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Trust, Verify-AI or Depend? Critical AI Literacy, Information Verification and Responsible AI Use among Management Students

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Abstract: *The increasing integration of generative artificial intelligence (GenAI) into higher education has created new opportunities for personalised learning, academic efficiency, and knowledge accessibility, while raising concerns about information reliability, cognitive dependence, and students' capacity for independent evaluation. Although AI literacy is increasingly recognised as an essential educational competency, less attention has been devoted to the relationship between students' self-reported verification practices and their expectations regarding institutional support for responsible AI use. This study investigates how management students engage critically with AI-generated information and identifies pedagogical priorities for strengthening responsible, reflective, and autonomous AI-supported learning. Drawing on a cross-sectional questionnaire completed by 93 management students, the research examines AI-related verification behaviours, perceptions of cognitive risks, approaches to academic problem-solving, and preferences for AI literacy education. Descriptive findings indicate that 44.7% of respondents report always or often verifying AI-generated information, whereas 69.9% identify the critical evaluation of AI outputs as a priority for university education. The 25.2-percentage-point difference highlights a contrast between reported verification behaviour and expressed educational priorities, although these indicators measure distinct constructs and should not be interpreted as a direct estimate of an individual competency deficit. Building on contemporary scholarship concerning AI literacy, responsible trust, epistemic responsibility, and human–AI collaboration, the article proposes VERIFY–AI, a pedagogical framework designed to support source evaluation, error detection, evidence-based reasoning, and accountable use of AI-generated content. The study contributes context-specific empirical evidence to discussions of responsible AI integration in management education and offers practical directions for curriculum development, assessment design, and critical AI literacy instruction. Given the modest sample size, reliance on self-reported data, and cross-sectional design, the findings are interpreted as exploratory rather than causal or broadly generalisable.*

Keywords: Generative artificial intelligence; Critical AI literacy; Information verification; Responsible AI use; Cognitive independence; Management education; Epistemic responsibility.

1. INTRODUCTION

The rapid diffusion of generative artificial intelligence (GenAI) across higher education is reshaping how students access information, construct arguments, complete academic assignments, and engage with complex disciplinary knowledge. Large language models and conversational AI systems can generate explanations, synthesise information, propose solutions, and support decision-making within seconds. These capabilities create opportunities to enhance learning accessibility and academic productivity, but they also introduce important questions concerning the reliability of AI-generated content and the intellectual responsibilities of its users. As AI becomes increasingly embedded in academic practices, the educational challenge extends beyond ensuring that students can operate these technologies to determining whether they can critically assess, substantiate, and responsibly apply the information they produce.

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This challenge is particularly relevant to management education, where students are expected to develop analytical reasoning, evidence-based decision-making, professional judgement, and the capacity to evaluate competing interpretations of organisational problems. AI-generated recommendations may appear coherent and authoritative even when their underlying assumptions, factual accuracy, or contextual relevance remain uncertain. Consequently, the educational value of GenAI cannot be assessed exclusively through its convenience or perceived usefulness. It must also be considered in relation to students' ability to recognise informational limitations, verify supporting evidence, and retain responsibility for their academic and professional conclusions. The distinction between technological proficiency and critical engagement is consistent with contemporary approaches to AI literacy, which conceptualise competence as extending beyond operational skills to include evaluation, ethical awareness, and informed application (Chiu et al., 2024).

A central concern emerging from this transformation is the relationship between trust and verification. Trust is necessary for the meaningful adoption of technological systems, yet uncritical acceptance of AI-generated information may weaken the scrutiny required for responsible knowledge construction. Conversely, indiscriminate distrust may prevent students from benefiting from legitimate forms of AI assistance. The relevant educational objective is therefore not to maximise or eliminate trust, but to cultivate appropriately calibrated trust: the capacity to determine when AI-generated outputs warrant acceptance, further investigation, modification, or rejection. Liao and Sundar (2022) provide a useful conceptual foundation for this perspective by examining responsible trust in AI systems from a communication-oriented standpoint. Applied to higher education, this perspective directs attention towards the relationship between perceived credibility, critical evaluation, and the user's continuing responsibility for decisions informed by AI.

Recent scholarship has increasingly connected AI literacy with cognitive independence, ethical decision-making, and responsible technology use. Chiu et al. (2024) propose a comprehensive framework for understanding AI literacy and competency, while Pramod (2025) examines responsible AI use in relation to digital literacy and ethical awareness. More recent contributions extend these discussions towards cognitive safety and structured approaches to AI-mediated information processing. In particular, Zainuddin et al. (2026) address the transition from AI literacy towards cognitive AI safety, whereas Zhou et al. (2026) propose an AI-information problem-solving model concerned with critical, ethical, and responsible use. Taken together, these perspectives support the argument that responsible AI engagement requires more than familiarity with technological functionality: it involves the capacity to evaluate information and exercise independent judgement.

The issue also intersects with the possibility of cognitive dependence. When students routinely delegate information retrieval, interpretation, or argumentative development to AI systems, the boundary between productive assistance and excessive reliance may become difficult to identify. In accounting education, Tajalla et al. (2026) examine generative AI dependence in relation to AI literacy, trust, and critical thinking disposition, highlighting the relevance of these constructs within professionally oriented higher education. Similarly, Petcu et al. (2026) situate human–AI interaction within a broader discussion of collaborative intelligence and the preparation of future professionals for AI-enabled workplaces. These contributions suggest that responsible educational integration should preserve meaningful human participation in evaluating, interpreting, and applying AI-supported knowledge. Nevertheless, the relationships among AI trust, actual verification behaviour, and cognitive independence require careful empirical investigation rather than being assumed from technological adoption alone.

Despite the expanding literature on AI literacy and responsible AI use, an important analytical distinction remains insufficiently developed in management education: the difference between what students report doing when evaluating AI-generated information and what they believe universities should teach them to do. Existing conceptual frameworks provide valuable guidance concerning desirable competencies, but educational priorities cannot be inferred directly from students' frequency of AI use or their perceptions of technological usefulness. Verification behaviour and preferences for institutional instruction represent related yet distinct dimensions of responsible AI engagement. Examining them together may therefore offer useful insights into the alignment between students' current academic practices and their expectations of university education.

The present study addresses this issue using data from a cross-sectional questionnaire completed by 93 management students. The investigation focuses on self-reported verification practices, perceptions of AI-related risks, approaches to academic problem-solving, and preferences regarding critical AI literacy education. The descriptive results indicate that 44.7% of respondents always or often verify AI-generated information, while 69.9% identify learning to critically evaluate AI-generated content as an educational priority. The difference of 25.2 percentage points provides an empirical starting point for examining the relationship between reported practices and perceived

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educational needs. However, because the two indicators measure different constructs, this contrast cannot establish that individual students lack verification skills or that institutional instruction would necessarily change their behaviour.

Against this background, the study addresses the following overarching research question:

RQ: To what extent do management students critically evaluate AI-generated information, and what educational strategies could strengthen responsible AI use?

To provide a more focused investigation, four subsidiary research questions are formulated:

RQ1: How frequently do management students report verifying information generated by AI systems?

RQ2: How do students perceive the potential risks of AI use for independent reasoning and responsible academic decision-making?

RQ3: What educational priorities do students identify regarding the critical evaluation and responsible use of AI-generated information?

RQ4: How can the study's descriptive findings, interpreted alongside contemporary AI literacy scholarship, inform the development of a pedagogical framework for responsible AI engagement in management education?

The study pursues three interconnected objectives. First, it provides exploratory empirical evidence concerning management students' self-reported verification behaviour and perceptions of AI-related educational risks. Second, it examines the contrast between existing verification practices and students' expressed priorities for critical AI literacy instruction. Third, it develops a pedagogical proposal, termed VERIFY–AI, intended to translate principles of critical information evaluation and epistemic responsibility into practical teaching and assessment activities.

The proposed framework is informed by scholarship on AI literacy, responsible trust, and AI-mediated information problem-solving (Chiu et al., 2024; Liao & Sundar, 2022; Zhou et al., 2026). Its purpose is to support students in evaluating source credibility, detecting informational errors, scrutinising AI-generated arguments, and accepting responsibility for the academic conclusions they produce. Rather than treating verification as a single technical action, the framework conceptualises it as a structured process of critical engagement through which AI-generated outputs become objects of investigation rather than unquestioned sources of authority.

The article makes three intended contributions. Empirically, it documents selected patterns of reported verification behaviour and educational preferences within a specific sample of management students. Conceptually, it distinguishes AI adoption and perceived usefulness from the critical practices required for responsible information use. Pedagogically, it proposes VERIFY–AI as a framework that may guide the design of learning activities and assessments intended to strengthen evidence-based reasoning, calibrated trust, and cognitive independence. These contributions are necessarily exploratory: the cross-sectional design, modest sample size, and reliance on self-reported responses do not permit causal conclusions or broad generalisation.

The remainder of the article is organised as follows. Section 2 reviews the literature on critical AI literacy, responsible trust, information verification, cognitive dependence, and pedagogical approaches to responsible AI use. Section 3 describes the research design, questionnaire, sample, and analytical procedures. Section 4 presents the descriptive findings, while Section 5 discusses their implications and develops the VERIFY–AI pedagogical framework. Section 6 concludes by outlining the study's contributions, limitations, and directions for future research.

2. LITERATURE REVIEW

2.1. From AI Literacy to Critical AI Literacy in Higher Education

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

The increasing integration of generative artificial intelligence (GenAI) into higher education has intensified scholarly interest in the competencies required for effective, ethical, and intellectually responsible interaction with AI systems. Early discussions of AI literacy primarily addressed the knowledge and skills necessary to understand artificial intelligence, recognise its applications, and interact with AI-enabled technologies. More recent conceptualisations have expanded this perspective to include critical evaluation, ethical reasoning, and awareness of the limitations of AI-generated information. Chiu et al. (2024) offer a comprehensive framework for AI literacy and competency, providing a foundation for distinguishing operational proficiency from broader forms of informed and responsible AI engagement.

Within this study, *critical AI literacy* is understood as the capacity to interrogate AI-generated outputs, assess their evidential foundations, recognise uncertainty and potential inaccuracies, and make independent judgements concerning their appropriate use. This conceptualisation extends beyond the ability to formulate effective prompts or obtain plausible responses. It positions students as active evaluators of AI-mediated information rather than passive recipients of technologically generated content.

Such a distinction is especially important in management education. Students preparing for managerial and organisational roles must frequently interpret incomplete information, compare alternative courses of action, and justify decisions under conditions of uncertainty. Accordingly, proficiency in using AI tools should not be treated as equivalent to competence in evaluating their recommendations. AI literacy becomes educationally meaningful when technological capabilities are integrated with disciplinary knowledge, critical reasoning, and professional accountability.

Recent scholarship reinforces the need to connect AI literacy with responsible use. Pramod (2025) examines the relationship between digital literacy, ethical awareness, and responsible AI engagement, while Zainuddin et al. (2026) introduce cognitive AI safety as a relevant consideration for educational AI use. These perspectives suggest that technological competence alone may be insufficient when students encounter persuasive but potentially inaccurate AI-generated explanations. However, the precise relationships between literacy, verification behaviour, and responsible decision-making remain empirical questions that require investigation within specific educational contexts.

2.2. Information Verification and Epistemic Responsibility

Information verification represents a central component of critical AI literacy because generative AI systems can produce linguistically coherent responses without providing independently verifiable evidence for every assertion. The fluency and apparent completeness of AI-generated content may encourage users to interpret plausibility as reliability. Consequently, students need to distinguish between information that appears convincing and information that has been adequately substantiated.

In academic settings, verification involves more than checking whether an AI-generated statement is factually correct. It may require examining the credibility of cited sources, assessing the relevance of supporting evidence, identifying omitted assumptions, comparing competing interpretations, and determining whether a conclusion is justified. These activities are closely associated with *epistemic responsibility*: the obligation to exercise appropriate judgement concerning the production, acceptance, and communication of knowledge.

Maturo et al. (2026) explicitly connect AI-generated plausibility with epistemic responsibility in higher education. Their conceptual focus is relevant to the present study because the perceived credibility of AI-generated information should not be confused with demonstrated evidential validity. Similarly, Jabeen et al. (2026) address AI, misinformation, and trust through the information literacy approaches of university librarians, suggesting the relevance of established information evaluation practices to emerging AI-mediated learning environments.

A complementary perspective is provided by Zhou et al. (2026), whose proposed AI-information problem-solving model emphasises critical, ethical, and responsible engagement with AI-generated information. Such approaches are particularly relevant to educational activities in which students must evaluate AI-supported explanations, business analyses, or recommendations before incorporating them into their own work.

For management students, the consequences of inadequate verification may extend beyond academic inaccuracies. In simulated business environments, AI-generated recommendations may influence interpretations of market conditions, financial information, strategic alternatives, or

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organisational decisions. The educational objective is therefore to cultivate verification as a habitual component of analytical reasoning rather than as an optional final check.

Nevertheless, the frequency with which students report verifying AI-generated content should not automatically be interpreted as a direct measure of their actual verification competence. Self-reported behaviour does not establish whether the procedures employed are sufficiently rigorous, whether credible sources are consulted, or whether students can reliably detect substantive errors. This distinction is essential for interpreting questionnaire-based evidence concerning responsible AI use.

2.3. Responsible Trust, Reliance, and Cognitive Dependence

Trust constitutes a fundamental dimension of human–AI interaction. AI systems must be sufficiently useful and credible to support meaningful engagement, yet excessive confidence in their outputs may encourage uncritical acceptance. Conversely, insufficient trust may prevent users from benefiting from appropriate forms of technological assistance. The challenge is therefore to develop *responsible trust*, understood as confidence that remains proportionate to the system's demonstrated capabilities, limitations, and suitability for a particular task.

Liao and Sundar (2022) provide an influential conceptual perspective on responsible trust in AI systems. Their communication-oriented approach offers a useful foundation for considering how information presentation, system characteristics, and user perceptions may shape reliance on AI-generated outputs. In higher education, this perspective raises an important question: do students evaluate AI-generated information because they recognise the need for independent verification, or do they accept outputs primarily because they appear coherent, accessible, and authoritative?

This distinction is closely related to cognitive dependence. AI assistance can reduce the effort required to retrieve information, generate preliminary explanations, or organise complex material. Such support may be educationally beneficial when it allows students to devote greater attention to interpretation and problem-solving. However, reliance becomes potentially problematic when essential processes of questioning, verification, and judgement are routinely delegated to AI systems.

Research concerning AI dependence has begun to examine the relationships among technological trust, literacy, and critical thinking. Tajalla et al. (2026) investigate these constructs in accounting education, a disciplinary context that shares management education's emphasis on evidence-based reasoning and professional accountability. Their research focus highlights the importance of distinguishing productive AI assistance from patterns of dependence that may constrain independent intellectual engagement.

Related discussions of digital trust and information verification among younger technology users are reflected in Fitroh et al. (2026), while Tas and Bittner (2026) examine conditional trust, agency, and critical AI literacy in a student context. Together, these contributions indicate that trust should be investigated alongside verification practices and user agency rather than treated exclusively as a predictor of technology acceptance.

Importantly, **AI reliance and cognitive dependence are not interchangeable constructs**. Reliance may be appropriate when students consciously delegate routine activities while retaining responsibility for evaluating outcomes. Cognitive dependence implies a more consequential reduction in autonomous engagement, which cannot be established solely through frequent AI use. The present study therefore treats self-reported verification practices and perceptions of cognitive risks as exploratory indicators rather than direct measurements of cognitive dependence.

2.4. Responsible AI Use as an Educational and Institutional Responsibility

The development of responsible AI capabilities cannot be attributed exclusively to individual students. Universities influence how AI is used through curriculum design, assessment practices, academic integrity policies, instructional guidance, and opportunities for experiential learning. Consequently, critical AI literacy should be understood as both an individual competency and an institutional educational responsibility.

Chiu et al. (2024) provide a basis for integrating AI literacy and competency development into

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

educational settings. Building on this broader perspective, Zainuddin et al. (2026) foreground cognitive AI safety, while Tran et al. (n.d.) propose a framework connecting AI literacy with responsible AI capability, institutional conditions, and human agency. These contributions support a shift from approaches centred primarily on technological adoption towards educational strategies that emphasise students' ability to make informed, accountable decisions.

Institutional responsibility also involves preparing students for professional environments in which human judgement and AI-supported processes increasingly coexist. Petcu et al. (2026) address collaborative intelligence and the preparation of future professionals for human–AI workplaces. This perspective is particularly relevant to management education, where graduates may be expected to evaluate AI-generated business intelligence, interpret algorithmic recommendations, and remain accountable for organisational decisions.

The broader institutional environment may also shape the implementation of responsible AI education. Enachescu and Petcu (2025) discuss leadership and emotional intelligence within hybrid academic ecosystems, while Aboderin (2025) considers the pedagogical and skills-development implications of emerging technologies in universities. Although these contributions do not directly establish the effectiveness of AI verification training, they situate responsible technology integration within wider questions of institutional capacity, educational leadership, and curriculum transformation.

From a pedagogical standpoint, universities may strengthen critical AI literacy by requiring students to document their verification procedures, justify the acceptance or rejection of AI-generated claims, compare outputs against credible evidence, and reflect on the limitations of automated recommendations. These strategies would make students' intellectual contributions more visible while preserving opportunities to benefit from AI assistance.

Such approaches are consistent with educational perspectives that emphasise active learning, transferable competencies, and reflective engagement. For example, Nguyen et al. (2025) review game-based learning and learning motivation, offering a broader pedagogical perspective that may inform the design of interactive verification activities. However, evidence concerning game-based learning in general should not be interpreted as direct proof that gamified AI verification exercises improve critical AI literacy. Their effectiveness would require dedicated empirical evaluation.

2.5. Research Gap and Conceptual Foundations of the VERIFY–AI Framework

The literature reviewed above provides several complementary perspectives on responsible AI engagement. AI literacy frameworks clarify the competencies required for informed technology use (Chiu et al., 2024). Research on responsible trust highlights the importance of appropriately calibrated reliance (Liao & Sundar, 2022). Emerging discussions of cognitive AI safety and AI dependence draw attention to the potential consequences of uncritical engagement (Tajalla et al., 2026; Zainuddin et al., 2026). Finally, AI-information problem-solving approaches emphasise the need for structured evaluation and ethical judgement (Zhou et al., 2026).

Despite these contributions, a specific empirical question warrants further attention: **how do students' reported practices of verifying AI-generated information relate descriptively to their expressed priorities for university-level instruction in critical AI evaluation?**

This question is particularly relevant because verification behaviour and educational preferences capture different dimensions of AI engagement. A student may recognise the importance of verification without consistently practising it. Conversely, a student who frequently verifies AI-generated information may still consider formal instruction valuable. Therefore, a difference between the proportions reporting verification and prioritising critical AI literacy education cannot, by itself, establish an individual-level behavioural gap or a causal relationship.

The present study addresses this issue through an exploratory investigation involving 93 management students. Its empirical contribution lies in documenting selected patterns of self-reported verification behaviour, perceived AI-related risks, and educational priorities. Its conceptual contribution is the development of **VERIFY–AI**, a proposed pedagogical framework that translates principles of critical AI literacy and epistemic responsibility into a structured approach to evaluating AI-generated information.

The framework is organised around six proposed educational practices:

V — Validate source credibility: Examine the provenance, authority, and relevance of information used to support AI-generated claims.

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

E — Examine factual accuracy: Identify statements requiring corroboration and compare them with reliable independent evidence.

R — Review reasoning and assumptions: Evaluate the logical consistency, completeness, and contextual appropriateness of AI-generated arguments.

I — Identify uncertainty and limitations: Recognise unsupported assertions, missing perspectives, potential bias, and situations in which AI-generated information may be unreliable.

F — Form independent judgements: Develop and justify conclusions through critical reasoning rather than automatic acceptance of AI recommendations.

Y — Yield accountable academic outputs: Ensure that the final work reflects the student's own understanding, appropriate acknowledgement of AI assistance, and responsibility for the accuracy and integrity of submitted content.

These six practices constitute a **proposed instructional framework**, not an empirically validated scale or established theory. Their purpose is to provide a coherent basis for designing educational interventions, assessment criteria, and future research instruments. The framework also offers a means of distinguishing the act of obtaining an AI-generated response from the more demanding process of determining whether that response deserves to inform academic or professional judgement.

Accordingly, the study advances the proposition that responsible AI education should be evaluated not merely by students' familiarity with AI tools, but also by their demonstrated ability to verify information, interrogate reasoning, recognise uncertainty, and remain accountable for the conclusions they produce. This proposition provides the conceptual foundation for interpreting the empirical findings and developing the pedagogical implications discussed in subsequent sections.

3. METHODOLOGY

3.1. Research Design and Analytical Approach

This study adopts a quantitative, cross-sectional, and exploratory research design to investigate management students' self-reported practices of verifying AI-generated information, their perceptions of AI-related cognitive and academic risks, and their preferences for responsible AI education. A questionnaire-based approach was selected to capture students' perspectives on emerging academic practices associated with generative artificial intelligence (GenAI).

The investigation is primarily descriptive. Rather than testing causal relationships or evaluating the effectiveness of a specific educational intervention, it seeks to identify patterns in reported behaviours and educational priorities that may inform subsequent research and pedagogical development. This approach is consistent with the study's central research question concerning the extent to which students critically evaluate AI-generated information and the educational strategies that might support more responsible engagement.

The research is conceptually informed by scholarship on AI literacy and competency (Chiu et al., 2024), responsible trust in AI systems (Liao & Sundar, 2022), and emerging approaches to AI-information problem-solving (Zhou et al., 2026). These perspectives guide the interpretation of the questionnaire findings but are not treated as previously validated measurement models for the present dataset.

The study therefore distinguishes between two analytical levels: the **empirical level**, comprising students' reported behaviours and preferences, and the **conceptual level**, comprising the interpretation of those findings and the development of the proposed VERIFY–AI pedagogical framework.

3.2. Participants and Research Context

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

The final study sample comprised **93 management students who completed the questionnaire**. The unit of analysis was the individual respondent, and the empirical findings presented in this article refer exclusively to these 93 completed questionnaires.

The selection of management students was relevant to the research objectives because management education requires the development of information evaluation, analytical reasoning, evidence-based decision-making, and professional judgement. These competencies are particularly important when AI-generated information is used to support academic assignments, business analyses, or managerial recommendations.

The study was conducted within a higher education context in which students had opportunities to engage with AI-supported academic activities. However, the available study documentation does not establish the precise sampling frame, recruitment procedure, institutional distribution, or demographic composition of the respondents. Consequently, the sample cannot be described as statistically representative of management students at the institutional, national, or international level.

No probability-based sampling assumptions are made. The findings are interpreted as evidence concerning the surveyed group rather than estimates of the prevalence of particular behaviours across the wider student population.

3.3. Research Instrument and Variables

Data were collected using a structured questionnaire comprising **15 questions** addressing students' experiences, perceptions, and educational expectations regarding AI use in academic activities.

The present article focuses on seven questionnaire items: **Q3, Q5, Q7, Q11, Q12, Q14, and Q15**. These items were selected because of their relevance to critical AI literacy, verification behaviour, perceived risks, problem-solving practices, and responsible AI education.

The analytical dimensions are summarised in Table 1.

Table 1. Analytical dimensions and questionnaire items selected for the study

Analytical dimension	Questionnaire items	Intended analytical focus
AI-related academic practices	Q3, Q5	Contextual characteristics of AI use and students' perceptions of AI-supported academic activities
Information verification	Q11	Self-reported frequency of verifying AI-generated information
Critical reasoning and problem-solving	Q7, Q12	Perceptions and practices relevant to independent reasoning and academic problem-solving
Responsible AI education	Q14	Preferred educational activities and competencies associated with responsible AI use

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

Perceived risks and recommendations	Q15	Students' perspectives on risks, limitations, and potential educational improvements

Note. The table identifies the intended analytical role of each selected item. Exact question wording, response categories, and coding must be checked against the original questionnaire before the final manuscript is submitted.

The primary descriptive indicator of information verification is the proportion of respondents reporting that they **always or often verify AI-generated information**. This indicator captures the reported frequency of verification, not the accuracy or methodological quality of the verification procedures undertaken.

A second indicator concerns the proportion of respondents identifying **critical evaluation of AI-generated information as a priority for university education**. This measure reflects an expressed educational preference rather than an observed deficiency in AI literacy.

The distinction is methodologically important. Students may value formal instruction in critical AI evaluation even when they already engage in verification practices. Similarly, frequent self-reported verification does not necessarily establish that students can successfully detect misinformation, fabricated references, or flawed arguments.

Accordingly, the study does not combine these indicators into a single AI literacy score or treat them as interchangeable measures of the same underlying construct.

3.4. Data Collection and Data Quality Considerations

The empirical dataset consists of 93 completed questionnaires. The study uses the descriptive percentages associated with this final sample.

The available documentation does not specify the exact data collection period, questionnaire administration platform, recruitment communication, participation incentives, or procedures used to prevent duplicate submissions. These details should be incorporated into the final manuscript once verified against the original research records.

For analytical transparency, the present study treats the reported percentages as descriptive summaries of the questionnaire responses. No missing-data imputation, respondent weighting, or post-stratification procedure is assumed.

An additional consideration concerns the numerical consistency of the reported percentages. Because the sample comprises 93 respondents, the percentages should be recalculated from the original item-level frequencies before publication. This is particularly important where published percentages may have been rounded or derived from an earlier version of the dataset.

Where an item permitted multiple responses, its percentages should be interpreted independently and should not be expected to sum to 100%. The response format of each item must therefore be confirmed before constructing the final tables.

3.5. Data Analysis

The analytical strategy is based on descriptive statistics, with emphasis on the distribution of responses relevant to information verification and critical AI literacy education.

The principal indicators currently available are:

- **44.7%** of respondents reported always or often verifying AI-generated information.
- **69.9%** identified learning to critically evaluate AI-generated information as a priority for university education.

The arithmetic difference between these proportions is **25.2 percentage points**.

This difference is used as a descriptive comparison between two survey indicators. It is not interpreted as a measure of the number of students who fail to verify information, nor as evidence that educational expectations exceed individual competence by a measurable amount.

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

Furthermore, the two proportions are derived from responses provided by the same sample to different questions. Without the underlying respondent-level data, their association cannot be established. In particular, it is not possible to determine from the aggregated percentages whether respondents who report infrequent verification are also those who prioritise critical AI literacy instruction.

For this reason, the study does not report inferential statistical tests, correlations, regression coefficients, or effect sizes that cannot be calculated from the information currently available.

If the anonymised respondent-level dataset becomes available, supplementary analyses could examine associations between verification frequency and selected indicators of AI use, perceived cognitive risks, and educational preferences. Depending on the response scales and observed cell frequencies, such analyses might include contingency tables, chi-square tests, Fisher's exact tests, or ordinal association measures. These procedures are identified as potential extensions rather than analyses already performed.

The interpretation of findings follows a construct-sensitive approach: verification frequency, perceived risk, educational preference, and critical AI literacy are treated as related but conceptually distinct variables.

3.6. Development of the VERIFY–AI Pedagogical Framework

In addition to the descriptive analysis, the study develops a conceptual pedagogical framework termed **VERIFY–AI**.

The framework is derived through an interpretive synthesis of the empirical themes addressed by the questionnaire and relevant scholarship concerning AI literacy, responsible trust, and critical information evaluation (Chiu et al., 2024; Liao & Sundar, 2022; Zhou et al., 2026).

Its six components are:

1. **Validate source credibility** — examine the provenance, authority, and relevance of information.
2. **Examine factual accuracy** — corroborate substantive claims against independent evidence.
3. **Review reasoning and assumptions** — evaluate logical consistency and the adequacy of supporting arguments.
4. **Identify uncertainty and limitations** — recognise missing information, potential bias, and unsupported claims.
5. **Form independent judgements** — develop conclusions through critical reflection rather than automatic acceptance.
6. **Yield accountable academic outputs** — assume responsibility for the accuracy, transparency, and integrity of submitted work.

The framework is intended as a pedagogical design proposal rather than a psychometrically validated instrument. The questionnaire did not directly measure all six components, and the present study does not claim to demonstrate their effectiveness.

The framework's potential educational value will be discussed in relation to teaching strategies, assessment practices, and future opportunities for empirical validation.

3.7. Ethical Considerations

The study addresses students' reported academic practices and perceptions of AI use. Ethical reporting therefore requires the protection of respondent confidentiality, transparent description of participation procedures, and responsible handling of questionnaire data.

The available information does not establish whether formal ethics committee approval was obtained, whether participants received a written information statement, or how consent was documented. These details must be verified from the original research records and accurately reported in the final manuscript.

No ethics approval number, consent procedure, or anonymisation protocol is asserted without supporting documentation.

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

3.8. Methodological Limitations

Several limitations should be considered when interpreting the findings.

First, the sample of 93 students is relatively modest, and its representativeness has not been established. Generalisation beyond the surveyed educational context should therefore be approached cautiously.

Second, the study relies on self-reported questionnaire responses. These may be influenced by recall limitations, social desirability, or differences in respondents' interpretations of terms such as *verification* and *critical evaluation*.

Third, the cross-sectional design captures perceptions and reported practices at a single point in time. It does not permit conclusions about changes in AI literacy, the development of dependence, or the causal effects of educational interventions.

Fourth, the available aggregated results do not support individual-level analysis of relationships among verification practices, perceived risks, and educational preferences.

Fifth, the study does not include an objective assessment of students' ability to identify factual errors, evaluate fabricated references, or detect weaknesses in AI-generated reasoning. Consequently, it examines **reported verification behaviour rather than demonstrated critical AI literacy competence**.

Finally, VERIFY–AI remains a proposed pedagogical framework. Its educational effectiveness, construct validity, and applicability across disciplinary contexts require subsequent investigation.

Notwithstanding these limitations, the study provides an exploratory basis for examining how management students perceive their responsibilities when using AI-generated information and what forms of educational support they consider important for responsible AI engagement.

4. RESULTS

4.1. Overview of the Empirical Findings

The analysis draws on questionnaire responses from 93 management students and examines selected dimensions of their engagement with generative artificial intelligence (GenAI). Particular attention is given to reported information verification practices, perceptions of AI-related cognitive risks, and educational priorities concerning the critical evaluation of AI-generated content.

The findings are presented descriptively, reflecting the exploratory nature of the investigation and the availability of aggregated survey indicators. The analysis does not assume that the reported percentages represent statistically significant differences or that they establish relationships between individual respondents' behaviours and preferences.

Two indicators are particularly relevant to the study's central research question. First, 44.7% of respondents reported that they always or often verify information generated by AI systems. Second, 69.9% identified the critical evaluation of AI-generated information as an important competency that universities should develop.

These findings suggest that information verification and critical AI literacy education occupy different positions within students' reported academic practices and educational expectations. However, the indicators represent distinct questionnaire constructs and should not be interpreted as interchangeable measurements of AI literacy.

4.2. Self-Reported Information Verification Practices

The first analytical dimension concerns the frequency with which management students report verifying AI-generated information.

According to the available questionnaire results, **44.7% of respondents indicated that they always or often verify AI-generated information**.

This finding suggests that frequent verification is reported by fewer than half of the surveyed students. Although it provides a relevant indication of how respondents describe their academic practices, it does not establish the quality, accuracy, or comprehensiveness of their verification procedures.

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

The remaining respondents are not classified into specific verification-frequency categories because the corresponding response distribution has not been confirmed from the original dataset. In particular, the available aggregate does not establish how many students selected intermediate-frequency responses or reported never verifying AI-generated content.

From the perspective of critical AI literacy, the result is noteworthy because verification represents an important safeguard against the uncritical acceptance of plausible but potentially inaccurate information. Nevertheless, a self-reported frequency measure cannot determine whether respondents consult reliable sources, identify fabricated references, or critically assess the reasoning underlying AI-generated conclusions.

Accordingly, the finding should be interpreted as a measure of **reported verification frequency**, rather than demonstrated competence in evaluating AI-generated information.

4.3. Students' Educational Priorities for Critical AI Evaluation

The second analytical dimension concerns students' expectations regarding the competencies that universities should develop to support responsible AI use.

The questionnaire findings indicate that **69.9% of respondents selected the critical evaluation of AI-generated information as an educational priority**.

This result suggests considerable interest within the surveyed group in university-level instruction that extends beyond the operational use of AI tools.

Such instruction may include identifying unreliable information, evaluating the credibility of sources, examining the assumptions underlying AI-generated recommendations, and developing independent conclusions based on corroborated evidence.

Importantly, the finding does not establish that 69.9% of respondents lack these competencies. Students who already engage in critical evaluation may also recognise the value of further instruction, particularly as AI systems become more sophisticated and their applications expand.

The result therefore provides evidence of an **expressed educational priority**, rather than a direct assessment of students' existing critical AI literacy.

4.4. Comparing Verification Behaviour and Educational Priorities

A central descriptive observation emerges when the two indicators are considered together.

As shown in Table 2, the proportion of respondents prioritising university instruction in critical AI evaluation is higher than the proportion reporting frequent verification of AI-generated information.

Table 2. Self-reported verification practices and critical AI literacy priorities (N = 93)

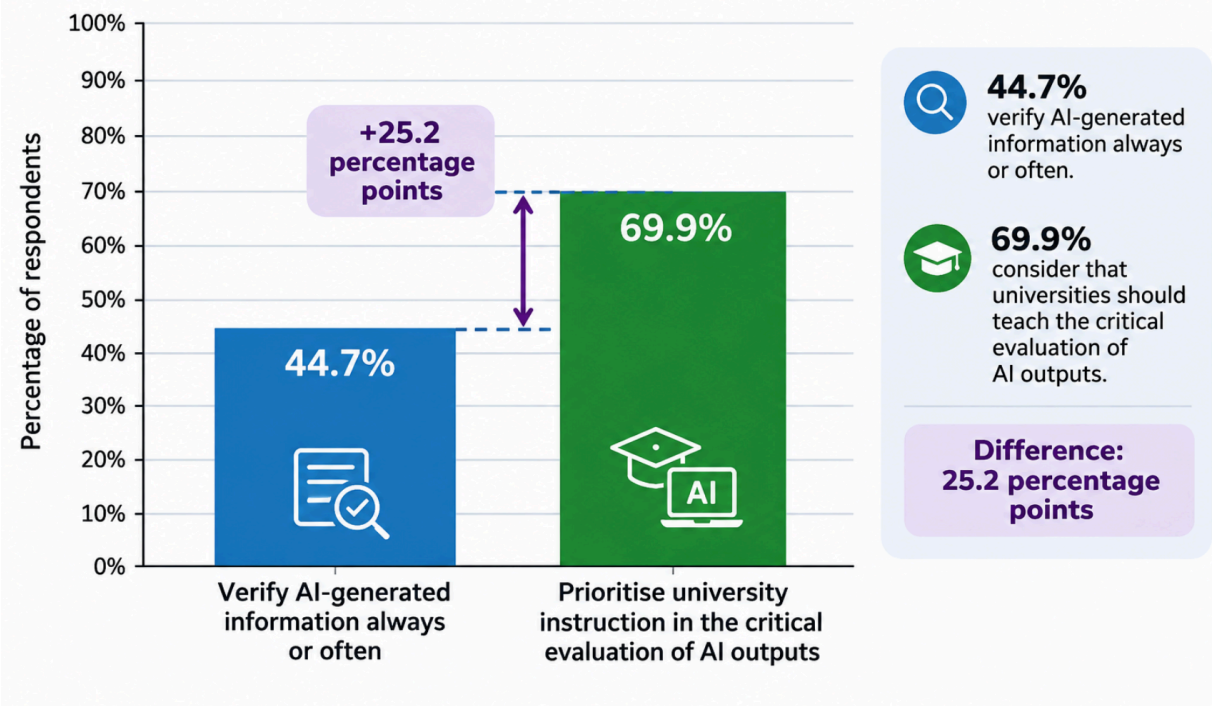
Survey indicator	Reported percentage
Always or often verify AI-generated information	44.7%
Prioritise university instruction in critically evaluating AI-generated information	69.9%

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Difference between reported percentages	25.2 points	percentage

Note. Percentages are reproduced from the available aggregated survey results and require reconciliation with the original response counts before publication. The indicators represent different questionnaire constructs. The percentage-point difference is descriptive and is not a statistical test or a direct measure of an individual-level competency gap.

To provide a visual representation of the study's central empirical finding, Figure 1 compares students' self-reported information verification practices with their educational priorities concerning critical AI literacy. While 44.7% of respondents indicated that they always or often verify AI-generated information, 69.9% identified critical evaluation of AI outputs as a priority for university instruction. The descriptive difference of 25.2 percentage points highlights the contrast between reported verification frequency and expressed educational expectations. However, these indicators measure distinct constructs, and their difference should not be interpreted as evidence of an individual-level competency deficit or a causal relationship.



Source: Authors' own conceptual contribution

Figure 1. Reported AI Information Verification and Educational Priorities among Management Students (N = 93)

Note. Percentages represent two distinct self-reported survey indicators (N = 93). The 25.2-percentage-point difference is descriptive and does not establish an individual-level discrepancy or statistical significance. Reported percentages should be verified against the original questionnaire frequencies before publication.

The observed difference of **25.2 percentage points** constitutes the central empirical contrast examined in this article.

An alternative interpretation is that students who already verify AI-generated information frequently may also express strong support for additional instruction. Both interpretations are plausible, and distinguishing between them would require respondent-level cross-tabulation.

Therefore, the observed difference should not be described as a statistically established

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behavioural gap, nor should it be used to infer that 25.2% of respondents need remedial instruction.

Rather, it identifies an educationally relevant contrast between **reported academic practice** and **expressed curricular priority**.

4.5. AI Use, Cognitive Independence, and the Context of Verification

The wider questionnaire provides additional descriptive context for interpreting students' verification practices.

The available results indicate that **78.0% of respondents use AI at least two or three times per week**, suggesting that AI-supported activities form a regular component of academic engagement for a substantial proportion of the surveyed students.

Furthermore, **74.0% perceive AI as very or extremely helpful for understanding concepts**, while **67.5% report estimated academic time savings of at least 10%**.

These findings indicate that AI is perceived as a useful academic resource, both for conceptual assistance and for improving task efficiency.

However, students' perceptions of AI's contribution to independent critical thinking are more differentiated. While **38.2% report an improvement in independent critical thinking**, **34.1% report a reduction**.

These results provide relevant context for the present investigation. They suggest that perceived usefulness and academic efficiency coexist with divergent assessments of AI's implications for independent reasoning.

Nevertheless, the available aggregated results do not establish whether respondents who perceive improvements in critical thinking are more likely to verify AI-generated information. Nor do they demonstrate that frequent AI use causes improvements or reductions in cognitive independence.

The relationship between perceived cognitive effects and verification practices therefore remains an important question for subsequent respondent-level analysis.

Table 3. Selected contextual indicators of AI engagement among management students (N = 93)

Dimension	Survey indicator	Reported percentage
AI adoption	Use AI at least two or three times per week	78.0%
Conceptual support	Consider AI very or extremely helpful for understanding concepts	74.0%
Academic efficiency	Estimate time savings of at least 10%	67.5%
Critical thinking	Report improved independent critical thinking	38.2%
Critical thinking	Report reduced independent critical thinking	34.1%

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Note. The indicators originate from different questionnaire items and should not be interpreted as mutually exclusive response categories or as components of a composite scale. The percentages are descriptive and remain subject to verification against the original dataset.

These contextual findings reinforce the importance of distinguishing technological adoption from critical engagement. Frequent use of AI does not, by itself, demonstrate that students systematically verify the information they receive.

Similarly, positive perceptions of AI-assisted understanding do not establish that students consistently apply independent evidential standards when evaluating AI-generated explanations.

4.6. Implications of the Findings for Responsible AI Education

The questionnaire also provides an indication of students' interest in broader AI-related educational development.

In addition to the **69.9%** prioritising critical evaluation skills, **65.9%** of respondents selected real-world AI-supported business projects as a desirable educational activity, while **59.3%** identified AI literacy as a relevant area for university instruction.

These results suggest that students' educational expectations extend across complementary dimensions: critical evaluation, practical application, and general AI-related competencies.

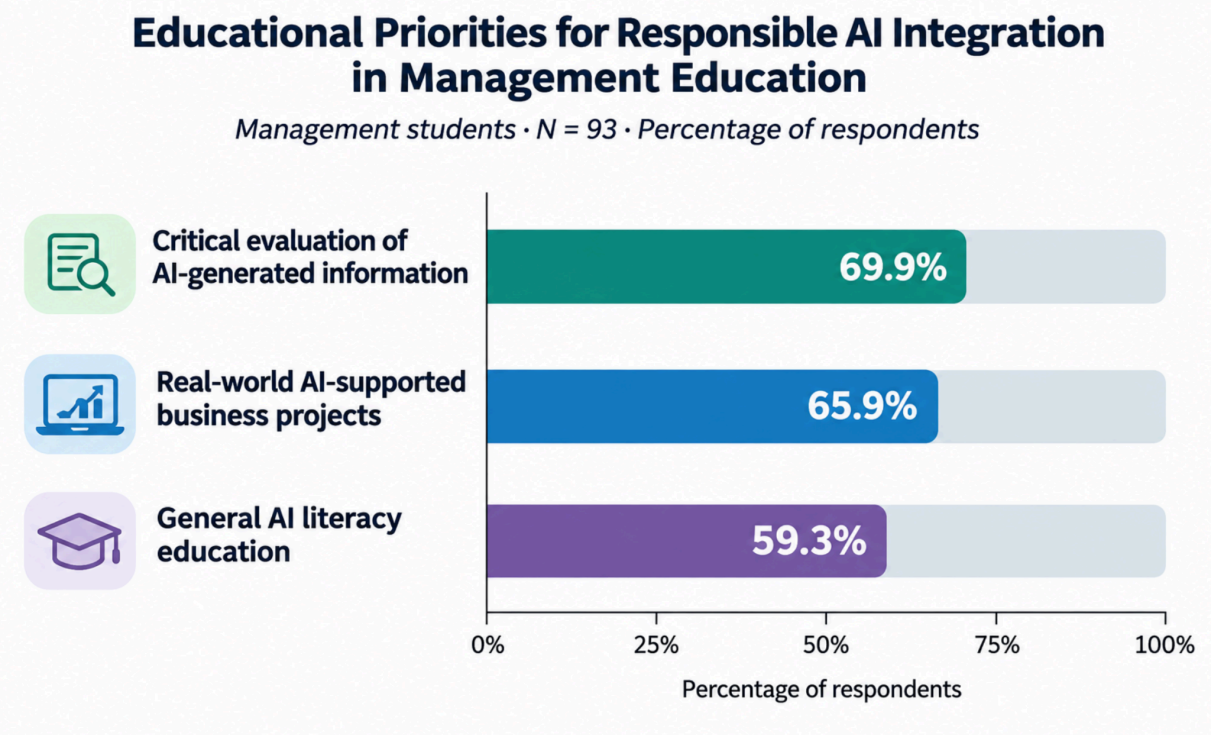
Table 4. Selected priorities for AI-related university education (N = 93)

Educational priority	Reported percentage
Critical evaluation of AI-generated information	69.9%
Real-world AI-supported business projects	65.9%
AI literacy education	59.3%

Note. These percentages represent separate selected priorities. If the questionnaire permitted multiple responses, they should not be expected to sum to 100%. The original response format must be verified.

Beyond students' reported verification practices, the survey identifies three educational priorities relevant to responsible AI integration in management education. As illustrated in Figure 2, critical evaluation of AI-generated information received the highest level of support (69.9%), followed by real-world AI-supported business projects (65.9%) and general AI literacy education (59.3%). These findings suggest that respondents value both critical evaluation competencies and opportunities to apply AI in authentic business contexts. The percentages represent separate educational priorities and should not be interpreted as mutually exclusive categories.

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Source: Authors' own conceptual contribution

Figure 2. Educational Priorities for Responsible AI Integration in Management Education (N = 93).

Note. Percentages represent separately reported educational priorities and are not mutually exclusive. Values are reproduced from the aggregated survey results and should be reconciled with the original response counts before publication.

The relatively strong interest in critical evaluation and practical business applications provides a basis for considering educational approaches that combine AI-supported tasks with explicit requirements for evidence verification and independent reasoning.

For example, students might be asked to assess AI-generated market analyses, verify the sources supporting business recommendations, identify unsupported assumptions, and justify alternative managerial decisions.

Such activities are proposed as pedagogical implications of the findings rather than as interventions whose effectiveness has been demonstrated by the present questionnaire.

The results therefore provide a descriptive foundation for the development of the VERIFY–AI framework, which will be examined in the Discussion section.

4.7. Synthesis of the Main Findings

The descriptive analysis identifies four findings relevant to the research questions.

First, **44.7% of surveyed students report always or often verifying AI-generated information**, indicating that frequent verification is not reported by a majority of respondents.

Second, **69.9% prioritise university instruction in the critical evaluation of AI-generated content**, demonstrating substantial expressed interest in developing this competency.

Third, the **25.2-percentage-point difference** between these indicators highlights a contrast between reported verification frequency and educational priorities. This difference does not establish an individual-level deficit or a causal relationship.

Fourth, contextual results indicate widespread AI use and generally favourable perceptions of its academic usefulness, alongside mixed perceptions of its implications for independent critical

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thinking.

Taken together, these findings suggest that responsible AI education should address not only access to and familiarity with AI systems, but also the critical practices through which students evaluate information and retain responsibility for their academic conclusions.

The empirical results provide a rationale for examining structured pedagogical approaches to verification, evidential reasoning, and responsible AI engagement. The proposed VERIFY–AI framework is developed in the following section as a conceptual response to these educational considerations.

5. DISCUSSION

5.1. Interpreting the Verification–Education Contrast

The present study investigated management students' self-reported information verification practices and their expectations regarding university-level instruction in responsible artificial intelligence use. Its central descriptive finding is that 44.7% of respondents reported always or often verifying AI-generated information, whereas 69.9% identified critical evaluation of AI-generated content as an educational priority. The resulting difference of 25.2 percentage points highlights a potentially important contrast between reported academic practices and perceived curricular needs.

This contrast requires careful interpretation. The two indicators capture different constructs: one concerns the frequency of a self-reported behaviour, while the other reflects the perceived importance of an educational competency. Their difference cannot establish that students who do not regularly verify AI-generated information are the same students who request additional instruction. Nor can it quantify an individual-level deficiency in critical AI literacy.

Nevertheless, the findings raise a relevant pedagogical question: how can universities translate students' recognition of the importance of critical AI evaluation into consistent, evidence-based academic practices? This question is especially pertinent in management education, where the credibility of information and the justification of decisions are integral to professional competence.

The findings can be interpreted in relation to the multidimensional understanding of AI literacy advanced by Chiu et al. (2024). From this perspective, effective engagement with AI involves more than technical familiarity or the ability to obtain useful outputs. It also requires competencies associated with evaluating information, recognising limitations, and exercising appropriate judgement. The present results suggest that these dimensions deserve explicit consideration in curriculum design, although the study does not directly measure students' mastery of them.

5.2. Responsible Trust: Between Uncritical Acceptance and Productive Skepticism

A central implication of the findings concerns the distinction between trusting AI-generated information and accepting it without adequate scrutiny. Trust is not inherently incompatible with critical reasoning. Students may appropriately rely on AI systems for preliminary explanations, idea generation, or routine analytical support while retaining responsibility for verifying consequential claims.

The concept of responsible trust provides a useful theoretical lens for interpreting this relationship. Liao and Sundar (2022) emphasise the importance of designing AI interactions that support appropriately calibrated trust rather than indiscriminate confidence. Applied to management education, this perspective suggests that students should learn to adjust their reliance on AI according to the nature of the task, the reliability of the available evidence, and the potential consequences of an inaccurate conclusion.

For example, an AI-generated explanation of a general management concept may serve as a useful starting point for learning. By contrast, an AI-generated financial interpretation, market assessment, or strategic recommendation may require more extensive verification before being incorporated into an academic assignment or managerial decision.

This distinction suggests that responsible AI education should not promote verification as an undifferentiated requirement applied identically to every output. Instead, students should develop the

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ability to identify which claims require corroboration, what forms of evidence are appropriate, and when uncertainty remains too substantial to justify reliance.

The study's finding that fewer than half of respondents report frequent verification is relevant to this discussion, but it should not be interpreted as evidence that the remaining students necessarily trust AI excessively. The questionnaire does not establish their reasons for verifying less frequently, the types of tasks involved, or the accuracy of the outputs they encounter.

Future research should therefore examine not only verification frequency but also **verification appropriateness**, including whether students adjust their checking behaviour to the evidential demands and risks of different academic tasks.

5.3. Critical AI Literacy and the Preservation of Cognitive Independence

The broader survey findings provide additional context for interpreting verification behaviour. AI use was reported as frequent by 78.0% of respondents, while 74.0% perceived AI as highly beneficial for understanding concepts and 67.5% estimated academic time savings of at least 10%.

These results indicate substantial perceived utility within the surveyed group. However, perceptions concerning independent critical thinking were more differentiated: 38.2% reported improvement, whereas 34.1% reported a reduction.

Although these indicators were examined more centrally in the earlier FAST–DEEP investigation, they remain relevant here because they illustrate why AI adoption and perceived usefulness should not be equated with critical information evaluation.

An AI system may facilitate access to explanations without ensuring that students evaluate the evidence supporting those explanations. Similarly, the ability to complete academic tasks more efficiently does not necessarily establish that students have exercised independent judgement throughout the process.

Research addressing AI dependence, trust, and critical thinking provides a conceptual basis for considering these issues. Tajalla et al. (2026) examine the relationship between generative AI dependence and relevant learner characteristics in accounting education. Their disciplinary focus is particularly pertinent because accounting and management education share expectations concerning analytical accuracy, professional accountability, and evidence-based reasoning.

The present study, however, cannot determine whether frequent AI use produces cognitive dependence or whether verification practices protect against it. Such relationships would require individual-level data and, ideally, longitudinal or experimental designs.

A more defensible interpretation is that critical AI literacy may serve as a pedagogical resource for preserving meaningful intellectual participation in AI-assisted learning. Verification requires students to examine claims, compare evidence, identify weaknesses, and justify conclusions. These activities can be incorporated into teaching strategies intended to sustain independent reasoning, although their effectiveness must be demonstrated empirically.

5.4. From AI Literacy to Epistemic Responsibility

The findings also invite consideration of a broader educational objective: the development of epistemic responsibility in AI-supported academic work.

AI literacy is often discussed in terms of knowledge, skills, and attitudes concerning artificial intelligence. Epistemic responsibility adds an important dimension by focusing on the student's accountability for the claims accepted, arguments developed, and conclusions communicated.

In this sense, a student may use AI appropriately as an intellectual resource without transferring responsibility for academic accuracy to the technology. The central issue is not whether AI contributed to the production of an answer, but whether the student can explain, substantiate, and defend the answer.

Maturo et al. (2026) address the relationship between AI-generated plausibility and epistemic responsibility in higher education. This perspective is relevant because fluent language and apparently coherent explanations may obscure the difference between a persuasive assertion and a justified conclusion.

Similarly, the educational concerns associated with misinformation and information literacy,

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discussed by Jabeen et al. (2026), indicate the potential importance of transferring established source-evaluation practices to AI-mediated information environments.

For management education, epistemic responsibility has particular significance. Graduates may increasingly encounter AI-generated reports, forecasts, recommendations, and decision-support outputs in professional settings. Responsible engagement requires the ability to identify unsupported assumptions, assess evidential quality, and communicate uncertainty appropriately.

Accordingly, universities should consider making the verification process visible in assessment rather than evaluating only the apparent quality of final submissions.

Possible approaches include requiring students to provide verification logs, annotate AI-generated claims, identify unreliable references, compare AI recommendations with disciplinary evidence, and explain why particular outputs were accepted, revised, or rejected.

These approaches are pedagogical proposals derived from the conceptual interpretation of the findings; their effectiveness was not tested in the present study.

5.5. The VERIFY–AI Pedagogical Framework

The principal conceptual contribution of this article is the proposed **VERIFY–AI framework**, designed to translate critical AI literacy and epistemic responsibility into an actionable sequence of educational practices.

The framework is informed by scholarship on AI literacy (Chiu et al., 2024), responsible trust (Liao & Sundar, 2022), and structured AI-information problem-solving (Zhou et al., 2026). It is not intended to replace existing theoretical approaches. Rather, it offers a management-education-oriented instructional synthesis that emphasises the evaluation of AI-generated information and the preservation of student accountability.

Table 5. The proposed VERIFY–AI pedagogical framework

Component	Core educational objective	Illustrative learning activity
V — Validate source credibility	Assess the authority, provenance, and relevance of information	Examine whether references provided by AI exist and support the stated claims
E — Examine factual accuracy	Corroborate substantive assertions against independent evidence	Compare AI-generated market or financial claims with credible datasets
R — Review reasoning and assumptions	Evaluate logical consistency and the adequacy of arguments	Identify unsupported assumptions in an AI-generated business recommendation
I — Identify uncertainty and limitations	Recognise missing information, potential bias, and contextual constraints	Assess what an AI-generated strategic analysis omits or treats as certain

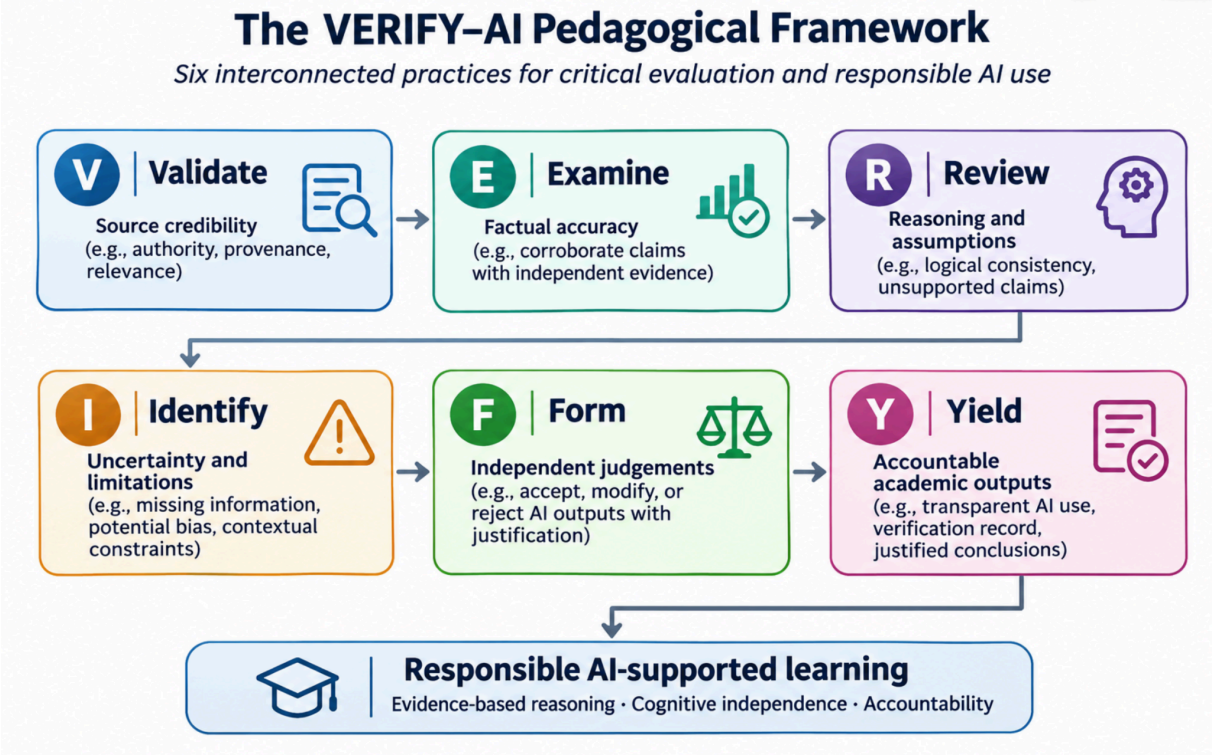
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F — Form independent judgements	Develop defensible conclusions based on critical evaluation	Accept, modify, or reject an AI recommendation and justify the decision
Y — Yield accountable academic outputs	Demonstrate transparency and responsibility for final work	Submit a brief verification statement documenting AI use and independent checks

Source: Authors' own conceptual contribution

Note. VERIFY–AI is a conceptual instructional proposal developed in this study. The six components have not been validated as a measurement scale or tested as an educational intervention.

Figure 3 illustrates the proposed VERIFY–AI pedagogical framework as a six-stage process for strengthening critical engagement with AI-generated information in management education. The framework progresses from source validation and factual verification to the examination of reasoning, recognition of uncertainty, independent judgement, and accountable academic output. These interconnected practices are intended to support students in moving beyond the passive acceptance of AI-generated content towards evidence-based reasoning and responsible human–AI collaboration. The framework represents a conceptual pedagogical proposal and has not yet been empirically validated.



Source: Authors' own conceptual contribution

Figure 3. The VERIFY–AI Pedagogical Framework for Critical Evaluation and Responsible AI Use

Note. VERIFY–AI is a proposed instructional framework comprising six practices: Validate, Examine, Review, Identify, Form, and Yield. The diagram illustrates a suggested pedagogical sequence rather than an empirically established causal model.

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The framework follows a progression from evaluating the informational foundations of an AI output to accepting responsibility for its use.

The first two components, **Validate** and **Examine**, emphasise evidential credibility and factual corroboration. Students are encouraged to distinguish between the existence of a source, the reliability of that source, and its actual relevance to the claim being made.

The third and fourth components, **Review** and **Identify**, focus on analytical reasoning. These activities require students to move beyond checking isolated facts and consider whether the overall argument is logically justified, sufficiently contextualised, and appropriately qualified.

The fifth component, **Form independent judgements**, places human reasoning at the centre of the learning process. Students are expected to reach defensible conclusions rather than simply reproduce AI-generated recommendations.

Finally, **Yield accountable academic outputs** connects critical evaluation with scholarly integrity. The final product should demonstrate that AI assistance has been appropriately acknowledged and that the student remains responsible for the content submitted.

The framework's proposed contribution lies in integrating these practices into a coherent instructional sequence that can be applied to management-related tasks. Its originality is therefore pedagogical and integrative, not a claim that the underlying verification principles are entirely new.

5.6. Implications for Curriculum Design and Assessment

The survey findings indicate that 69.9% of respondents prioritise instruction in critical AI evaluation, while 65.9% express interest in real-world AI-supported business projects and 59.3% identify AI literacy education as a relevant curricular priority.

Taken together, these indicators suggest that responsible AI education could benefit from combining conceptual instruction with practical, discipline-specific activities.

A first implication concerns the **integration of verification into existing management courses**. Rather than treating AI literacy as an isolated technical topic, instructors could embed verification requirements within assignments involving marketing, strategic management, finance, entrepreneurship, or organisational analysis.

For example, students might receive an AI-generated market-entry recommendation and be required to examine its sources, evaluate the assumptions underlying its forecasts, and construct an alternative recommendation supported by independently verified evidence.

A second implication concerns **assessment design**. If assessment focuses exclusively on the final written answer, it may provide limited visibility into whether students critically evaluated AI-generated content. Process-oriented assessment could therefore include evidence annotations, source-verification records, reflective commentaries, or oral justification of analytical decisions.

A third implication concerns **responsible human–AI collaboration**. Petcu et al. (2026) discuss the preparation of future professionals for human–AI workplaces through the concept of collaborative intelligence. Within management education, this perspective supports learning activities in which AI assists with information processing while students retain responsibility for interpreting evidence and making decisions.

A fourth implication concerns **instructional differentiation**. Students may vary in their familiarity with AI tools, confidence in evaluating outputs, and ability to identify unreliable information. Universities should therefore avoid assuming that frequent AI users necessarily possess advanced critical AI literacy.

Finally, the development of responsible AI education should be accompanied by clear institutional guidance concerning acceptable AI assistance, source attribution, disclosure, and accountability. Such guidance can support consistent expectations across courses while preserving opportunities for innovative teaching.

5.7. Theoretical and Empirical Contributions

The study offers three contributions to the emerging literature on responsible AI use in higher education.

First, it provides **context-specific descriptive evidence** concerning information verification and educational preferences among management students. The contrast between the 44.7% reporting

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frequent verification and the 69.9% prioritising critical AI evaluation instruction identifies a relevant topic for further empirical investigation.

Second, it advances a **conceptual distinction between AI literacy, verification behaviour, responsible trust, and epistemic responsibility**. These constructs are related but should not be treated as equivalent. Operational familiarity with AI does not establish verification competence, and expressed support for critical AI education does not necessarily indicate an individual deficiency.

Third, it proposes the **VERIFY–AI framework** as a pedagogical synthesis intended to make critical evaluation more explicit in AI-supported management education.

These contributions should be interpreted within the boundaries of the research design. The study does not establish a new causal theory of AI dependence, demonstrate the effectiveness of verification instruction, or validate the six VERIFY–AI components psychometrically.

Instead, it develops an empirically motivated and theoretically informed proposal that can be examined through subsequent research.

5.8. Limitations and Directions for Future Research

Several limitations constrain the interpretation and generalisability of the findings.

The study relies on a relatively modest sample of 93 management students whose representativeness has not been established. The cross-sectional design also prevents the identification of changes in verification practices or AI-related competencies over time.

Furthermore, the questionnaire captures self-reported behaviour rather than directly observed verification performance. Respondents who indicate that they frequently verify AI-generated information may employ procedures of varying quality, and the available data do not establish whether they can detect factual inaccuracies, fabricated references, or misleading arguments.

The analysis is also limited by the availability of aggregated percentages. Without respondent-level data, it is not possible to determine whether verification frequency is associated with AI usage intensity, perceived cognitive effects, or preferences for critical AI literacy instruction.

The reported percentages should additionally be reconciled with the original questionnaire frequencies and item-specific denominators before publication.

Future research could address these limitations through three complementary approaches.

First, **performance-based assessments** could measure students' actual ability to evaluate AI-generated information. Participants could be asked to identify fabricated citations, unsupported claims, incomplete analyses, and misleading business recommendations.

Second, **longitudinal and experimental studies** could examine whether structured VERIFY–AI instruction improves verification accuracy, the quality of independent reasoning, and the appropriateness of reliance on AI systems.

Third, **multi-institutional research** could investigate the framework's applicability across educational settings, academic disciplines, and student populations.

The proposed framework would also benefit from systematic expert review, refinement of its instructional components, and the development of transparent assessment rubrics. Only after such work could claims concerning its effectiveness or broader applicability be substantiated.

5.9. Discussion Synthesis

The findings highlight a relevant educational tension: AI is widely used and perceived as beneficial by the surveyed management students, yet frequent verification of AI-generated information is reported by fewer than half of respondents, while a larger proportion prioritises instruction in critical AI evaluation.

This pattern does not demonstrate widespread cognitive dependence or deficient critical thinking. It does, however, provide a rationale for examining whether current educational practices adequately support students in evaluating AI-generated information and retaining responsibility for their conclusions.

The central argument of this article is that responsible AI education should move beyond teaching students how to obtain useful outputs towards teaching them how to **question, verify, contextualise, and justify** those outputs.

The proposed VERIFY–AI framework offers one possible approach to operationalising this objective within management education. Its value remains a proposition for future empirical evaluation rather than an established outcome of the present study.

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6. CONCLUSION

The growing integration of generative artificial intelligence into higher education requires universities to reconsider not only how students use AI systems, but also how they evaluate the reliability of AI-generated information and retain responsibility for their academic decisions. In management education, where evidence-based reasoning, analytical judgement, and professional accountability constitute essential learning outcomes, the capacity to critically assess AI-supported information is particularly important.

This study examined management students' self-reported information verification practices, perceptions of AI-related cognitive risks, and educational priorities concerning responsible AI use.

Drawing on questionnaire responses from 93 students, the investigation identified a central descriptive contrast: **44.7% of respondents reported always or often verifying AI-generated information, whereas 69.9% prioritised university instruction in the critical evaluation of AI outputs**. The difference of 25.2 percentage points suggests that critical AI evaluation occupies a more prominent position among expressed educational priorities than among reported frequent verification practices.

This finding must nevertheless be interpreted cautiously. The two indicators measure distinct constructs and do not establish an individual-level discrepancy between students' competencies and educational expectations. Moreover, self-reported verification frequency cannot determine whether students possess the skills required to identify misinformation, evaluate source credibility, or recognise weaknesses in AI-generated reasoning. The findings therefore provide exploratory evidence concerning reported practices and perceived educational needs rather than a direct assessment of critical AI literacy.

The study's broader results further contextualise this interpretation. Although AI was frequently used and generally perceived as beneficial for conceptual understanding and academic efficiency, respondents expressed differentiated perceptions of its implications for independent critical thinking. This combination reinforces the importance of distinguishing technological adoption and perceived usefulness from the critical evaluation practices required for responsible academic engagement. Such a distinction is consistent with multidimensional approaches to AI literacy and competency (Chiu et al., 2024) and with the concept of appropriately calibrated trust in AI systems (Liao & Sundar, 2022).

The principal conceptual contribution of the article is the proposed **VERIFY–AI pedagogical framework**, which translates principles of critical AI literacy and epistemic responsibility into six complementary educational practices: **Validate source credibility, Examine factual accuracy, Review reasoning and assumptions, Identify uncertainty and limitations, Form independent judgements, and Yield accountable academic outputs**. The framework conceptualises responsible AI use as an active process of evidential scrutiny, reflective judgement, and academic accountability rather than the uncritical acceptance of technologically generated information.

From a pedagogical perspective, the findings support consideration of educational strategies that integrate AI information verification into management curricula. Such strategies may include evaluating AI-generated business recommendations, identifying unsupported claims, corroborating information against credible sources, documenting verification procedures, and defending independently formulated conclusions. These activities could be incorporated into authentic business projects and process-oriented assessments to make students' reasoning and accountability more visible. Their effectiveness, however, remains to be established through dedicated empirical evaluation.

The study is subject to several limitations, including its modest sample size, cross-sectional design, reliance on self-reported responses, and lack of respondent-level analyses. Its findings cannot establish causal relationships, determine the prevalence of cognitive dependence, or demonstrate the effectiveness of the proposed framework. In addition, the reported percentages require final verification against the original questionnaire frequencies and item-specific denominators before publication.

Future research should extend the present investigation through performance-based assessments of students' verification abilities, longitudinal analyses of critical AI literacy development, and experimental evaluations of VERIFY–AI instructional activities. Studies involving larger and more diverse samples could also examine how verification practices relate to AI trust, academic self-efficacy, disciplinary knowledge, and independent decision-making.

In conclusion, the educational challenge posed by generative AI is not simply whether students can obtain accurate or useful answers, but whether they can **critically determine which answers deserve to be trusted, how those answers should be verified, and when independent**

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human judgement must prevail. Responsible AI integration in management education should therefore aim to develop graduates who are not merely proficient users of intelligent technologies, but reflective, evidence-oriented, and accountable decision-makers. The VERIFY–AI framework offers a conceptual starting point for pursuing this objective while providing a foundation for further empirical investigation.

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REFERENCES

1. Aboderin, O. S. (2025). Exploring integration of 4IR technologies in Nigerian universities: Implications for pedagogy and skills development. *International Journal of Education, Leadership, Artificial Intelligence, Computing, Business, Life Sciences, and Society, 2*(2), 50–66. https://doi.org/10.65222/VIRAL.2025.9.9
2. Chiu, T. K. F., Ahmad, Z., Ismailov, M., & Sanusi, I. T. (2024). What are artificial intelligence literacy and competency? A comprehensive framework to support them. *Computers and Education Open, 6*, Article 100171. https://doi.org/10.1016/j.caeo.2024.100171
3. Enachescu, V., & Petcu, C. (2025). Transformational leadership and emotional intelligence in hybrid academic ecosystems: Managerial paradigms for enhancing institutional resilience and student wellbeing. *International Journal of Education, Leadership, Artificial Intelligence, Computing, Business, Life Sciences, and Society, 1*(1), 59–75. https://doi.org/10.65222/viral.2025.1.4
4. Fitroh, I., Fuadi, M. H., Riswanto, D., & Romadon, B. (2026). Digital trust and information verification behavior among Generation Z in the era of artificial intelligence. *ESPD: Ephemeris Serena Populus et Doctrina, 1*(1), 65–78.
5. Jabeen, M., Lux, C., & Encheva, M. (2026). *AI, misinformation, and trust in higher education: Information literacy approaches of university librarians in Germany and Bulgaria*.
6. Liao, Q. V., & Sundar, S. S. (2022). Designing for responsible trust in AI systems: A communication perspective. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1257–1268). Association for Computing Machinery. https://doi.org/10.1145/3531146.3533182
7. Maturo, F., Micozzi, A., & Porreca, A. (2026). AI-generated plausibility and epistemic responsibility in higher education: Implications for knowledge, learning, and society. *SN Social Sciences, 6*(9), Article 386.
8. Nguyen, T. D., Le, T. Q., Luong, G. T., Nguyen, D. T., & Nguyen, T. T. (2025). A review of applying game-based learning and learning motivation: Game-based learning and learning motivation. *International Journal of Education, Leadership, Artificial Intelligence, Computing, Business, Life Sciences, and Society, 3*(3), 67–74. https://doi.org/10.65222/VIRAL.2025.12.20
9. Petcu, C., Bărbulescu, R., & Bălțăreț, C. (2026). Toward a theory of collaborative intelligence: Educating future professionals for human–AI workplaces. *International Journal of Education, Leadership, Artificial Intelligence, Computing, Business, Life Sciences, and Society, 9*, 88–112. https://doi.org/10.65222/VIRAL.2026.6.39.59
10. Pramod, D. (2025). Decoding responsible AI use: The influence of digital literacy and ethical awareness. *Cogent Education, 12*(1), Article 2592371.
11. Tajalla, S. A., Karsa, B. D., Hadrianti, B., & Harun, M. S. (2026). Measuring dependence on generative AI in accounting education: The role of AI literacy, trust, and critical thinking disposition. *The Indonesian Journal of Accounting Research, 29*(2), 251–284.

DOI: https://doi.org/10.65222/VIRAL.2026.9.51.71

12. Tas, E., & Bittner, E. (2026). *Negotiating ethical coexistence with AI: A grounded theory of Japanese students' conditional trust, agency, and the development of critical AI literacy*.
13. Tran, K. D., Nguyen, T. A. D., & Tran, K. P. (n.d.). *From AI literacy to responsible AI capability in higher education: Institutional conditions, human agency, and a testable framework*. SSRN.
14. Zainuddin, Z., Churiyah, M., Xiaoyu, W., & Halili, S. H. (2026). From AI literacy to cognitive AI safety: Rethinking safe AI use in education. *Interactive Technology and Smart Education*, 1–22.
15. Zhou, X., Liu, G., & Chiu, T. K. (2026). A five-step AI-information problem solving (AI-IPS) model for critical, ethical, and responsible usage. *Interactive Learning Environments*, 1–20.