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Distinguishing AI-generated and real images: implications for media literacy instruction

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ABSTRACT

This study aimed to assess the detection accuracy and usefulness of determinants for distinguishing artificial intelligence (AI)-generated and real images among senior high school students in Western Visayas during the academic year 2025–2026. It examined the significant differences in the two mentioned constructs across students' demographic profiles. It employed a quantitative design- the descriptive-comparative approach. A random sample of 104 students was involved, using a validated, reliability-tested 33-item researcher-made questionnaire. Descriptive and comparative statistical analyses were employed. Mean, standard deviation (SD), Mann-Whitney U test, and Kruskal-Wallis H test were used. The findings revealed that the students demonstrated a moderate level of detection accuracy (M=5.16, SD=1.61). The students rated the usefulness of the determinants as helpful (M=3.78, SD=0.74). Additionally, it was found that there is a significant difference in detection accuracy when grouped by school type [U=965.500, p=0.011] compared to its counterparts. Significant differences were found in the usefulness of determinants for distinguishing AI from real images when grouped by type of school [U=815.000, p=0.001] and frequency of use of AI [H(2)=11.989, p=0.002]. The findings of the study may provide teachers with insights into developing instructional strategies and interventions to enhance students' critical thinking and digital literacy skills.

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1. INTRODUCTION

Artificial intelligence (AI) refers to the ability of computer systems to perform tasks that typically require human intelligence, such as learning, reasoning, and problem-solving [1]. In recent years, AI tools have rapidly evolved and become integrated into various sectors, including education [2]. In the school context, AI is used to enhance teaching and learning processes through tools such as intelligent tutoring systems and content-generation platforms [3]. Among students, AI has become increasingly accessible through applications that generate text, images, and multimedia outputs. Globally, surveys indicate that a significant proportion of students are now engaging with AI-powered tools, with estimates suggesting that more than 60% have used AI for academic tasks [4]. The positive uses of AI among students include improved efficiency in completing assignments and access to personalized learning resources [5]. However, the growing reliance on AI also has negative implications, such as academic dishonesty, overreliance on automated systems, and difficulty distinguishing between authentic and AI-generated content, particularly in images that are becoming increasingly realistic [6].

In the Philippine context, the integration and use of AI among senior high school students is also steadily increasing. A local study found that a substantial number of students use AI tools for academic assistance, particularly for generating written outputs and visual materials [7]. In fact, the Department of Education (DepEd) recognizes the impact of digital technologies, including AI. It has incorporated media and information literacy (MIL) into the kindergarten through twelfth grade (K to 12) curricula to equip students with critical thinking and evaluative skills [8]. Although MIL is included in the K-12 curriculum, many senior high school students still struggle to evaluate AI-generated images critically, increasing the risk of misinformation and weakened academic integrity in classroom learning. Additionally, concerns persist about students' misuse of AI to complete assignments and assessments, as well as their limited ability to critically assess digital content. Reports indicate that some students submit AI-generated outputs without proper verification, raising concerns about authenticity and academic integrity [9]. Furthermore, with the proliferation of AI-generated images on social media and other online platforms, students often struggle to distinguish between real and artificially generated visuals, highlighting a gap in their ability to detect and evaluate these images [10].

The need to conduct this study is underscored by students' increasing exposure to digital and social media platforms, where AI-generated images are widely circulated [11], [12]. As active users of these platforms, students are particularly vulnerable to misinformation and manipulation through highly realistic AI-generated visuals, which are often perceived as authentic and may influence their beliefs and understanding of reality [13]–[15]. This concern is especially significant among senior high school students, who are at a critical stage of cognitive development characterized by emerging higher-order thinking skills such as analysis and evaluation. At this level, these students are expected to independently assess the credibility of information and engage with complex digital content. Moreover, they are directly exposed to the MIL course in the Philippine curriculum, where competencies in evaluating media content are explicitly developed, and their academic tasks frequently require research, multimedia production, and source evaluation. Failure to accurately distinguish between AI-generated and real images may negatively affect academic performance and compromise the quality of assessments, as students may rely on misleading visual content. It may also contribute to misconceptions in classroom discussions, thereby undermining learning outcomes. These concerns highlight the need to investigate students' detection accuracy and the determinants influencing this ability, including cognitive, technological, and socio-demographic factors [16], [17]. The findings have practical value in informing teaching strategies and assessment practices that enhance digital literacy and critical evaluation skills. Furthermore, teachers play a crucial role in guiding students to critically engage with digital content by integrating AI awareness and detection skills into classroom instruction to maintain instructional quality and assessment validity [18]–[20].

Several studies have examined digital literacy, misinformation detection, and the identification of AI-generated or manipulated content. Vaccari and Chadwick [11] and Nightingale and Farid [21] demonstrate that individuals struggle to distinguish synthetic media from authentic content as AI-generated images become increasingly realistic. However, these studies are constrained in scope. The former focused on politically contextualized deepfakes involving figures familiar to a United Kingdom audience, thus limiting relevance to school-based populations. The latter restrict their analysis to perceptual judgments of AI-synthesized faces, without accounting for a broader range of visual determinants. Kozyreva *et al.* [17] and Wineburg and McGrew [18] argue that individuals tend to rely on superficial heuristics rather than rigorous verification strategies when evaluating online information. The studies are primarily conceptual, offering intervention frameworks grounded in psychological science, but neither empirically measure detection accuracy nor focus on student populations. Similarly, Westerlund [12] and Groh *et al.* [15] underscore the challenges posed by AI-generated media but exhibit notable methodological limitations. The former relies on qualitative analyses of online news discourse, lacking quantitative assessment and theoretical grounding in models such as signal detection theory (SDT). The latter employed experimental identification tasks but confined their analysis to video-based deepfakes. Moreover, the study does not extend its implications to instructional or classroom contexts.

Within the Philippine context, Barrot [22] and Atoy *et al.* [23] document varying levels of digital literacy among students. These studies do not provide empirical evidence on students' ability to detect AI-generated visuals, nor do they examine the visual features or cues underpinning such judgments in educational settings. The existing literature reveals a critical gap. This study addresses these limitations by rigorously examining detection accuracy and the value of visual determinants in distinguishing AI-generated from real images among senior high school students across demographic profiles. This study offers new insights by moving beyond general digital literacy and existing research on AI, focusing on how accurately senior high school students can distinguish between AI-generated and real images. It further advances the field by translating the identified determinants into practical cues that can be integrated into classroom-based media literacy instruction. The findings are particularly useful for teachers as they inform and enhance teaching strategies aimed at improving students' ability to identify AI-generated content. Moreover, the study fills a gap in the literature by contextualizing detection accuracy and the usefulness of these determinants within the school setting.

This study assumed that the detection accuracy and usefulness of determinants for distinguishing between AI-generated and real images vary across the demographic profiles of senior high school students. Hence, this assumption was anchored on the SDT developed by Tanner and Swets [24]. SDT is a framework for measuring how individuals make decisions under uncertainty, particularly when distinguishing between the presence and absence of a given stimulus. It posits that decision-making is influenced by two key components: sensitivity, or the ability to accurately differentiate between signals and noise, and decision criterion, which refers to the threshold or bias an individual applies when making judgments. In this study, sensitivity is reflected in students' ability to distinguish AI-generated images from real ones. At the same time, the decision criterion is associated with their reliance on and evaluation of various visual cues. Thus, SDT provides a suitable theoretical lens for analyzing how students process visual information and make classification decisions, as well as how these processes vary across different demographic groups. The theory fits the topic because students must distinguish real from synthetic images under uncertainty.

Figure 1 shows that the demographic profile of senior high school students serves as the independent variable influencing the study's outcomes. These variables are linked to two key dependent variables: detection accuracy in identifying AI-generated and real images, and the perceived usefulness of various determinants. The results of these relationships are expected to inform the development of instructional strategies and interventions to improve students' critical thinking and digital literacy skills.

This study aimed to assess the detection accuracy and usefulness of determinants for distinguishing between AI-generated and real images among senior high school students in Western Visayas during the academic year 2025–2026. Specifically, it examined significant differences in detection accuracy across respondents grouped by gender, strand, year level, type of school, and frequency of AI software use. It also examined significant differences in the usefulness of determinants for distinguishing AI-generated from real images across respondents' demographic profiles. The study's findings may serve as benchmark data, providing insights into students' ability to distinguish between AI-generated and real images for teachers in MIL courses.

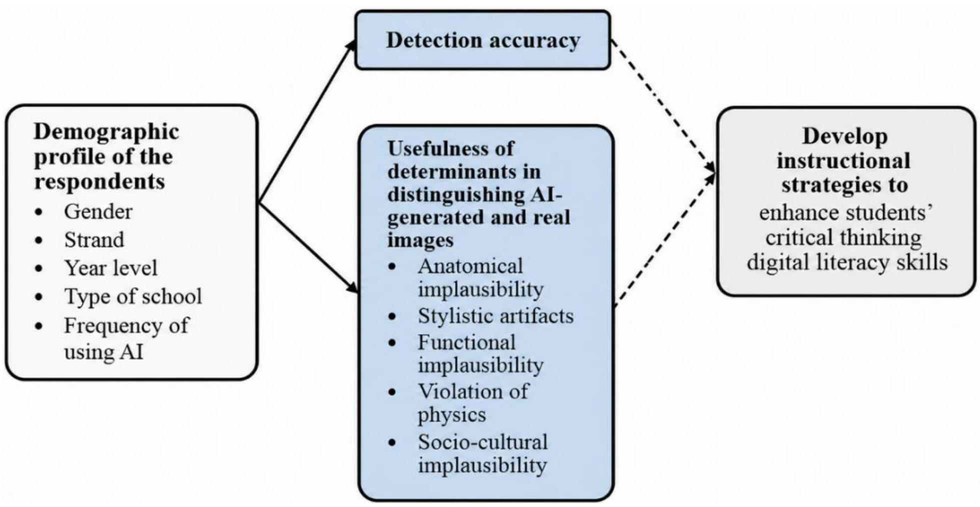

Figure 1. Conceptual model

2. METHOD

This study employed a quantitative research design, specifically the descriptive-comparative approach, which enabled statistical analysis of variables to address theory-guided research questions [25]. A descriptive-comparative design was suitable for this study because it describes students' detection accuracy and perceived usefulness of determinants while examining differences across demographic groups without manipulating variables or implementing an intervention. The descriptive component was used to assess students' detection accuracy and the usefulness of the determinants involved in distinguishing between AI-generated and real images among senior high school students. The comparative component examined significant differences in detection accuracy and the usefulness of determinants across demographic groups, including gender, strand, year level, type of school, and frequency of AI software use. From a population of

140 senior high school students in one public school and one private school in Western Visayas, the fishbowl technique was applied, with name slips thoroughly mixed and drawn randomly, observing the proportional allocation by school type, to select 104 participants as determined by a Raosoft calculator set at a 95% confidence level and a 5% margin of error.

Table 1 presents the profile of respondents according to gender, strand, year level, type of school, and frequency of AI use. The majority of respondents are female (65.4%; n=68). Most are enrolled in the science, technology, engineering, and mathematics (STEM) strand (63.5%; n=66). In addition, most respondents are Grade 12 students (69.2%; n=72). Regarding the type of school, slightly more come from private schools (52.9%; n=55). Lastly, with respect to frequency of AI use, most respondents reported using AI weekly (71.2%; n=74).

Table 1. Demographic profile of the respondents

Variable		n	Percentage (%)
Gender	Male	36	34.6
	Female	68	65.4
Strand	STEM	66	63.5
	ABM	12	11.5
	HUMSS	26	25.0
Year level	Grade 11	32	30.8
	Grade 12	72	69.2
Type of school	Private	55	52.9
	Public	49	47.1
Frequency of using AI	Daily	23	22.1
	Weekly	74	71.2
	Never	7	6.7
Whole		104	100.0

2.1. Data collection procedure

Data were collected using a validated and reliability-tested 33-item researcher-made questionnaire. The questionnaire consisted of three sections. The first section collected demographic information from senior high school students. The second section comprised a 9-item multiple-choice test with four options per item, designed to assess respondents' detection accuracy in distinguishing AI-generated from real images. Each item presented two images, and respondents were required to determine whether each image was AI-generated, real, or a combination of both. All images used in this section were personally captured by the researchers. The initial pool consisted of 20 items, which were subjected to content validity ratio (CVR) and reliability analyses. Based on these procedures, nine items were retained as they demonstrated acceptable validity and reliability in measuring students' detection accuracy. The use of nine items was deemed appropriate as each item required detailed visual analysis, deliberate judgment, and balanced levels of difficulty. The images used in the test were developed and refined with the assistance of ChatGPT to remove, add, or enhance visual elements included in the response choices. However, all modifications were critically reviewed and finalized by the researchers to ensure accuracy and alignment with the study's objectives. Thus, ChatGPT was not used to determine the final content of the instruments but only to support the refinement process under strict researcher oversight. The third section included a 24-item scale assessing the usefulness of determinants for distinguishing AI-generated and real images, organized into five dimensions: anatomical implausibility, stylistic artifacts, functional implausibility, violation of physics, and socio-cultural implausibility. These dimensions were adopted from the 2024 guide by Kamali *et al.* [26]. The mentioned dimensions were anchored on an established conceptual model for identifying visual inconsistencies and evaluating image authenticity. Responses were measured using a 5-point Likert scale, ranging from 1–strongly not helpful to 5–strongly helpful.

The questionnaire was validated by 10 subject-matter experts using Lawshe's content validity method [27]. The analysis yielded a CVR of 0.82 for the detection accuracy section and 0.90 for the determinants in distinguishing AI section. To ensure the questionnaire's reliability, it was pilot-tested with 30 non-actual respondents, resulting in a Kuder–Richardson Formula 20 (KR-20) reliability coefficient of 0.80 for the detection accuracy section and a Cronbach's alpha of 0.92 for the section on determinants for distinguishing AI-generated and real images. Lastly, the data were gathered via a Google Form that also included the informed consent form, the study's objective, and the selection criteria for respondents. Figure 2 illustrates the response choices in section two of the questionnaire, designed to measure respondents' detection accuracy in distinguishing between AI-generated and real images. To avoid any copyright infringement, all photographic materials utilized in this study are original and were personally captured by the researchers.

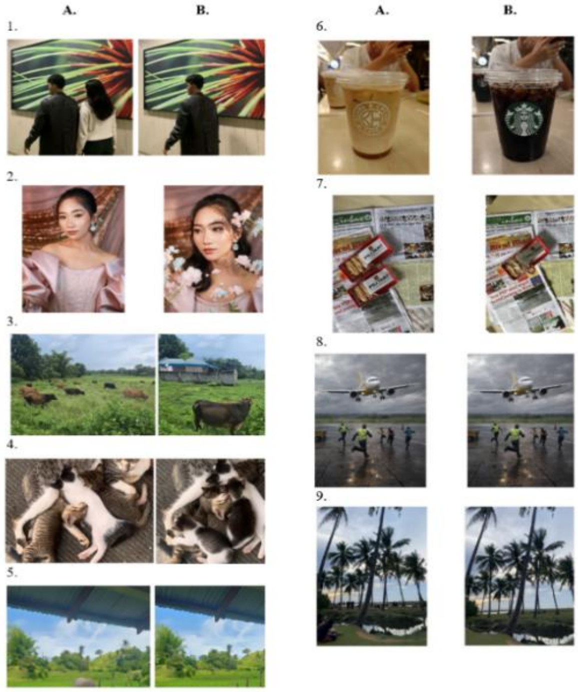

Figure 2. Choices between AI-generated and real images

2.2. Data analysis procedure

In analyzing the data, descriptive and comparative statistical analyses were employed. Mean and standard deviation (SD) were used to assess the detection accuracy and usefulness of determinants in distinguishing between AI-generated and real images. Additionally, this study used a mean range to interpret the descriptive result for detection accuracy, ranging from 0.00-1.80=very low to 7.21-9.00=very high. This mean range is supported by Koo and Yang [28], which divides numerical ranges into corresponding descriptive levels for meaningful data interpretation. Moreover, in interpreting the descriptive results on the usefulness of determinants in distinguishing AI-generated and real images, values spanning 1.00-1.80 (strongly not helpful) to 4.21-5.00 (strongly helpful) are considered arbitrary cut-offs. To justify the use of this mean range in this study, it was noted that Hoşgör and Yaman [29] also employed the same range.

The Shapiro-Wilk test was used to assess the normality of the data. The results showed that detection accuracy [W=0.948, p=0.000] and usefulness of determinants [W=0.954, p=0.001] are not normally distributed. Since the p-values are less than 0.05, the data do not follow a normal distribution. Therefore, the assumption of normality is violated, which justifies the use of nonparametric tests for subsequent analysis. Hence, the Mann-Whitney U test and the Kruskal-Wallis H test were used to determine significant differences in detection accuracy across demographic groups.

2.3. Ethical consideration

This study followed the Philippine Health Research Ethics Board (PHREB) guidelines and the Helsinki ethical principles and was approved by the institutional review board before implementation. The school administrators' approval was sought, and the respondents were informed about the research's goal and their voluntary participation. They were assured complete confidentiality and privacy of their data. The materials that contained raw information accessed from them were stored in password-protected files and disposed of by manual shredding within a given period.

3. RESULTS AND DISCUSSION

3.1. Detection accuracy in distinguishing AI-generated and real images of students

As shown in Table 2, the students demonstrated a moderate level of detection accuracy in distinguishing between AI-generated and real images (M=5.16, SD=1.61). This indicates that, across demographic variables, respondents possess a fair ability to identify AI-generated content. However, the results suggest that there is still room for improvement in detection skills across different profile variables.

Table 2. Level of detection accuracy in distinguishing AI-generated and real images

Variable		M	SD	Interpretation
Gender	Male	5.03	1.25	Moderate
	Female	5.24	1.77	Moderate
Strand	STEM	5.38	1.66	Moderate
	ABM	4.50	1.68	Moderate
	HUMSS	4.92	1.35	Moderate
Year level	Grade 11	5.06	1.54	Moderate
	Grade 12	5.21	1.64	Moderate
Type of school	Private	5.55	1.68	High
	Public	4.73	1.43	Moderate
Frequency of using AI	Daily	5.14	1.42	Moderate
	Weekly	5.20	1.70	Moderate
	Never	4.57	0.98	Moderate
Whole		5.16	1.61	Moderate

Mean range: 0.00-1.80=very low, 1.81-3.60=low, 3.61-5.40=moderate, 5.41-7.20=high, 7.21-9.00=very high

Regarding gender, the respondents demonstrated moderate detection accuracy (M=5.16, SD=1.61). Both male (M=5.03, SD=1.25) and female (M=5.24, SD=1.77) respondents exhibited a moderate level of ability, indicating comparable ability to distinguish AI-generated from real images regardless of gender. Regarding the strand, the respondents also showed moderate detection accuracy. STEM students (M=5.38, SD=1.66), accountancy, business, and management (ABM) students (M=4.50, SD=1.68), and humanities and social sciences (HUMSS) students (M=4.92, SD=1.35) all demonstrated a moderate level of detection ability, suggesting that detection ability is consistent across academic strands. Regarding year level, both Grade 11 (M=5.06, SD=1.54) and Grade 12 (M=5.21, SD=1.64) students exhibited a moderate level of detection accuracy, indicating similar skill in distinguishing AI-generated from real images. For the type of school, respondents from private schools demonstrated a high level of detection accuracy (M=5.55, SD=1.68). In contrast, those from public schools showed a moderate level (M=4.73, SD=1.43), indicating that students from private schools tend to have slightly higher detection accuracy. In terms of frequency of AI use, respondents who use AI daily (M=5.14, SD=1.42), weekly (M=5.20, SD=1.70), and those who never use AI (M=4.57, SD=0.98) all exhibited a moderate level of detection accuracy, suggesting that frequency of AI use does not substantially differentiate detection ability.

The findings suggest that the respondents exhibited a moderate level of detection accuracy in distinguishing AI-generated from real images across gender, strand, year level, type of school, and frequency of AI software use. This means that while students possess a certain degree of discernment, their ability to consistently and accurately identify AI-generated content remains limited and not yet fully developed. This could be because senior high school students in the Philippines are still developing digital literacy and critical evaluation skills, particularly in navigating emerging AI technologies that are not yet deeply integrated into the basic education curriculum. This finding is consistent with the studies [13], [18], [30], which highlight that high school students often struggle to evaluate digital content despite frequent exposure to online media. Additionally, this finding can be attributed to the uneven exposure and practical experience of students with AI tools, where frequency of use does not necessarily equate to a deeper understanding of how such technologies manipulate visual outputs. This claim is supported by studies [3], [31], which emphasize that familiarity with AI does not automatically translate into critical competence for identifying AI-generated images. This implies that teachers, particularly those handling media literacy and computer subjects at the high school level, should strengthen instructional strategies by integrating hands-on and analytical activities that enhance students' critical evaluation of AI-generated and real images.

3.2. Level of usefulness of determinants in distinguishing AI-generated and real images

As shown in Table 3, the students demonstrated a helpful level of usefulness (M=3.78, SD=0.74). When grouped by gender, both male (M=3.80, SD=0.72) and female (M=3.76, SD=0.75) respondents exhibited a helpful level of helpfulness. Across strand, STEM (M=3.90, SD=0.69), ABM (M=3.78, SD=0.45), and HUMSS (M=3.46, SD=0.87) all demonstrated a helpful level. In terms of year level, both Grade 11 (M=3.75, SD=0.78) and Grade 12 (M=3.79, SD=0.72) showed a helpful level of support. Regarding school type, private (M=3.98, SD=0.65) and public (M=3.54, SD=0.76) respondents reported a helpful level. Based on frequency of AI use, daily (M=3.59, SD=0.81) and weekly (M=3.90, SD=0.62) users showed a helpful level. In contrast, those who never use AI (M=2.92, SD=1.02) demonstrated a moderately helpful level, indicating that familiarity with AI may influence perceived usefulness of the determinants.

Table 3. Level of usefulness of determinants in distinguishing AI-generated and real images

Variables		Anatomical implausibility		Stylistic artifacts		Functional implausibility		Violations of physics		Sociocultural implausibility		Usefulness of determinants	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Gender	Male	3.90	0.78	3.69	0.71	3.90	0.88	3.76	0.87	3.76	0.88	3.80	0.72
	Female	3.79	0.89	3.80	0.79	3.79	0.86	3.71	0.78	3.68	0.85	3.76	0.75
Strand	STEM	3.90	0.82	3.84	0.73	3.95	0.78	3.91	0.76	3.90	0.79	3.90	0.69
	ABM	4.02	0.44	3.78	0.59	3.93	0.54	3.58	0.70	3.52	0.69	3.78	0.45
	HUMSS	3.57	1.01	3.55	0.90	3.48	1.08	3.35	0.85	3.32	0.98	3.46	0.87
Year level	Grade 11	3.71	0.97	3.63	0.84	3.89	0.92	3.79	0.88	3.71	0.87	3.75	0.78
	Grade 12	3.89	0.79	3.82	0.72	3.81	0.84	3.70	0.78	3.71	0.86	3.79	0.72
Type of school	Private	4.04	0.77	3.92	0.75	4.02	0.77	3.98	0.70	3.95	0.71	3.98	0.65
	Public	3.59	0.88	3.59	0.75	3.62	0.92	3.45	0.84	3.44	0.94	3.54	0.76
Frequency of using AI	Daily	3.75	0.85	3.56	0.83	3.76	0.99	3.42	0.93	3.40	0.99	3.59	0.81
	Weekly	3.97	0.72	3.91	0.61	3.93	0.76	3.88	0.68	3.82	0.78	3.9	0.62
	Never	2.51	1.05	2.89	1.30	2.94	1.14	2.94	1.00	3.43	1.02	2.92	1.02
Whole		3.83	0.85	3.76	0.76	3.83	0.86	3.73	0.81	3.71	0.86	3.78	0.74

Mean range: 1.00-1.80 (strongly not helpful), 1.81-2.60 (not helpful), 2.61-3.40 (moderately helpful), 3.41-4.20 (helpful), 4.21-5.00 (strongly helpful)

Regarding anatomical implausibility, the respondents demonstrated a helpful level (M=3.83, SD=0.85). When grouped by gender, both male (M=3.90, SD=0.78) and female (M=3.79, SD=0.89) respondents exhibited a helpful level of support. Across strand, STEM (M=3.90, SD=0.82), ABM (M=4.02, SD=0.44), and HUMSS (M=3.57, SD=1.01) all demonstrated a helpful level. In terms of year level, both Grade 11 (M=3.71, SD=0.97) and Grade 12 (M=3.89, SD=0.79) showed a helpful level of support. Regarding school type, private (M=4.04, SD=0.77) and public (M=3.59, SD=0.88) respondents both reported a helpful level. Based on frequency of AI use, daily (M=3.75, SD=0.85) and weekly (M=3.97, SD=0.72) users showed a helpful level. In contrast, those who never use AI (M=2.51, SD=1.05) demonstrated a not helpful level.

Regarding stylistic artifacts, the respondents demonstrated a helpful level (M=3.76, SD=0.76). Both male (M=3.69, SD=0.71) and female (M=3.80, SD=0.79) respondents exhibited a helpful level of support. Across strand, STEM (M=3.84, SD=0.73), ABM (M=3.78, SD=0.59), and HUMSS (M=3.55, SD=0.90) all demonstrated a helpful level. In terms of year level, Grade 11 (M=3.63, SD=0.84) and Grade 12 (M=3.82, SD=0.72) both showed a helpful level of support. Regarding school type, private (M=3.92, SD=0.75) and public (M=3.59, SD=0.75) respondents reported a helpful level. In terms of frequency of AI use, daily (M=3.56, SD=0.83) and weekly (M=3.91, SD=0.61) users reported a helpful level of use. In contrast, those who never use AI (M=2.89, SD=1.30) demonstrated a moderately helpful level.

Regarding functional implausibility, the respondents demonstrated a helpful level (M=3.83, SD=0.86). Both male (M=3.90, SD=0.88) and female (M=3.79, SD=0.86) respondents showed a helpful level of support. Across strand, STEM (M=3.95, SD=0.78), ABM (M=3.93, SD=0.54), and HUMSS (M=3.48, SD=1.08) all demonstrated a helpful level. In terms of year level, Grade 11 (M=3.89, SD=0.92) and Grade 12 (M=3.81, SD=0.84) showed a helpful level. Regarding school type, private (M=4.02, SD=0.77) and public (M=3.62, SD=0.92) respondents both reported a helpful level. In terms of frequency of AI use, daily (M=3.76, SD=0.99) and weekly (M=3.93, SD=0.76) users reported a helpful level of use. In contrast, those who never use AI (M=2.94, SD=1.14) demonstrated a moderately helpful level.

Regarding violations of physics, the respondents demonstrated a helpful level (M=3.73, SD=0.81). Both male (M=3.76, SD=0.87) and female (M=3.71, SD=0.78) respondents showed a helpful level of support. Across strands, STEM (M=3.91, SD=0.76) and ABM (M=3.58, SD=0.70) exhibited a helpful level, while HUMSS (M=3.35, SD=0.85) demonstrated a moderately helpful level. In terms of year level, both Grade 11 (M=3.79, SD=0.88) and Grade 12 (M=3.70, SD=0.78) showed a helpful level. Regarding school type, private (M=3.98, SD=0.70) and public (M=3.45, SD=0.84) respondents demonstrated a helpful level. In terms of frequency of AI use, daily (M=3.42, SD=0.93) and weekly (M=3.88, SD=0.68) users reported a helpful level of use. In contrast, those who never use AI (M=2.94, SD=1.00) demonstrated a moderately helpful level.

For sociocultural implausibility, the respondents demonstrated a helpful level (M=3.71, SD=0.86). Both male (M=3.76, SD=0.88) and female (M=3.68, SD=0.85) respondents showed a helpful level of support. Across strands, STEM (M=3.90, SD=0.79) and ABM (M=3.52, SD=0.69) exhibited a helpful level, while HUMSS (M=3.32, SD=0.98) demonstrated a moderately helpful level. In terms of year level, both Grade 11 (M=3.71, SD=0.87) and Grade 12 (M=3.71, SD=0.86) showed a helpful level. Regarding school type, private (M=3.95, SD=0.71) and public (M=3.44, SD=0.94) respondents demonstrated a helpful level. In terms of frequency of AI use, daily (M=3.40, SD=0.99) users demonstrated a moderately helpful level, while weekly (M=3.82, SD=0.78) and never users (M=3.43, SD=1.02) showed a helpful level.

The findings suggest that respondents perceived anatomical implausibility, stylistic artifacts, functional implausibility, violations of physics, and sociocultural inconsistencies as helpful in distinguishing AI-generated from real images across demographic variables. This indicates that students do not rely on random judgment but instead use these determinants as diagnostic cues in their evaluation process. Specifically, these cues appear to function as heuristic triggers: when students encounter irregularities, they are more likely to classify an image as AI-generated. This pattern may be explained by senior high school students' frequent exposure to digital images through social media platforms, which enables them to develop familiarity with common visual inconsistencies. Repeated exposure appears to support the formation of learned heuristics, allowing students to associate specific anomalies with artificial generation. This interpretation aligns with the studies of Groh *et al.* [15] and Nightingale and Farid [21], which show that individuals rely on visual and contextual anomalies when identifying manipulated or AI-generated images. Similarly, other studies [11], [17] emphasize that sustained interaction with digital media enhances users' ability to detect misleading content through experience-based pattern recognition. Importantly, the findings suggest that while students can identify relevant cues, their use of these determinants may remain largely heuristic and surface-level. This highlights the need to examine not only the presence of these cues but also how they are weighted and interpreted during decision-making. In this regard, teachers handling media literacy and computer-related subjects play a crucial role in scaffolding students' cognitive processes by transforming these intuitive cues into structured analytical strategies. By explicitly teaching how and when such determinants should be applied, instruction can move students from intuitive detection toward more systematic and critical evaluation of digital images.

3.3. Differences in detection accuracy when grouped according to demographic profile

As shown in Table 4, in terms of gender [U=1124.000, p=0.487], year level [U=1079.000, p=0.601], strand [H(2)=3.455, p=0.178], and frequency of using AI [H(2)=3.025, p=0.220], there are no significant differences between groups. Since all p-values are greater than 0.05, the null hypothesis is not rejected. This indicates that detection accuracy is comparable across these profile variables. In contrast, the type of school [U=965.500, p=0.011] shows a significant difference. Since p<0.05, the null hypothesis is rejected. Respondents from private schools demonstrated significantly higher detection accuracy (M=5.55) compared to those from public schools (M=4.73). Overall, the results indicate that detection accuracy varies significantly only when respondents are grouped by school type, while it remains consistent across gender, year level, strand, and frequency of AI use.

Table 4. Difference in detection accuracy when grouped according to demographic profile

Variable	U	z	p	Effect size	95% CI
Gender	1124.000	-0.696	0.487	r=0.069	[-0.110, 0.240]
Year level	1079.000	-0.523	0.601	r=0.052	[-0.130, 0.220]
Type of school	965.500	-2.532	0.011	r=0.249	[-0.080, 0.400]
	H	df	p		
Strand	3.455	2	0.178	ε^2=0.024	[0.000, 0.070]
Frequency of using AI	3.025	2	0.220	ε^2=0.019	[0.000, 0.060]

Note: the difference is significant when p≤0.05

The findings suggest that detection accuracy in distinguishing AI-generated from real images does not differ significantly by gender, year level, strand, or frequency of AI use, but varies significantly by type of school, with private school students demonstrating higher accuracy than their public school counterparts. This means that students' ability to discern AI-generated images is generally consistent regardless of individual demographic characteristics. Yet, institutional context plays a critical role in shaping this competence. This could be because private schools in the Philippines often have greater access to technological resources, updated digital literacy programs, and guided exposure to emerging technologies such as AI, which may enhance students' evaluative skills. This finding is consistent with study of [32], [33], which emphasize that access to ICT resources and school support significantly influence students' digital competence. Additionally, this finding can be attributed to disparities in instructional support and in the availability of technology-enhanced learning environments, in which private school students may receive more structured training in analyzing digital content. This claim is supported by studies [34]–[36], which highlight that inequalities in digital access and skills development contribute to differences in digital performance outcomes. This implies that teachers, particularly in public schools, occupy a pivotal role in bridging these gaps by fostering more inclusive, context-sensitive learning environments that strengthen students' critical evaluation of AI-generated and real images.

3.4. Differences in the level of usefulness of determinants when grouped according to demographic profile

As shown in Table 5, in terms of gender [U=1121.000, p=0.481], year level [U=1145.000, p=0.961], and strand [H(2)=5.891, p=0.053], there are no significant differences between groups. Since all p-values are greater than 0.05, the null hypothesis is not rejected. This indicates that the perceived usefulness of determinants is comparable across these profile variables. In contrast, the type of school [U=815.000, p=0.001] shows a significant difference. Since p<0.05, the null hypothesis is rejected. Respondents from private schools reported significantly higher perceived usefulness (M=3.98) than those from public schools (M=3.54).

Table 5. Difference in the usefulness of determinants when grouped according to demographic profile

Variable	U	z	p	Effect size	95% CI
Gender	1121.000	-0.704	0.481	r=0.069	[-0.110, 0.240]
Year level	1145.000	-0.049	0.961	r=0.005	[-0.190, 0.200]
Type of school	815.000	-3.469	0.001	r=0.342	[-0.160, 0.500]
	H	df	p		
Strand	5.891	2	0.053	ε^2=0.047	[0.000, 0.110]
Frequency of using AI	11.989*	2	0.002	ε^2=0.106	[0.020, 0.190]

Note: the difference is significant when p≤0.05

Similarly, the frequency of AI use [H(2)=11.989, p=0.002] shows a significant difference. As shown in Table 6, post hoc analysis revealed a significant difference between weekly and never users (p=0.006), with respondents who use AI weekly demonstrating higher perceived usefulness (M=3.90) than those who never use AI (M=2.92). No significant differences were found between daily and weekly users (p=0.079) and between daily and never users (p=0.126). Overall, the results indicate that the perceived usefulness of determinants varies significantly by school type and frequency of use of AI, while remaining consistent across gender, year level, and strand.

Table 6. Post hoc for usefulness (frequency of using AI applications)

Frequency of using AI applications	Test statistic	Std. Error	Std. Test statistic	Sig.
Daily - weekly	-12.880	7.322	-1.759	0.079
Daily - never	20.010	13.085	1.529	0.126
Weekly - never	32.890	11.924	2.758	0.006

The findings suggest that the perceived usefulness of determinants for distinguishing AI-generated from real images does not differ significantly by gender, year level, or strand, but does vary significantly by school type and the frequency of AI application use. This means that while students generally recognize the value of these determinants regardless of basic demographic characteristics, their appreciation of such cues is influenced by their learning environment and level of engagement with AI technologies. This could be because private school students and those who use AI more frequently, particularly every week, are more exposed to structured digital tasks and to the exploratory use of AI tools, enabling them to understand better and apply evaluative cues such as anatomical or contextual inconsistencies. This finding is consistent with the studies by Cabero-Almenara *et al.* [32] and Scherer *et al.* [37], which highlight that both access to digital resources and the frequency of technology use significantly shape students' digital competence and perceptions of technological tools. In addition, this finding can be attributed to experiential learning, in which repeated, guided interaction with AI enhances students' awareness of how such systems generate outputs. This claim is supported by studies such as those of Holmes *et al.* [3] and Zawacki-Richter *et al.* [5], which emphasize that hands-on engagement with AI technologies strengthens learners' understanding and critical evaluation skills. This implies that teachers, particularly in media literacy and computer-related subjects, serve as key agents in creating learning experiences that deepen students' engagement with AI tools and sharpen their ability to meaningfully apply detection criteria across diverse contexts.

3.5. Theoretical analysis

The findings provide partial support for the assumptions of SDT in explaining students' ability to distinguish AI-generated from real images. While the theory posits that sensitivity and decision criterion may vary across students, the results revealed no significant differences in detection accuracy and perceived usefulness of determinants across most demographic variables, such as gender, year level, and strand, suggesting a relatively uniform level of sensitivity and decision making among students. However, the significant differences observed in school type and AI use frequency indicate that certain contextual and experiential factors influence both sensitivity and decision criteria, aligning with the theory's core propositions. In this regard, the study extends SDT by applying its core constructs to the school-based context of students' evaluation of AI-generated images. Specifically, it reconceptualizes AI-generated images as "signals" and authentic images as "noise", while examining how students' detection accuracy reflects their perceptual sensitivity and decision-making biases in a digitally mediated environment. It further extends the theory by incorporating technological exposure and socio-demographic factors as contextual variables that may influence detection performance. The study contributes theoretically by clarifying how SDT operates in the context of students' evaluation of AI-generated images, and practically by providing evidence-based guidance for designing media literacy instruction that enhances critical image verification.

3.6. Limitations of the findings

Despite its contributions, this study is subject to several limitations that should be considered when interpreting the findings. First, the sample size of 104 respondents was limited to senior high school students in Western Visayas, which may restrict the generalizability of the results to other regions or educational contexts. Second, the use of a researcher-made questionnaire, while validated and tested for reliability, may still be constrained by inherent measurement biases, particularly in capturing the complexity of students' detection accuracy and their perceived usefulness of determinants. Third, the 9-item multiple-choice test may not fully encompass the wide variability and evolving sophistication of AI-generated images, potentially limiting the depth of assessment. Additionally, the study relied on self-reported data for certain variables, such as frequency of AI software use, which may be subject to response bias. Finally, the descriptive-comparative design limits the ability to establish causal relationships between demographic factors and detection accuracy or the usefulness of determinants. Notwithstanding these limitations, future research may expand the sample to include a more diverse and larger population across different regions and educational levels to enhance generalizability. Moreover, subsequent studies may employ experimental or mixed-methods designs to more deeply examine causal relationships and capture nuanced insights into students' evaluative processes when identifying AI-generated content.

4. CONCLUSION

The findings underscore that teachers, particularly those teaching media literacy and computer-related subjects, play a pivotal role in strengthening students' media literacy education and AI readiness in schools by developing their capacity to evaluate AI-generated and real images critically. This is achieved by fostering learning environments that move beyond passive exposure to active, analytical engagement. Across diverse demographic contexts, this underscores the importance of instructional approaches that integrate hands-on, contextually grounded, and experience-driven activities to deepen students' understanding of detection determinants and their practical application. More importantly, the identified determinants serve as perceptual cues that students rely on to evaluate image authenticity. The study suggests that media literacy instruction should explicitly scaffold how these cues are recognized, interpreted, and systematically applied in verification processes. It also highlights the pivotal role of educators, especially in public school settings, in addressing disparities in digital competence by creating inclusive and responsive learning experiences that strengthen evaluative skills. Ultimately, these insights point to the need for a more intentional alignment of pedagogy with emerging technological realities, where students are guided not only to recognize visual inconsistencies but also to develop sustained critical awareness in navigating AI-mediated digital content.

Based on the findings, it is recommended that teachers, particularly those handling media literacy and computer-related subjects, implement structured classroom activities that explicitly train students to analyze and evaluate AI-generated and real images using clear detection criteria such as anatomical accuracy, contextual consistency, and realism. Specifically, teachers may incorporate comparison tasks in which students systematically examine paired real and AI-generated images. These cue training activities help students identify indicators of AI-generated content and source-checking exercises that require verification of image origins through reverse image search and credibility assessment. Guided analysis and critique tasks using structured rubrics may also be employed, along with project-based learning activities where students create and evaluate digital content using AI tools. Public schools may further support these strategies by providing access to free or low-cost AI platforms and integrating real-world examples from social media to enhance relevance. At the same time, collaborative activities such as peer evaluation and group discussions can strengthen students' critical thinking and justification of judgments.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
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Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
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CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

The authors obtained informed consent from all participants in this study.

DATA AVAILABILITY

All the data stated in the study can be requested from the authors upon reasonable request. References and citations can be verified and accessed through Google Scholar, Crossref, and Scopus databases.

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