

The Relationship Between Digital Literacy, User Skepticism, and Verification Behavior in Evaluating Generative AI Responses

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ABSTRACT

Research Objective. This study is motivated by the transformation of information evaluation practices in the era of Generative Artificial Intelligence (Generative AI), in which users increasingly evaluate AI-generated responses rather than directly assess the credibility of sources. Given that Generative AI can produce highly fluent but not always accurate responses, digital literacy and user skepticism have become critical factors in the information evaluation process. This study aims to analyze the relationships among digital literacy, user skepticism, and verification behavior in the evaluation of Generative AI responses. **Research Method.** This study employed a quantitative cross-sectional design, using cross-tabulation and chi-square analysis. **Analysis Data.** Data were analyzed using cross-tabulation and chi-square tests in SPSS to identify distribution patterns and relationships among categorical variables. The study used secondary data from the Kaggle platform, involving 1000 respondents; therefore, the findings should be interpreted within the limitations of the dataset's representativeness. **Results.** The findings indicate that digital literacy is not significantly associated with age or educational attainment. In contrast, both digital literacy and educational level are significantly associated with users' skepticism toward Generative AI. However, no significant relationship was found between users' digital literacy levels and the fact-checking methods they employed. **Conclusions.** Within this dataset, age and formal education do not demonstrate significant relationships with digital literacy levels. Nevertheless, users with higher levels of digital literacy and educational attainment tend to exhibit greater skepticism toward Generative AI responses. These findings may indicate a tendency toward more proportionate patterns of trust, although this study does not directly measure calibrated trust. Digital literacy emerges as a potentially important factor associated with how users understand the limitations of AI systems, evaluate AI-generated responses, and determine whether additional verification is necessary.

Keywords: *Generative AI Response Evaluation; AI User Skepticism; Digital Literacy*

A. INTRODUCTION

The development of Generative Artificial Intelligence (Generative AI) has reconfigured the landscape of human-information interaction. Whereas users in the era of conventional search engines interacted with lists of documents and independently selected information sources, the Generative AI paradigm presents users with automatically generated responses, coherently formatted in a

conversational format. This transformation represents not only a change in technological interfaces but also a shift in information evaluation mechanisms from source-based to output-based evaluation. Users no longer directly assess the credibility of documents or the authority of information sources; instead, they evaluate responses that have been synthesized and generated through large language models (LLMs).

The ability of Generative AI to produce highly fluent text can create an illusion of understanding, in which perceptions of accuracy are established by linguistic coherence rather than factual correctness. Consequently, Generative AI introduces significant challenges concerning the ambiguity between linguistic fluency and factual truth, often leading users to develop misleading perceptions of accuracy. This condition has stimulated discussions surrounding the concept of stochastic parrots, a metaphor describing how LLMs operate by reproducing patterns from their training data without possessing a substantive understanding of meaning or factual truth. As a result, such systems not only have the potential to generate inaccurate information but also tend to reproduce biases embedded within their training datasets (Bender et al., 2021).

In this context, the need for critical evaluation of Generative AI responses has become increasingly urgent. However, individuals' capacities to conduct such evaluations are not homogeneous. Digital literacy constitutes one of the key variables that may influence how users understand system limitations, assess response accuracy, and determine whether additional verification is required (W. Ng, 2012). Digital literacy is defined as the ability to understand and produce various forms of digital content while simultaneously evaluating and utilizing information from online sources, emphasizing cognitive and critical dimensions, including information-seeking skills, the ability to assess content accuracy, and the capacity to establish networks for managing information flows (Santos & Gomes, 2024).

Further support for the conceptualization of digital literacy can be found in the Digital Competence Framework for Citizens (DigComp) 2.2. This framework positions the enhancement of digital competence as a strategic agenda within the digital transformation of modern societies. DigComp 2.2 identifies five principal domains of digital competence: information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. Each domain is elaborated through indicators encompassing knowledge, skills, and attitudes and is organized into eight proficiency levels ranging from foundational and intermediate to advanced and highly specialized stages (Vourikari et al., 2022). This structure demonstrates that digital literacy extends beyond operational abilities and should be understood as a multidimensional competence requiring evaluative, reflective, and participatory capacities in the use of digital technologies.

The present study focuses specifically on the information and data literacy domain, which encompasses digital literacy competencies related to individuals' ability to identify information needs, effectively search for and access data and digital content, and navigate diverse information sources in digital environments. This competence also encompasses the ability to analyze, compare, and critically evaluate the credibility, relevance, and reliability of information sources and digital

content. Furthermore, information and data literacy includes the capacity to interpret information reflectively, enabling users to understand the quality and accuracy of the information they receive.

Accordingly, within the context of Generative AI, digital literacy involves not only the technical ability to operate AI platforms but also the analytical capacity to identify potential biases, factual inaccuracies, and the probabilistic nature of AI-generated outputs. In addition to digital literacy, demographic characteristics such as age and educational attainment may contribute to variations in how individuals interact with information technologies. In this regard, demographic characteristics are among the factors influencing information behavior in the process of acquiring relevant information (Wilson, 2020).

On the other hand, evaluating Generative AI responses cannot be separated from the issue of human–AI trust. Trust in AI is fundamentally a multidimensional concept that encompasses not only a system's technical performance but also human perceptions of its reliability, transparency, and ability to support decision-making. John D. Lee and Katrina A. developed a more specific conceptualization of trust in automated systems See through the framework of trust in automation, which posits that trust emerges from users' perceptions of a system's performance, process, and purpose (Lee & See, 2004).

This framework is particularly relevant to AI studies because it explains that users evaluate not only AI outputs but also how systems operate and the purposes for which the technology is employed. Within the context of human–AI interaction, user skepticism can be understood as a spectrum of trust toward AI capabilities. Categories such as blind trust, moderate trust, and highly skeptical represent varying levels of confidence in AI-generated outputs. Conceptually, this spectrum aligns with Lee and See's (2004) notion of trust calibration, which suggests that users' trust should correspond to a system's actual capabilities. Within this framework, blind trust reflects overtrust, whereas being highly skeptical reflects a tendency toward distrust. Meanwhile, moderate trust may be interpreted as an initial indication of more proportionate trust, although it is not equivalent to a direct measurement of calibrated trust.

Trust in Generative AI is fundamentally formed through the dimension of cognitive trust, namely users' rational assessments of the competence, reliability, and usefulness of a technology in assisting specific tasks. Compared with conventional technologies, establishing cognitive trust in Generative AI is considerably more complex due to transparency issues. Generative AI systems often operate as black boxes, with internal mechanisms that are opaque and therefore difficult for ordinary users to understand. This uncertainty is further influenced by the dynamic nature of Generative AI reliability, whereby the system may produce different responses to similar inputs due to data-driven learning processes. Within this context, user skepticism can be understood as a critical response when system transparency and reliability are perceived as insufficient (Glikson & Woolley, 2020). Consequently, evaluating the accuracy of information generated by Generative AI is essential to determine whether it is sufficiently credible to support factual decision-making.

Previous research by Bahçekapili and Boztaş (2025) demonstrated the role of digital literacy in shaping intentions to adopt Generative AI. However, the study primarily focused on technology acceptance and did not specifically examine how users evaluate the accuracy of Generative AI responses. Similarly, research by Syamsuddin et al. (2026) investigated students' readiness to engage with Generative AI through the lens of advanced digital literacy and found that, although students were operationally prepared, they remained weak in evaluative dimensions such as information verification, understanding of AI mechanisms, and digital ethics. These findings suggest a gap between the ability to use AI technologies and the critical thinking skills required to assess the accuracy and biases of AI-generated outputs. Nevertheless, neither study specifically addressed information evaluation behavior from the perspectives of user skepticism, verification strategies, and demographic variations. Accordingly, a research gap remains regarding the relationship between digital literacy, skepticism, and verification behavior in evaluating Generative AI outputs.

Based on these considerations, the urgency of this study stems from the changing ways society evaluates information in the era of Generative AI. Whereas users previously assessed credibility through sources or documents, they now increasingly rely on answers summarized and directly presented by Generative AI systems. Such responses may appear highly fluent and convincing while not necessarily being factually accurate. At the same time, existing digital literacy frameworks remain largely focused on the ability to search for and evaluate online sources rather than on the ability to assess synthetic, often non-transparent Generative AI outputs critically. Therefore, this study addresses the following research questions: RQ1: Is there a significant relationship between age groups, educational attainment, and digital literacy levels in the context of Generative AI use? RQ2: Is there a significant relationship between digital literacy levels, educational attainment, and user skepticism toward Generative AI responses? RQ3: Is there a significant relationship between digital literacy levels and the selection of fact-checking methods in evaluating Generative AI responses?

This study seeks to analyze the relationships among digital literacy, skepticism, and verification behavior across demographic characteristics in order to contribute conceptually to the development of information behavior research in the era of Generative AI. The findings are expected to provide theoretical contributions to the advancement of digital literacy and information behavior studies in the context of Generative AI while also serving as practical references for educational institutions, policymakers, and technology developers in designing strategies to strengthen digital literacy and promote more critical information verification practices.

B. METHODS

This study employed a quantitative cross-sectional design to examine the distribution patterns and associations among categorical variables using cross-tabulation and chi-square tests. The dataset represents information collected at a single point in time without repeated observations of respondents.

Conceptually, cross-tabulation is a method of data presentation in tabular form that displays the frequency of cases based on combinations of values from one or more categorical variables with other categorical variables, arranged in rows and columns (Kent, 2015). Meanwhile, the chi-square test is a non-parametric statistical method used to determine whether a significant association exists between two categorical variables (Kremelberg, 2011).

The analysis was conducted using secondary data obtained from the open-access Kaggle platform. The dataset contains survey data from 1000 respondents regarding the use and evaluation of Generative AI responses, encompassing demographic characteristics, levels of digital literacy, user skepticism, and information verification behavior (Saher, 2026). Secondary data were used because the dataset already contained variables relevant to this study's focus, particularly those concerning digital literacy, user skepticism, and fact-checking behavior in evaluating Generative AI responses. The use of secondary data was considered appropriate given the efficiency of the research process, the alignment of the variable structure with the study focus, and the relatively large number of respondents in the Kaggle dataset, which was adequate for mapping distribution patterns through cross-tabulation analysis and testing statistical significance using the chi-square test.

Nevertheless, the use of secondary data introduces methodological implications that require careful attention. The researcher had no direct control over the sampling process, instrument design and validation, or the geographical and social contexts of the respondents included in the dataset. This limitation restricts the scope of interpretation, particularly concerning the generalizability of the findings. Variable operationalization in this study relied entirely on the pre-existing categories in the Kaggle dataset rather than being remeasured through instruments specifically developed by the researcher. Therefore, the construct validity of this study is constrained because the researcher could not directly assess how well the dataset's indicators represented the theoretical constructs of digital literacy, user skepticism, and fact-checking behavior.

The unit of analysis in this study was each respondent in the dataset, treated as an independent unit of analysis. The analysis was conducted using SPSS, with a focus on distribution patterns and relationships between variables. Prior to the analysis, the data were examined to ensure the appropriateness of variable formats, the completeness of categories, and the suitability of the data for cross-tabulation analysis and the chi-square test. The cross-tabulation analyses conducted in this study are presented as follows:

Table 1. Analytical Framework and Data Mapping Based on Research Questions

RQ	Cross-tabulation	Objective
RQ1	Age group × Digital literacy level	To identify the distribution of digital literacy levels across age groups and examine variations in digital competencies among generations within the context of Generative AI evaluation.
	Educational attainment × Digital literacy level	To describe the distribution of digital literacy levels according to educational attainment and examine variations in digital competencies across educational levels.
RQ2	Digital literacy level × User skepticism level	To analyze the distribution of user skepticism levels according to digital literacy levels when evaluating the accuracy of Generative AI responses.
	Educational attainment × User skepticism level	To map the distribution of user skepticism levels according to formal educational attainment in the evaluation of Generative AI responses.
RQ3	Digital literacy level × Fact-checking method selection	To describe preferences for fact-checking strategies across different levels of digital literacy in the evaluation of Generative AI responses.

C. RESULT AND DISCUSSION

The initial stage of the analysis presents an overview of the data through frequency distributions by respondent characteristics and research variables. This analysis aims to provide a preliminary understanding of user profiles and patterns of information evaluation in the context of Generative AI use before examining relationships among variables through cross-tabulation and chi-square analyses. The results of the study are presented as follows:

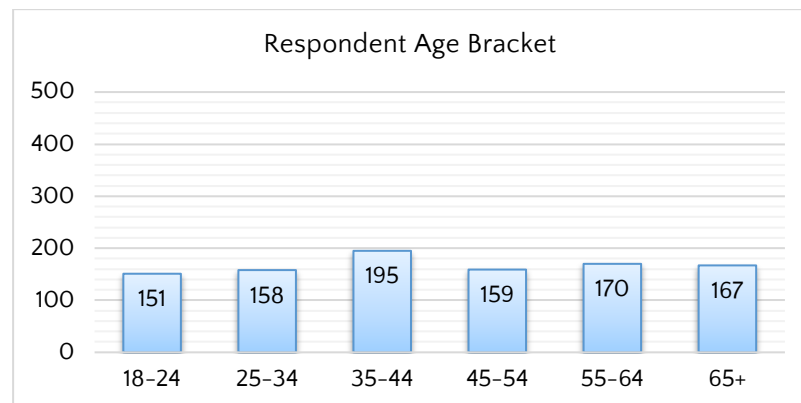


Figure 1. Respondent Age Bracket

Based on the data analysis, respondents aged 35–44 years constituted the largest age group, accounting for 195 respondents (19.5%). However, the difference between this group and the other age categories was relatively small; therefore, this finding should be interpreted as a descriptive tendency rather than a strong dominance. Within this age group, respondents were primarily individuals with master's degrees (22.1%), doctoral degrees (19%), and professional practitioner backgrounds (18.5%).

The predominance of Generative AI use among individuals in this age group may be explained by a combination of professional demands and pressures associated with adapting to digital transformation. This tendency is likely related to professional requirements, pressures to adapt to digital technologies, and the use of technology to improve work efficiency. However, these factors were not directly measured in the present study (Gudynaite et al., 2025). The finding should therefore be interpreted cautiously in relation to the professional needs of adults in their productive working years. Nevertheless, the data are insufficient to conclude that individuals aged 35–44 have more advanced AI competencies than those in other age groups. This pattern may instead reflect their position as active members of the workforce, many of whom occupy managerial roles and consequently have greater demands for work efficiency and technology-supported decision-making (Mayer et al., 2025). Overall, these findings suggest that AI use among middle-aged adults is primarily functional and strategic rather than recreational, supporting professional performance in an increasingly digitalized environment shaped by higher educational attainment.

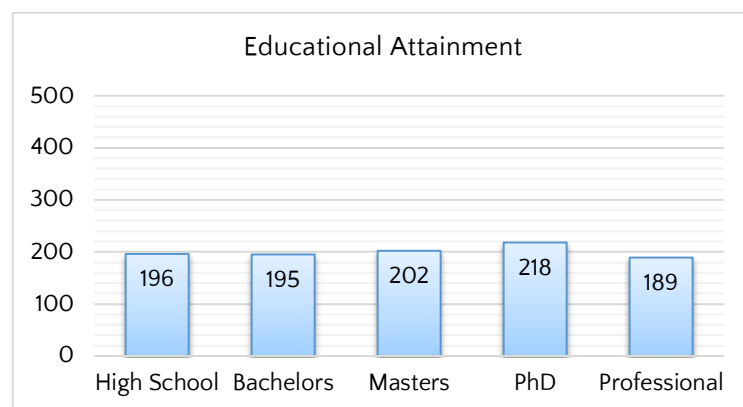


Figure 2. Educational Attainment

Across educational categories, the use of Generative AI appeared relatively evenly distributed. However, respondents holding doctoral and master's degrees exhibited slightly higher frequencies than those in other educational groups. This difference is descriptive and does not directly indicate differences in the intensity or quality of AI use. This finding is consistent with previous studies showing that individuals with higher educational attainment tend to utilize AI for various academic activities, including writing, data analysis, and research planning. Such patterns reflect more complex demands for AI-based technological support within higher education environments. Nevertheless, the frequency of AI use does not necessarily indicate the effectiveness of its application in supporting academic activities (Akbar, 2025).

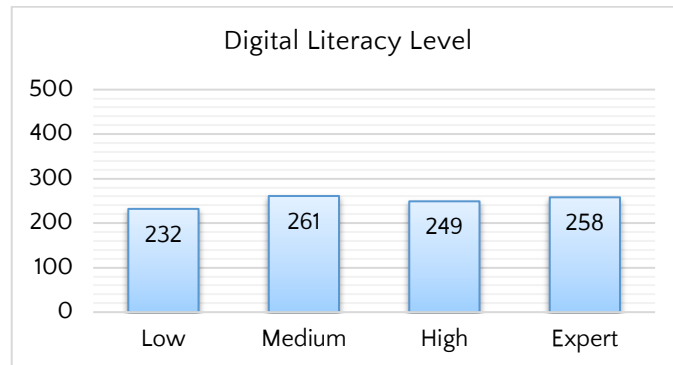


Figure 3. Digital Literacy Level

The frequency distribution across digital literacy levels was relatively balanced. This distribution indicates that users within the dataset were spread across a range of digital literacy levels, from low to expert. The finding suggests that most users in this study possessed a sufficient foundation of digital capabilities to navigate information within digital environments.

On the other hand, users with low levels of digital literacy still accounted for a considerable proportion of the sample, comprising 232 respondents (23.2%). This phenomenon may be explained by differences in technology adoption mechanisms associated with varying levels of digital literacy. Individuals with lower digital literacy may face greater challenges in evaluating and verifying information, potentially leading to more passive acceptance of information, including in interactions with AI systems. However, because this study did not directly measure dependency on AI, such interpretations should be approached with caution. Conversely, users with higher levels of digital literacy are likely to possess a better understanding of technological benefits and to integrate AI more strategically into their activities. Accordingly, these findings reflect a dual pattern of AI adoption based on both trust and competence (Bahçekapili & Boztaş, 2025).

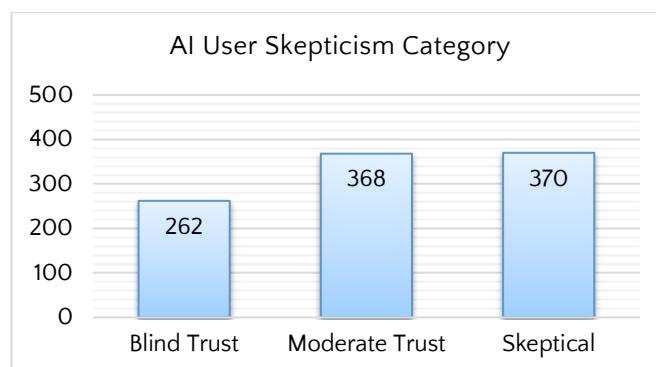


Figure 4. User Skepticism Category

The distribution of user skepticism toward Generative AI responses was dominated by skeptics, comprising 370 (37%). This figure was nearly identical to the number of respondents classified as having moderate trust, totaling 368 respondents (36.8%). Nevertheless, the proportion of users categorized as exhibiting blind trust remained relatively high, with 262 respondents (26.2%).

This pattern suggests that trust in Generative AI responses exists along a contextual spectrum rather than as a binary condition. Previous studies have

demonstrated that most individuals tend to adopt a moderate stance toward AI use while maintaining human involvement in the information evaluation process. At the same time, skepticism among some users raises concerns about the accuracy, reliability, and transparency of AI-generated outputs. Meanwhile, the relatively large proportion of users exhibiting blind trust highlights potential risks associated with limited critical evaluation of AI responses. Taken together, these varying levels of trust reflect a complex interplay among technology acceptance, critical awareness, and users' digital literacy levels (Bretter et al., 2026).

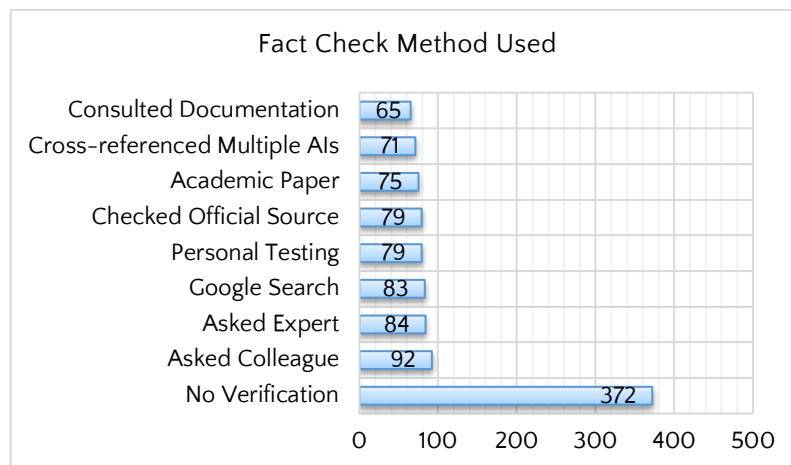


Figure 5. Fact Check Method Used

The data indicate that verification practices for Generative AI responses were dominated by the no-verification category, with 372 respondents (37.2%). This means that more than one-third of respondents did not perform any fact-checking activities. Further analysis of respondents who did not engage in verification revealed that this category was dominated by individuals with senior high school education (30.1%) and bachelor's degrees (22%).

These findings suggest a tendency among some users to accept Generative AI responses without adequately validating the information. The pattern indicates that verification practices are not yet consistently applied in the evaluation of Generative AI outputs. Consequently, the findings highlight that the use of Generative AI is not always accompanied by sufficient evaluative capabilities, potentially increasing the risk of misinformation and misinterpretation.

This finding is consistent with previous studies demonstrating that some users tend to accept AI-generated outputs without verification when the responses appear satisfactory or align with their expectations. In contrast, others evaluate through cross-validation using search engines, academic sources, or consultation with experts (Ou et al., 2024). Other studies have similarly reported that AI users with higher levels of critical thinking tend to employ more diverse verification strategies when evaluating AI-generated responses (Lau et al., 2025).

Table 2. Verification Duration

	N	Minimum	Maximum	Mean	Std. Deviation
Verification Duration (minutes)	1000	.0	45.0	14.840	15.1823

The results indicate that the average time spent verifying information was 14.84 minutes, with a wide range extending from 0 to 45 minutes. The minimum value of 0 minutes indicates that some users did not verify Generative AI responses at all. In contrast, the maximum value of 45 minutes suggests that some users devoted substantial time to verifying information. The relatively high standard deviation (15.18) indicates considerable variation and heterogeneity in verification behavior among respondents.

This condition suggests substantial differences in information evaluation practices across users. While some respondents tended to accept Generative AI responses without conducting verification, others invested considerably more time in checking the information provided. Overall, the findings demonstrate that evaluation practices regarding Generative AI responses remain highly diverse and have not yet converged into a consistent pattern of verification behavior.

The subsequent analysis examines relationships among variables using cross-tabulation and chi-square tests. This approach enables the analysis to move beyond descriptive overviews of individual variables and assess the statistical significance of relationships among variables. The results of these analyses are presented below.

Relationship Between Age Groups, Educational Attainment, and Digital Literacy Levels in the Context of Generative AI Use

Table 3. Distribution of Digital Literacy Levels by Age Group

		Respondent Age Bracket						Total
		18-24	25-34	35-44	45-54	55-64	65+	
Digital Literacy Level	Low	26	39	42	45	37	43	232
		17,2%	24,7%	21,5%	28,3%	21,8%	25,7%	23,2%
	Medium	41	45	51	42	41	41	261
		27,2%	28,5%	26,2%	26,4%	24,1%	24,6%	26,1%
	High	38	43	37	40	47	44	249
		25,2%	27,2%	19,0%	25,2%	27,6%	26,3%	24,9%
	Expert	46	31	65	32	45	39	258
		30,5%	19,6%	33,3%	20,1%	26,5%	23,4%	25,8%
Total		151	158	195	159	170	167	1000
		100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

The data presented in Table 3 indicate that the study population was distributed relatively evenly across the various levels of digital literacy. Overall, the results suggest no linear relationship between digital literacy and age. Nevertheless, variations in the distribution reveal that the highest proportions of respondents classified as experts were among individuals aged 35–44 years (33.3%) and 18–24 years (30.5%). The chi-square test results indicated no statistically significant relationship between age groups and digital literacy levels ($\chi^2 = 19.992$, $df = 15$, $p = 0.172$). This finding suggests that variations in digital literacy levels across age groups do not form a sufficiently strong pattern to demonstrate a statistically meaningful association.

An interesting finding emerged in the 35–44 age group, which recorded the highest proportion of respondents classified as experts (33.3%). This phenomenon may indicate the influence of professional demands on the development of digital literacy, reflecting the flexibility component within the framework of 21st-century digital skills. Flexibility refers to an individual's ability to adapt their mindset, attitudes, and behaviors to a dynamic information and communication technology (ICT) ecosystem. Work-related pressures associated with automation encourage individuals in their productive working years to develop self-direction skills, including initiative, goal-setting, and self-monitoring, as they learn new technologies to maintain professional relevance. Such adaptation extends beyond basic digital literacy and evolves into a lifelong learning strategy through the exploration and integration of digital technologies in professional environments. Accordingly, the high proportion of expert-level users within this age group suggests that learning barriers in adulthood can be overcome when digital competencies are perceived as strategic resources for solving complex problems and fostering innovation amid ongoing digital transformation (van Laar et al., 2017).

A similarly high proportion of expert-level users was also observed among respondents aged 18–24 years (30.5%). However, the findings further revealed that a substantial proportion of respondents within the same age group remained in the low digital literacy category (17.2%). This result highlights that belonging to Generation Z does not automatically guarantee a high level of digital literacy. Recent literature suggests that the digital divide has shifted from issues of access to disparities in individuals' abilities to use technology effectively and critically, commonly referred to as the second-level digital divide (van Deursen & van Dijk, 2019). In other words, although most members of Generation Z have grown up in similar digital environments, differences in the quality of experience, intensity of use, and purposes of technology utilization contribute to varying levels of digital competence.

These findings indicate that age is not the sole determinant of digital literacy. Rather, digital literacy appears to be associated with a combination of factors, including professional experience, technology-related needs, and the extent of individuals' engagement within digital environments.

Table 4. Distribution of Digital Literacy Levels by Education Level

		Education Level					Total
		High School	Bachelors	Masters	PhD	Professional	
Digital Literacy Level	Low	59	41	46	37	49	232
		30,1%	21,0%	22,8%	17,0%	25,9%	23,2%
	Medium	43	45	51	69	53	261
		21,9%	23,1%	25,2%	31,7%	28,0%	26,1%
	High	39	52	53	56	49	249
		19,9%	26,7%	26,2%	25,7%	25,9%	24,9%
	Expert	55	57	52	56	38	258
		28,1%	29,2%	25,7%	25,7%	20,1%	25,8%
Total		196	195	202	218	189	1000
		100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

The cross-tabulation results indicate that the distribution of digital literacy across educational attainment levels does not exhibit a fully linear pattern. The chi-square test results revealed no statistically significant relationship between educational attainment and digital literacy levels ($\chi^2 = 19.722$, $df = 12$, $p = 0.073$). This finding suggests that formal educational attainment does not consistently determine respondents' levels of digital literacy in this study.

Although respondents with higher educational qualifications, such as master's and doctoral degrees, comprised relatively large proportions in the high and expert digital literacy categories, the expert category was also notably prevalent among respondents with senior high school and bachelor's degrees. This finding indicates that formal education is not the sole determinant of digital literacy. Rather, digital literacy is also influenced by factors such as experience with technology use, the intensity of digital engagement, professional demands, and self-directed learning capabilities. This condition reflects a shift in the paradigm of digital literacy in the era of Generative AI, where digital competencies are no longer developed exclusively through formal education but are also cultivated through active and contextual engagement with technology in everyday life (D. T. K. Ng et al., 2021).

Nevertheless, the presence of respondents in the low digital literacy category across all educational levels suggests that formal education does not automatically guarantee high digital literacy. This pattern highlights variations in the quality of digital experiences, motivation to learn new technologies, and the ability to adapt to ongoing digital transformation. Consequently, digital literacy in the era of Generative AI should be understood as a combination of technical competencies and critical thinking skills that develop through sustained interaction with technology, as well as through individuals' reflective capacities to evaluate information and AI systems critically.

Relationship Between Digital Literacy Levels, Educational Attainment, and User Skepticism Toward Generative AI Responses

Table 5. Distribution of Skepticism Toward *Generative AI* Accuracy by Digital Literacy Level

		Digital Literacy Level				Total
		Low	Medium	High	Expert	
User Skepticism Category	Blind Trust	74	78	46	64	262
		31,9%	29,9%	18,5%	24,8%	26,2%
	Moderate Trust	81	92	99	96	368
		34,9%	35,2%	39,8%	37,2%	36,8%
	Skeptical	77	91	104	98	370
		33,2%	34,9%	41,8%	38,0%	37,0%
Total		232	261	249	258	1000
		100,0%	100,0%	100,0%	100,0%	100,0%

The cross-tabulation results indicate that users' skepticism when evaluating the accuracy of Generative AI responses tends to increase with higher levels of digital literacy. Furthermore, the chi-square test results revealed a statistically significant relationship between digital literacy levels and user skepticism ($\chi^2 = 13.918$, $df = 6$, $p = 0.031$).

Among respondents in the low digital literacy category, the proportion of users exhibiting blind trust remained relatively high (31.9%) and was nearly equal to that categorized as skeptical (33.2%). In contrast, among respondents with high and expert levels of digital literacy, the skeptical category represented the largest proportion (41.8% and 38.0%, respectively). In comparison, the proportion of blind trust users declined (18.5% and 24.8%, respectively). This pattern suggests that higher levels of digital literacy are associated with greater skepticism toward algorithmic bias, AI hallucinations, and the limitations of AI systems' accuracy. These findings support the concept of AI literacy, which emphasizes that contemporary digital literacy extends beyond technical competencies to encompass the ability to understand, evaluate, and critically reflect upon AI systems (D. T. K. Ng et al., 2021).

In addition, the distribution of responses indicates that the moderate trust category was relatively consistent across all levels of digital literacy, with proportions ranging from 34.9% to 39.8%. This phenomenon suggests that users generally recognize that, although Generative AI can be highly beneficial, information verification remains necessary. From the perspective of trust calibration, this condition reflects an adaptive position in which users begin to develop more proportionate levels of trust while continuing to utilize AI as a cognitive support tool, accompanied by processes of verification and critical evaluation of the generated outputs. In this context, moderate trust may be interpreted as calibrated trust, whereas the increasing proportion of users categorized as skeptical reflects a tendency to avoid overtrusting AI systems. These findings demonstrate that digital literacy plays an important role in shaping users' ability to position AI appropriately, neither accepting AI-generated outputs uncritically (blind trust) nor completely rejecting the technology (distrust) (Lee & See, 2004).

Table 6. Distribution of Skepticism Toward *Generative AI* Accuracy by Education Level

		Education Level					Total
		High School	Bachelors	Masters	PhD	Professional	
User Skepticism Category	Blind Trust	72	56	55	37	42	262
		36,7%	28,7%	27,2%	17,0%	22,2%	26,2%
	Moderate Trust	60	78	68	86	76	368
		30,6%	40,0%	33,7%	39,4%	40,2%	36,8%
	Skeptical	64	61	79	95	71	370
		32,7%	31,3%	39,1%	43,6%	37,6%	37,0%
Total		196	195	202	218	189	1000
		100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

Based on the cross-tabulation results, educational attainment exhibited a generally linear pattern with skepticism toward the accuracy of Generative AI responses, such that respondents with higher levels of education tended to exhibit greater skepticism. The chi-square test results further revealed a statistically significant relationship between educational attainment and user skepticism ($\chi^2 = 26.750$, $df = 8$, $p < 0.001$).

The analysis showed that respondents with lower educational attainment, particularly those with a senior high school education, exhibited the highest proportion of blind trust (36.7%). In contrast, respondents with higher educational qualifications, such as doctoral degrees (PhD), displayed the lowest proportion of blind trust (17.0%) and the highest proportion of skeptical users (43.6%). This pattern suggests that higher levels of education are associated with stronger evaluative and reflective capacities when assessing the reliability of AI-generated outputs.

Individuals with higher educational attainment are generally more accustomed to information validation processes, analytical thinking, and understanding the methodological limitations of digital technologies, making them less likely to accept AI-generated outputs uncritically and without verification. These capacities may enable more educated users to assess AI-generated outputs more critically, particularly by questioning the validity, consistency, and source basis of the information produced by Generative AI (Celik, 2023). This interpretation is supported by previous research on students' perceptions of Generative AI, which found that users with higher educational backgrounds tend to express greater concerns regarding the accuracy, ethical implications, and academic consequences of AI use than users with lower educational attainment (Chan & Hu, 2023). Therefore, skepticism toward Generative AI appears to be influenced not only by access to technology but also by analytical reasoning capabilities that may develop through higher levels of educational experience.

Relationship Between Digital Literacy Levels and the Selection of Fact-Checking Methods in the Evaluation of Generative AI Responses

Table 7. Fact Check Method Used by Digital Literacy Level

		Digital Literacy Level				Total
		Expert	High	Low	Medium	
Fact Check Method Used	No Verification	93	77	95	107	372
		36,0%	30,9%	40,9%	41,0%	37,2%
	Personal Testing	23	23	20	13	79
		8,9%	9,2%	8,6%	5,0%	7,9%
	Google Search	26	25	16	16	83
		10,1%	10,0%	6,9%	6,1%	8,3%
	Cross-referenced Multiple Als	15	23	17	16	71
		5,8%	9,2%	7,3%	6,1%	7,1%
	Asked Colleague	29	24	21	18	92
		11,2%	9,6%	9,1%	6,9%	9,2%
	Consulted Documentation	14	17	17	17	65
		5,4%	6,8%	7,3%	6,5%	6,5%
	Checked Official Source	16	21	16	26	79
		6,2%	8,4%	6,9%	10,0%	7,9%
	Academic Paper	19	20	14	22	75
		7,4%	8,0%	6,0%	8,4%	7,5%
	Asked Expert	23	19	16	26	84
		8,9%	7,6%	6,9%	10,0%	8,4%
Total		258	249	232	261	1000
		100,0%	100,0%	100,0%	100,0%	100,0%

The cross-tabulation results indicate that fact-checking methods used to evaluate Generative AI responses varied across levels of digital literacy, with no dominant pattern emerging in any particular group. The chi-square test results further revealed no statistically significant relationship between digital literacy levels and the fact-checking methods employed by users ($\chi^2 = 23.880$, $df = 24$, $p = 0.468$).

All digital literacy groups were predominantly characterized by the no verification category, particularly among respondents with medium (41.0%) and low (40.9%) levels of digital literacy. In contrast, respondents in the expert and high-literacy categories exhibited relatively lower proportions of no-verification behavior (36.0% and 30.9%, respectively). Although the relationship was not statistically significant, the distribution suggests a tendency for users with lower levels of digital literacy to exhibit a higher proportion of no-verification behavior when evaluating Generative AI responses.

The prevalence of the no verification category across all levels of digital literacy indicates that verification practices remain a significant challenge in the use of Generative AI. This finding suggests a gap between possessing digital literacy competencies and applying verification behaviors when using AI-mediated information. The accessibility and efficiency of AI systems may encourage cognitive offloading, namely the tendency to delegate information evaluation to automated systems without sufficient critical reflection (Bari et al., 2026). Consequently, efforts to strengthen digital literacy in the era of Generative AI should focus not only on developing technical competencies for using technology but also on fostering critical thinking skills, source evaluation skills, and awareness of the limitations inherent in AI systems.

D. CONCLUSION

The distribution of digital literacy within this dataset did not exhibit a linear pattern across either age groups or levels of educational attainment. The chi-square test results indicated no statistically significant relationships between digital literacy levels and either age groups or educational attainment. Therefore, in this dataset, age and formal education were not significantly associated with digital literacy levels. Digital literacy appears to be related to a broader set of factors, including experience with technology use, professional demands, self-directed learning capabilities, and computational thinking. Both younger generations and individuals in their productive working years demonstrated relatively high levels of digital literacy; however, lower levels were still observed across all age groups and educational categories.

On the other hand, this study found that both digital literacy and educational attainment were significantly associated with user skepticism toward Generative AI responses. However, these relationships are associative in nature and should not be interpreted as evidence of causality. The chi-square test results demonstrated significant associations between digital literacy levels, educational attainment, and user skepticism. Users with higher levels of digital literacy and educational attainment tended to be more critical of algorithmic bias, AI hallucinations, and the accuracy limitations of Generative AI systems. Meanwhile,

the prevalence of the moderate trust category suggests the emergence of calibrated trust, characterized by trust that remains accompanied by processes of information evaluation and verification.

This study also revealed that verification practices for Generative AI responses remain highly diverse and inconsistent, with the no-verification category continuing to dominate across all levels of digital literacy. The chi-square test results indicated no statistically significant association between digital literacy levels and the fact-checking methods users employ. These findings suggest that the use of Generative AI remains vulnerable to cognitive offloading, highlighting the need for digital literacy initiatives that extend beyond technical competencies to encompass critical thinking skills and reflective evaluation of information.

Research Limitations

This study has several limitations that should be considered when interpreting its findings. As the study relied on secondary data obtained from a publicly available dataset, the researchers had no direct control over the sampling process, respondent selection, instrument development, or validation procedures employed during the original data collection. Consequently, the variables analyzed were limited to those available in the dataset. The measurement of digital literacy, skepticism, and verification behavior was based on predefined categories provided in the dataset and did not involve the development of new measurement instruments. Accordingly, the operationalization of these variables strictly followed the categories available in the original dataset.

In addition, this study focused on users' evaluative behavior regarding the accuracy of Generative AI responses rather than on objectively assessing the accuracy of the AI systems themselves. The generalizability of the findings is also limited by the characteristics of the respondents represented in the dataset. Therefore, the findings cannot be assumed to directly represent any specific population at either the national or global level. Accordingly, the findings should be interpreted as patterns of association identified within the analyzed dataset rather than as causal conclusions or as representations of the broader population of Generative AI users.

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