.135	.072	.020	200
Adjusted Predicted Value	2.5342	3.8903	3.1535	.31150	200
Residual	-2.00415	1.76237	.00000	.74129	200
Std. Residual	-2.697	2.371	.000	.997	200
Stud. Residual	-2.705	2.384	.000	1.002	200
Deleted Residual	-2.01660	1.78049	-.00001	.74852	200
Stud. Deleted Residual	-2.750	2.412	.000	1.006	200
Mahal. Distance	.000	5.556	.995	1.175	200
Cook's Distance	.000	.039	.005	.007	200
Centered Leverage Value	.000	.028	.005	.006	200

a. Dependent Variable: Varification_Mean

Table 23. Tests of Normality for Standardized Residuals

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	.039	200	.200*	.993	200	.468

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

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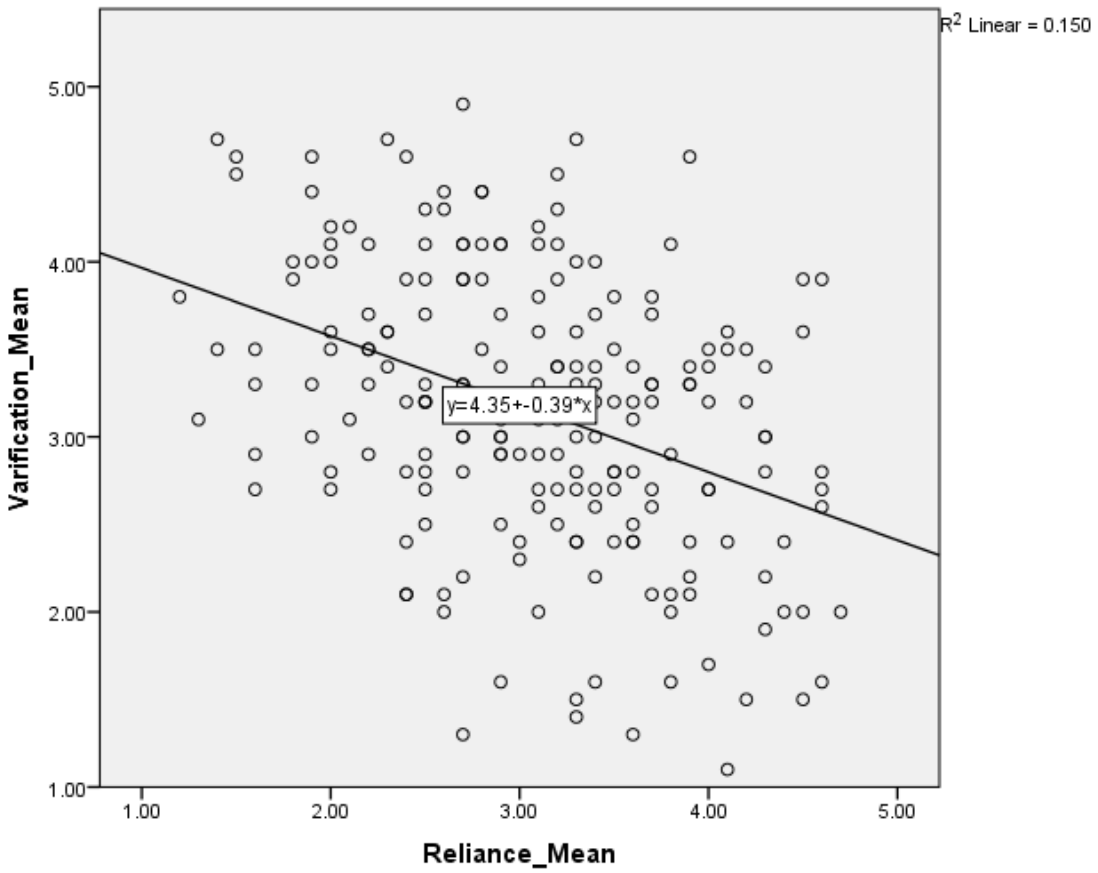

Figure 5. Scatterplot of Reliance Mean and Verification Mean

Hypothesis Decision

H1 was supported. The primary Pearson analysis identified a statistically significant negative relationship between reliance on GenAI-generated information and information-verification practices. Students with higher reliance scores tended to report lower verification practices in the analysed sample.

Discussion

The study examined whether reliance on GenAI-generated information was related to information-verification practices among undergraduate mass communication students in Pakistan. The primary result was a statistically significant negative relationship, $r = -.387$, $p < .001$. Students who reported greater reliance on GenAI-generated information tended to report less frequent verification. The Spearman correlation was similar in direction and magnitude, which indicates that the result did not depend only on the assumptions of the Pearson test. The regression model also showed that reliance accounted for 15.0% of the variance in verification scores.

The finding supports H1 and is consistent with research connecting AI dependence with reduced critical engagement. Tian and Zhang (2025) reported a negative association between AI dependence and critical thinking, with cognitive fatigue contributing to the relationship. Abbas et al. (2024) also found that frequent ChatGPT use was related to undesirable academic and cognitive outcomes in their university samples. The present study extends this concern to information verification. Rather than measuring general critical thinking or academic performance, it focuses on the

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specific checking behaviours required when students use generated claims, sources, statistics, and quotations.

The result can be interpreted through cognitive offloading. GenAI reduces the effort required to locate, summarise, and organise information, which can be beneficial when the saved effort is directed toward evaluation and synthesis (Risko & Gilbert, 2016). However, reliance may become problematic when the student offloads both production and monitoring. The negative relationship found in this study suggests that heavier reliance was accompanied by weaker oversight in the sample. This pattern is compatible with the concept of automation misuse, in which over-reliance contributes to failures of monitoring or biased decisions (Parasuraman & Riley, 1997).

The size of the relationship should be interpreted carefully. Reliance explained 15.0% of the observed variance in verification, which is meaningful but leaves most of the variance unexplained. Verification is likely to be influenced by many factors that were not included in the model, such as prior fact-checking training, AI literacy, information literacy, task difficulty, academic workload, confidence, access to databases, assessment requirements, and the perceived consequences of an error. The result therefore identifies reliance as one relevant correlate rather than a complete explanation of verification behaviour.

The finding also requires distinction between reliance and use. Stojanov et al. (2024) identified different profiles of student reliance, and some students with higher reliance also reported critical use of ChatGPT. Their profile-based findings show that high use can sometimes coexist with stronger AI literacy or active evaluation. The present result does not contradict that possibility. It indicates an average negative relationship across the current sample. Some students may use GenAI extensively and verify carefully, while others may rely on it for task delegation with little checking. Future research should examine these patterns directly rather than assuming that all high-reliance students behave in the same way.

Acosta-Enriquez et al. (2024) connected the intention to verify information with responsible ChatGPT use. The present study adds evidence that the tendency to verify may decline as reliance rises, which gives educational significance to the difference between having a favourable attitude toward responsible use and routinely performing verification actions.

The result is particularly important because AI-generated information may appear credible even when its references are incorrect. Walters and Wilder (2023) documented both fabricated citations and substantive citation errors in generated literature reviews. For a mass communication student, failure to verify does not remain only an academic problem. The same habit may transfer into professional tasks involving public claims, quotations, statistics, and attribution. A student who becomes accustomed to accepting plausible AI output may be less prepared to recognise when an apparently complete answer has no traceable evidentiary foundation.

At the same time, the negative association should not be used to justify a complete rejection of AI in journalism education. Research shows that AI can be included in journalism education through planned learning activities that develop relevant skills while also addressing ethical and critical issues (Wenger et al., 2025). Guided activities can also require students to check AI-generated claims, compare them with reliable sources, and explain their conclusions based on evidence (Holzmann et al., 2025). This suggests that the effects of AI use may depend on how learning activities are designed. Tasks that require students to check sources and explain their reasoning may support critical thinking, while simply asking students to produce a final answer may provide fewer opportunities for careful evaluation.

The Pakistani context provides another reason for a balanced interpretation. Alghazo et al. (2025) found that Pakistani university students recognised ChatGPT's usefulness but also reported concerns about inaccurate information, dependency, academic integrity, and reduced deep thinking. The present study

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moves beyond general perceptions by showing a behavioural association between reliance and self-reported verification among mass communication students. The finding suggests that awareness of risk may not be sufficient. Students can know that AI sometimes produces unreliable information and still fail to verify consistently when they depend on it for completing work.

The measurement results support the internal coherence of the two constructs in this sample. Cronbach's alpha was .866 for reliance and .872 for verification, and removal of individual items did not improve the complete measures. The principal component analyses also supported one retained component for each item set. These results provide a reasonable basis for using composite scores, although they should not be treated as full validation of the instruments. The reliance and verification items were researcher-developed, and principal component analysis in one sample cannot establish measurement invariance or confirm that the same structure will appear in other institutions and populations.

The regression coefficient provides a practical expression of the relationship. A one-unit increase in reliance was associated with an estimated .389-unit decrease in verification. This estimate does not mean that increasing reliance will necessarily cause verification to fall by that amount, because the study was cross-sectional and nonexperimental. It indicates the expected difference in verification associated with a one-unit difference in reliance within the fitted model. The acceptable residual diagnostics support the statistical use of the model, but they do not convert association into causation.

Taken together, the findings support a view of AI literacy that includes observable verification behaviour. Technical proficiency in prompting and generating content is insufficient for journalism education. A student should also be able to trace a claim to an original source, distinguish a primary source from a repeated report, check whether a quotation is accurate, confirm the context of a statistic, and document how contradictory information was resolved. These activities preserve human judgement at the point where AI output enters academic or professional communication.

Theoretical Implications

The study contributes to the developing literature by connecting reliance with a specific form of critical oversight. Much of the early GenAI literature examined adoption, attitudes, usefulness, academic integrity, or general learning outcomes (Lo, 2023; McGrath et al., 2025). The present model separates reliance from verification and tests their relationship directly. This distinction is useful because a technology can be accepted and frequently used while the quality of oversight varies substantially.

The findings also extend cognitive offloading and automation-reliance perspectives into journalism education. Cognitive offloading explains why students may transfer information work to AI, while automation research explains why monitoring can weaken when a system is trusted beyond its reliability (Parasuraman & Riley, 1997; Risko & Gilbert, 2016). Information verification acts as the human control mechanism within this process. It is the activity through which a generated answer is converted from a plausible suggestion into evidence that can be defended.

Finally, the study supports the inclusion of verification within conceptions of AI and media literacy. Livingstone (2004) described media literacy as involving critical evaluation of mediated information. The present result shows why critical evaluation should extend to AI-generated information. In an AI-mediated information environment, media literacy includes not only understanding messages and platforms, but also determining whether algorithmically generated content is traceable, accurate, and contextually appropriate.

Practical Implications for Journalism and Mass Communication Education

The findings support curriculum designs in which AI use and verification are taught together. Students should not be given only general warnings that GenAI may be inaccurate. They should practise specific routines: opening cited sources, searching article

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titles and DOIs, locating original quotations, identifying the primary dataset behind a statistic, comparing claims across independent sources, and recording the evidence used to accept or reject an AI-generated statement.

Assessment design can make these routines visible. A student who uses GenAI for research could be required to submit a verification log showing the original AI claim, the sources consulted, the decision made, and any correction introduced. Journalism assignments could include deliberately flawed AI-generated briefs that students must fact-check. Marks could be allocated separately for source quality, verification reasoning, and the accuracy of the final product rather than only for fluency and presentation.

Newsroom simulations can also help students understand the professional consequences of verification. In a timed exercise, students may use AI to develop an initial background brief, but every name, date, quotation, and numerical claim would require confirmation before publication. Such exercises preserve the productivity benefit of AI while placing responsibility for accuracy with the student. They also demonstrate that verification is not an abstract ethical principle; it is a sequence of actions under deadline pressure.

Institutional policies should distinguish acceptable assistance from unacknowledged delegation. A policy that simply permits or prohibits AI use may not address the more important question of how students evaluate the output. Clear guidance can specify when AI use must be declared, which claims require primary-source confirmation, how generated citations should be checked, and what evidence students should retain. This approach is more educationally useful than assuming that access alone produces either responsible or irresponsible use.

Faculty development is equally important. Journalism educators need sufficient AI literacy to design verification tasks, recognise common failure patterns, and assess student reasoning. They do not need to treat every AI output as false, but they should model calibrated trust. This means using the tool for appropriate purposes, checking claims in proportion to their importance, and explaining why some sources are authoritative while others are not. The same practice can help students move from either uncritical enthusiasm or complete avoidance toward disciplined professional use.

Limitations

There are a few limitations which should be considered. First, the cross-sectional design does not establish causation. The data show that reliance and verification were negatively associated. Longitudinal and experimental designs are required to examine direction more clearly.

Second, both constructs were measured through self-report. Students may overstate responsible practices, understate dependence, or interpret questionnaire items differently. Self-reported verification does not necessarily correspond with performance when a student is required to detect a false citation or evaluate a disputed claim. Behavioural measures would provide a stronger test of whether reported habits are applied in practice.

Finally, the study focused on undergraduate mass communication students from four universities. The findings therefore offer insights into this particular educational context, rather than representing all students, disciplines, or professional groups in Pakistan. The study also described differences in university sector and year of study, although it did not specifically examine whether the relationship between reliance and verification varied across these groups. Future studies could build on these findings by including a wider range of disciplines, educational levels, and participant groups.

Future Research

Future research should combine self-report scales with behavioural verification tasks. Students could be presented with AI-generated news briefs containing a mixture of accurate claims, unsupported statements, altered quotations, and fabricated references. Researchers could then measure which problems are detected, what sources are consulted, how long verification takes, and

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whether students revise the final answer correctly.

Longitudinal studies could examine whether reliance and verification habits change across a semester in which students receive structured AI-literacy and fact-checking instruction. Experimental studies could compare unrestricted AI use, AI use with a verification checklist, and non-AI conditions. Such designs would help determine whether verification prompts preserve the benefits of AI assistance while reducing uncritical acceptance.

Further studies should also examine moderators and mediators. AI literacy, information literacy, epistemic motivation, trust, time pressure, cognitive fatigue, task complexity, and perceived accountability may explain when reliance is more or less strongly related to verification. Comparisons across public and private universities, years of study, journalism specialisations, and professional experience would show whether the relationship is consistent across educational contexts.

Qualitative interviews and observation could add detail that a composite score cannot provide. Students may verify high-stakes political claims but not routine background information, or they may check sources only when a teacher requires evidence. Understanding these decisions would help educators design instruction that is proportionate to risk and realistic for newsroom practice.

Conclusion

Generative AI is becoming part of the information environment in which mass communication students learn and will work. Its value lies in the speed with which it can support searching, summarising, drafting, and analysis. The same fluency creates a risk when students accept generated information without tracing its evidence. This study examined that problem by testing the relationship between reliance on GenAI-generated information and information-verification practices among undergraduate mass communication students in Pakistan.

The results showed a statistically significant negative association. Students with higher reliance scores tended to report lower verification practices, and the regression model accounted for 15.0% of the variance in verification. The finding does not establish a causal effect and does not imply that all frequent AI use is harmful. It shows that reliance deserves attention because dependence on generated information can coexist with reduced oversight.

For journalism and mass communication education, the practical response is not to separate AI use from professional standards. Students should learn both how to use GenAI and how to challenge it. Source tracing, citation checking, quotation verification, statistical confirmation, and comparison with independent evidence should be included in teaching, assessment, and policy. When verification remains visible, GenAI can function as a support for professional reasoning rather than a substitute for it.

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