

Article

Generative AI Literacy and Research Self-Efficacy in Relation to Attitudes Toward Scientific Research Among Health Sciences Students: A Cross-Sectional Study

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Abstract

Generative artificial intelligence (GenAI) has rapidly entered undergraduate research training, yet its relationship with research self-efficacy and attitudes toward scientific research remains underexplored among Health Sciences students. This cross-sectional study examined how self-reported GenAI literacy and research self-efficacy are associated with attitudes toward scientific research, separately and when modelled together. Of 101 submissions from undergraduate Health Sciences students enrolled in research courses at a private Peruvian university, 91 were analysed after 10 invariant response patterns were excluded. Students completed a 36-item self-report questionnaire whose items had been reviewed for content relevance and clarity by three experts. Analyses combined Spearman correlations, multiple regression with HC3 standard errors, a bootstrapped indirect-effect model and exploratory fuzzy-set qualitative comparative analysis (fsQCA). Reliability computed from the three dimension scores of each construct was $\alpha = 0.861$ for GenAI literacy, 0.927 for research self-efficacy and 0.790 for attitudes. GenAI literacy correlated with attitudes ($\rho = 0.475$, Holm-adjusted $p < 0.001$), but in the female–male regression model ($n = 90$), research self-efficacy was the only one of the two capability scores that retained a statistically significant adjusted association ($b = 0.353$, 95% CI 0.087 to 0.619, $p = 0.010$; GenAI literacy $b = 0.088$, 95% CI -0.214 to 0.389 , $p = 0.564$; $R^2 = 0.405$). The indirect term through research self-efficacy (0.313, 95% CI 0.092 to 0.536) is a statistical decomposition of overlapping, contemporaneous scores rather than evidence of a mechanism. Discriminant validity between GenAI literacy and research self-efficacy was not established (HTMT = 0.912), and parallel analysis favoured two factors rather than three. Under the primary calibration (theoretical anchors 2–3–4 with crossover memberships assigned to 0.501), functional knowledge and the critical–ethical evaluation of GenAI appeared in both terms of the intermediate fsQCA solution (consistency = 0.913, coverage = 0.741), but the minimised solutions changed with alternative anchors and with the handling of cases at the crossover. The findings describe associations among self-reported measures; whether developing both capabilities jointly improves research attitudes remains a question for future evaluation.



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1. Introduction

The eruption of generative artificial intelligence (GenAI) tools has, within a few months, altered the study, writing and bibliographic consultation routines of university students. The Higher Education Policy Institute survey reported that the proportion of undergraduate students using GenAI for assessed tasks rose from 53% to 88% in barely twelve months, while general use of these tools climbed from 66% to 92% between 2024 and 2025 (Freeman, 2025), and a global poll by the Digital Education Council placed, at 86%, the proportion of students who turn to AI in their studies, with more than half doing so weekly (Digital Education Council, 2024). This adoption is not evenly distributed: male students and those enrolled in science, engineering or health programmes report higher rates of use and confidence than their peers, which configures an emerging digital divide that reproduces pre-existing inequalities (Freeman, 2025).

The speed of this incorporation has outpaced the institutional capacity to respond: in 2024, only 18% of students considered that university staff were well prepared to work with AI, a figure that rose to 42% in 2025 without reaching a majority (Freeman, 2025). In the specific terrain of research training, recent evidence shows both promise and tension. On the one hand, Zhu and Yang (2026) found that GenAI use is associated with greater research competence in postgraduate students, mediated by critical thinking, and Teng et al. (2026) verified, through structural equation modelling, that GenAI can strengthen self-efficacy when integrated under a social-cognitive approach. On the other hand, Hou et al. (2026) warned that, without deliberate intervention in critical thinking, working with GenAI leads to overreliance behaviours that erode problem-solving quality, and Giray et al. (2026) documented that a fraction of the student body employs these tools for purposes of academic dishonesty. The coexistence of benefits and risks suggests that the relationship between GenAI and research disposition is not automatic, but depends on the competencies with which the student uses it.

Despite the growing volume of studies on GenAI in higher education, a precise knowledge gap persists. Most of the literature examines adoption, acceptance or general academic performance (Ursavaş et al., 2025; Colbran et al., 2026; Joseph et al., 2026; Oubibi, 2026) or else concentrates on academic writing, feedback and language learning (Nelson et al., 2025; Lo et al., 2026; S. B. Wang et al., 2026; Zheng & Pan, 2026). Research on GenAI literacy, understood as the set of competencies for understanding, using and critically evaluating these tools, has advanced in the construction of self-efficacy scales for teachers and researchers (Xia et al., 2026) and in the analysis of social-cognitive pathways linking literacy to creative identity (Li et al., 2026). In the literature reviewed for this study, we did not identify research that examined GenAI literacy and research self-efficacy together in relation to attitudes toward scientific research among undergraduate Health Sciences students, a population in which research competence underpins evidence-based clinical practice. The contribution of the present study is to examine these relationships in one such sample; it does not rest on a claim of priority.

The relevance of this intersection rests on two prior bodies of evidence. As regards attitudes toward research, studies in medical and nursing students describe favourable dispositions at the declarative level that do not always translate into effective participation (Muhandiramge et al., 2021; Quintero et al., 2025). To this is added that concrete formative experiences, such as writing an undergraduate thesis or participating in research courses

with a practical component, have been associated with improved research attitudes and confidence (Gros-Navés et al., 2022; Pavlova et al., 2021; Griffioen, 2019). As regards research self-efficacy, the evidence identifies it as a consistent correlate of research intention and perceived competence (Almarwani, 2025; Pfundt & Peterson, 2024; Makinde et al., 2025) and reports increases after structured training programmes (Falola et al., 2025). Examining both bodies of evidence alongside GenAI literacy is therefore the focus of the present study.

The participating institution is a private Peruvian university with campuses in different regions of the country. The present study did not measure institutional research output, funding, mentorship or institutional policy based on the use of GenAI, so no claim about these conditions at the participating university is made here. International surveys describe a gap between students' rapid adoption of GenAI and the preparedness of institutions to guide its use (Freeman, 2025), but whether a comparable gap exists at the participating university was not assessed, and those surveys are cited only as background. The setting is used as one context in which to describe how self-reported GenAI literacy and research confidence relate to attitudes toward research among students taking research courses.

Faced with this gap, the study set as its general objective to determine the relationship among GenAI literacy, research self-efficacy and attitudes toward scientific research in undergraduate Health Sciences students enrolled in research courses. Three specific objectives were derived from it. The first consisted of identifying the levels of GenAI literacy, research self-efficacy and attitudes toward research. The second sought to establish the relationship between GenAI literacy and attitudes toward research. The third was aimed at analysing the joint contribution of GenAI literacy and research self-efficacy to explaining attitudes toward research when both constructs are considered simultaneously. The study examines the two capability constructs within the same models, which the literature has mostly treated separately, and complements the variable-centred analyses with an exploratory fuzzy-set configurational analysis that describes combinations of conditions accompanying high attitudes toward research.

The justification for the study operates on three complementary planes. On the practical plane, the findings may inform, although they cannot by themselves justify, educational initiatives that address GenAI literacy and research self-efficacy together, rather than as disconnected competencies, and the responsible incorporation of GenAI into students' research tasks. On the theoretical plane, the study examines the joint applicability of self-efficacy theory and the tripartite model of attitude in an emerging technological domain and contributes preliminary evidence on the empirical distinction between GenAI literacy and research self-efficacy. Finally, the research aligns with Sustainable Development Goals 4, 3 and 9, insofar as the research competence of future health professionals underpins evidence-based practice and quality higher education in a setting of accelerated technological innovation.

2. Theoretical Framework and Hypothesis Development

2.1. Generative Artificial Intelligence Literacy

AI literacy has been conceptualised as the set of competencies that allow a person to understand the basic functioning of AI systems, use them appropriately and critically evaluate their outputs and ethical implications (Long & Magerko, 2020). Transferred to the generative domain, GenAI literacy comprises both functional knowledge of tools such as ChatGPT (Free version, GPT-5.6 Luna), Gemini (Free version, Gemini 3 Flash), or Claude (Free version, Claude Sonnet 5.5) and the ability to employ them in academic tasks and to discern their limitations, among them the generation of inaccurate or fabricated information. Recent literature has operationalised this construct in self-efficacy scales oriented to teachers and researchers (Xia et al., 2026) and has shown that GenAI literacy is associated

with relevant educational outcomes. From this perspective, [Li et al. \(2026\)](#) evidenced a social–cognitive pathway in which GenAI literacy, self-efficacy and growth mindset converge to explain the student’s creative identity, while [Colbran et al. \(2026\)](#) described, through a human-centred mixed design, how perceptions of generative chatbots condition their integration into learning. In contrast with this optimistic reading, [Athanasopoulos et al. \(2026\)](#) noted that, alongside perceived benefits, students recognise challenges linked to reliability and academic integrity, which reinforces the need for a literacy that includes the critical and ethical component. A complementary line of work treats AI literacy as a multidimensional meta-skill spanning functional, critical, ethical and strategic domains, rather than a single instrumental ability, and examines how institutions embed that capability in curriculum, pedagogy and assessment and how prepared students are to operate in AI-enabled academic environments ([Che, 2026a, 2026b, 2026c](#)). This reading is pertinent to research training, where the distinction among exposure to generative tools, perceived capability and responsible use conditions is what students can actually do with them. The construct is designated throughout this article as GenAI literacy, and that label is used consistently in place of the expressions GenAI competence, AI competence or generative competence, which refer to the same construct. In the present study, it is measured via self-report, so the scores describe the perceived understanding, reported practices and normative judgements about GenAI rather than demonstrated competence.

The academic-research use of GenAI constitutes a dimension of particular interest for this study. The evidence documents its employment in literature searching and organisation, writing improvement and the comprehension of methodological concepts ([Lo et al., 2026](#); [S. B. Wang et al., 2026](#); [El-Soussi & Yousef, 2026](#)). In writing tasks and in project-based learning environments, several works report improvements in motivation and performance when GenAI is integrated with pedagogical scaffolding ([Zhang et al., 2026](#); [L. Wang & Ren, 2025](#); [Llerena-Izquierdo et al., 2024](#); [Jaramillo-Fierro et al., 2026](#)). This use, however, does not by itself guarantee better outcomes. [Hou et al. \(2026\)](#) reported that the absence of critical thinking during collaboration with GenAI was associated with more dependence behaviours and lower quality of problem solving, while [Zhu and Yang \(2026\)](#) estimated a mediation model in which critical thinking transmits the effect of GenAI use on research competence, with research self-efficacy acting as a moderator. This last clarification is central, since it positions self-efficacy as a factor conditioning the productive use of GenAI in research tasks.

2.2. Research Self-Efficacy

Research self-efficacy is grounded in [Bandura \(1997\)](#)’s self-efficacy theory, according to which a person’s beliefs about their capacity to successfully execute a task determine their effort, persistence and results. Applied to the research process, it refers to the student’s confidence in their ability to formulate problems, design methodologies, analyse data and communicate findings. Empirical evidence consistently associates it with research intention and behaviour. As reported by [Pfundt and Peterson \(2024\)](#) in a theoretically grounded investigation, self-efficacy and attitudes jointly predict the intention to use the library for research purposes. Along convergent lines, [Almarwani \(2025\)](#) verified, through a structural equation model, that self-efficacy is linked to research competence and attitudes in nursing students, and [Makinde et al. \(2025\)](#) confirmed the association among information literacy, attitudes toward research and research competence. Taken together, these studies position self-efficacy as a consistent correlate of research disposition, although most of this evidence is cross-sectional and does not establish temporal precedence.

Research self-efficacy is not a fixed trait but a belief that is malleable through experience. Structured training programmes are associated with higher self-efficacy and more

favourable attitudes toward research in medical students (Falola et al., 2025), and laboratory courses with a research component are associated with gains in students' skills, confidence and attitudes (Pavlova et al., 2021). Beyond the research domain, self-efficacy is reported as a correlate of effort regulation, academic engagement and career intention, persistence, motivation, disciplinary learning and retention across educational contexts (Maluenda-Albornoz et al., 2026; İter, 2026; Wilson-Fetrow et al., 2026; Chen et al., 2025; Hu et al., 2025; Lin et al., 2026; Pulukuri et al., 2025; Espino et al., 2026). This cross-cutting relevance supports the pertinence of examining research self-efficacy as a correlate of attitudes in the specific context of Health Sciences education.

2.3. Attitudes Toward Scientific Research

Attitudes toward research are conceptualised from the tripartite model of attitude, which distinguishes cognitive, affective and behavioural components, with Ajzen (1991)'s theory of planned behaviour, which posits that attitudes, together with subjective norms and perceived control, precede intention and behaviour, used here only as background for the attitude construct. Subjective norms, perceived behavioural control, intention and behaviour were not modelled, so the theory itself is not tested in this study. In Health Sciences students, the evidence describes a recurrent pattern in which favourable cognitive attitudes, referring to recognition of the importance of research for professional practice, are not always accompanied by an equivalent behavioural commitment (Muhandiramge et al., 2021; Quintero et al., 2025). These attitudes are also reported to vary with formative experience: writing the undergraduate thesis is associated with more favourable attitudes toward research in nursing (Gros-Navés et al., 2022), research attitudes are associated with the intention to use research in future professional practice (Griffioen, 2019), and active teaching strategies in Health Sciences education are associated with students' motivation, confidence and disposition toward inquiry (Cao et al., 2026; Jerntorp et al., 2026; Kulkarni et al., 2025).

2.4. Relationships Between Constructs and Hypotheses

The articulation of the three theoretical bodies allows the study hypotheses to be derived. Regarding the relationship between GenAI literacy and attitudes toward research, the evidence suggests that competence in critically using generative tools in searching, writing and analysis tasks may accompany a greater appreciation of research, insofar as it reduces perceived barriers and broadens mastery experiences (Zhu & Yang, 2026; Li et al., 2026). This association, however, might not be independent, given that GenAI literacy and research self-efficacy share a substrate of perceived competence (Teng et al., 2026). As for research self-efficacy, its association with research attitudes enjoys consistent support in previous studies (Almarwani, 2025; Pfundt & Peterson, 2024). On this basis, the following hypotheses were posed.

H1. A descriptive expectation rather than a statistical hypothesis, since the moderate and high bands were not defined prospectively and are evaluated against the operational cut-off described in Section 4.2. The levels of GenAI literacy, research self-efficacy and attitudes toward research are predominantly moderate to high in undergraduate Health Sciences students. H2. GenAI literacy and attitudes toward scientific research are positively and significantly associated. H3. GenAI literacy and research self-efficacy, considered jointly, account for a significant share of the variance in attitudes toward scientific research, and research self-efficacy retains an adjusted association once the variance shared between both constructs is taken into account.

3. Materials and Methods

3.1. Approach, Scope and Research Design

The research was situated within the positivist paradigm and adopted a quantitative approach, given that the measurement of the constructs relied on the numerical assignment of perceptions through standardised scales and on the statistical treatment of the data to examine the formulated hypotheses (Hair et al., 2019). With respect to scope, the study articulated three complementary levels. The descriptive level made it possible to characterise the levels of generative artificial intelligence literacy, research self-efficacy and attitudes toward scientific research. The correlational level enabled an examination of the magnitude and direction of the associations between these constructs. The comparative level made it possible to contrast the scores obtained according to grouping variables such as the degree programme, sex and prior research experience (Ato et al., 2013).

On this premise, the design was non-experimental, since the variables were observed in their natural state without deliberate manipulation by the researchers, and cross-sectional, as data collection took place at a single point in time (Ato et al., 2013). The analytical strategy combined correlational and regression estimation, which provide a symmetric, variable-centred description of net associations, with fuzzy-set qualitative comparative analysis (fsQCA), which provides an asymmetric, set-theoretic description of combinations of conditions (Pappas & Woodside, 2021). These approaches address different questions about the same self-report data; they do not compensate for the design limitations of the study, namely self-report measurement, convenience sampling, overlap between constructs and limited configurational diversity, which apply to all of them.

With the aim of examining the internal structure of the instrument before estimating the substantive relationships, the analysis was organised into two successive phases following the logic of the measurement-model and structural-model evaluation proposed by Hair et al. (2019). The first phase was oriented to cleaning the database and checking the metric quality of the constructs, that is, their reliability, convergent validity and discriminant validity. The second phase addressed the estimation of associations, subgroup contrasts, multivariable modelling and configurational analysis.

3.2. Participants

The population comprised undergraduate students enrolled in the 2026 academic cycle in Health Sciences programmes at a private Peruvian university with campuses in different regions of the country, who were taking courses linked to scientific research. The unit of analysis was the undergraduate Health Sciences student enrolled in those courses during the period indicated. The inclusion criterion restricted participation to those effectively exposed to research training and to generative artificial intelligence tools, a substantive condition for answering the items with informed judgement. Thus, the reference population was not the entire student body of the university but the specific subset meeting that profile, which precisely delimits the universe to which the inferences extend.

The sample was obtained through non-probabilistic convenience sampling, since participation depended on access to the research courses and on the voluntary willingness of students (Otzen & Manterola, 2017); this procedure does not support statistical generalisation to the reference population. According to the enrolment lists, 157 students were registered in the eligible research courses during the 2026 cycle, and the link to the questionnaire was shared with all of them. The online form received 101 submissions (64.3% of the students invited), all with consent to participate and with no missing item responses. Before the analytical dataset was assembled, 10 submissions in which the same response option had been selected for all 36 items were excluded as invariant response patterns; no

other record was excluded. The analytical dataset therefore comprised 91 students (58.0% of those invited).

The adequacy of the sample size is appraised with caution. No a priori power analysis was carried out: the size of the sample was determined by the number of students in the research courses of the 2026 cycle who agreed to take part. The Kaiser–Meyer–Olkin measure (0.895) and Bartlett’s test of sphericity ($\chi^2(36) = 579.73$; $p < 0.001$) indicate that the nine dimension scores shared enough variance to be factorised, not that 91 cases suffice to validate a 36-item instrument. A post hoc power estimate is not used as evidence of adequacy, because it is a direct function of the observed effect. The sample is treated as adequate for an exploratory cross-sectional study and as clearly limited for instrument development, for comparisons between small subgroups and for a six-condition configurational analysis, whose informativeness depends on the diversity of observed configurations, which proved scarce.

Table 1 presents the sociodemographic characteristics of the 91 students in the analytical dataset. The composition was predominantly female (62; 68.13%), with 28 male students (30.77%) and one participant who preferred not to declare sex (1.10%). Ages ranged from 18 to 54 years ($M = 24.0$; $SD = 5.4$; median = 22). More than half of the students were in semesters VII–VIII (52.75%), and the rest were in semesters I–II (9.89%), III–IV (7.69%), V–VI (20.88%) and IX–X (8.79%). More than half reported no prior research experience (57.14%), while 23.08% had taken part in research projects and 19.78% in student research groups. ChatGPT was the most used GenAI tool (59.34%), followed by Gemini (26.37%) and Claude (8.79%). By degree programme, Dentistry (34.07%) and Nursing (31.87%) accounted for about two thirds of the sample, followed by Psychology (16.48%), Medicine (9.89%), Obstetrics (4.40%) and other Health Sciences programmes (3.30%). Categories with fewer than three participants (undeclared sex; Copilot, other tools and no tool) were described but excluded from inferential comparisons, whereas Obstetrics ($n = 4$) and other Health Sciences programmes ($n = 3$) were retained, with correspondingly imprecise estimates.

Table 1. Sociodemographic characteristics of the participants ($n = 91$).

Characteristic	Category	f	%
Sex	Female	62	68.13
	Male	28	30.77
	Prefer not to say	1	1.10
Age (years)	18–20	16	17.58
	21–23	43	47.25
	24–29	25	27.47
	30 or older	7	7.69
Academic cycle	Semesters I–II	9	9.89
	Semesters III–IV	7	7.69
	Semesters V–VI	19	20.88
	Semesters VII–VIII	48	52.75
	Semesters IX–X	8	8.79
Prior research experience	No prior experience	52	57.14
	Research projects	21	23.08
	Student research groups	18	19.78
Most used GenAI tool	ChatGPT	54	59.34
	Gemini	24	26.37
	Claude	8	8.79
	Copilot	2	2.20
	Other	2	2.20
	None	1	1.10

Table 1. *Cont.*

Characteristic	Category	f	%
Degree programme	Dentistry	31	34.07
	Nursing	29	31.87
	Psychology	15	16.48
	Medicine	9	9.89
	Obstetrics	4	4.40
	Other Health Sciences	3	3.30

Note. analytical dataset of 91 students (101 submissions minus 10 invariant response patterns). f = absolute frequency; % = percentage of the 91 students. Other GenAI tools: Perplexity (1) and an unspecified Google tool (1). Other Health Sciences: Pharmaceutical Chemistry, Pharmacy and Pharmacy Technician (one student each). Age: M = 24.0, SD = 5.4, median = 22, range 18–54; two students were older than 40 years.

3.3. Data Collection Instrument

Information was collected through the Scale of Generative AI Literacy, Research Self-Efficacy and Attitudes Toward Scientific Research in Health Sciences Students (EAIAAIC-ECS), a self-report questionnaire comprising 36 items distributed across three higher-order constructs, each operationalised in three dimensions. The first construct, generative AI literacy, was conceptually grounded in the competency proposal of Long and Magerko (2020) and grouped the dimensions of functional knowledge of generative AI (items 1 to 4), academic-research use (items 5 to 8) and critical and ethical evaluation (items 9 to 12). The second construct, research self-efficacy, drew on Bandura (1997)'s self-efficacy theory and on the Research Self-Efficacy Scale of Bieschke et al. (1996), and comprised the dimensions of conceptualisation and design (items 13 to 16), execution and analysis (items 17 to 20) and communication and dissemination (items 21 to 24). The third construct, attitudes toward scientific research, was anchored in the tripartite model of attitude and in Ajzen (1991)'s theory of planned behaviour and included the cognitive (items 25 to 28), affective (items 29 to 32) and behavioural (items 33 to 36) dimensions.

Each item was answered on a five-point Likert scale, with anchors ranging from 1 (strongly disagree) to 5 (strongly agree). The item pool was generated deductively: every dimension was first defined operationally from its source framework, and items were then drafted so that each dimension was represented by four indicators of comparable specificity, each referring to a single observable behaviour or belief and avoiding double formulations and negative wording. The content relevance and clarity of the items were reviewed by three expert researchers selected for holding a doctoral degree, for accredited teaching and supervision experience in research methodology and for an active publication record in the Health Sciences field. Each expert independently assessed the relevance, clarity and coherence of every item with respect to its dimension and to the corresponding construct and returned written observations; these were incorporated as wording adjustments in the items flagged as ambiguous, and the 36-item structure was retained in the final version. No pilot administration preceded fieldwork. This expert review provides limited content-related evidence from three judges without an empirical pretest and does not constitute validation of the instrument, a constraint taken up in the limitations section. Administration was carried out in digital format through an online form structured in three sections. The first presented the study title and the informed consent form, with a branched question on voluntary acceptance as a condition for continuing. The second collected the sociodemographic variables, namely degree programme, academic cycle, sex, age, prior research experience and most used generative AI tool. The third gathered the 36 items of the study constructs.

The evaluation of internal structure was conducted at the level of the nine dimensions that make up the three higher-order constructs, taken as second-order indicators. Dimension scores are the mean of their four items and construct scores the unweighted mean of their three dimensions, so each dimension contributes equally to its construct score. This decision responded to the ratio between indicators and cases: with 91 participants, a factor analysis of the 36 items would have fallen well below the case-per-item ratios ordinarily recommended, so the dimension scores were adopted as the unit of analysis in order to keep that ratio interpretable. Item-level evidence is nonetheless reported in full as Supplementary Materials, including the wording of the 36 items, their descriptive statistics, the corrected item-total correlations, the reliability of each first-order dimension and the reliability of each construct estimated directly based on its twelve items. What the present sample does not support is a confirmatory factor model of the complete instrument, so the internal-structure evidence reported below is preliminary and does not amount to a completed validation of the EAIAAIC-ECS: first-order confirmatory testing and factorial invariance remain pending for independent samples of greater size. Because all items are self-report statements, the scores describe self-reported literacy, confidence and dispositions: the GenAI-literacy items combine perceived understanding (functional knowledge), reported practices (academic-research use) and normative judgements (for example, item 12 on the importance of disclosing GenAI use), and the attitude items combine beliefs, enjoyment, willingness, intentions and reported opportunity seeking. The composites are therefore analysed as theoretically organised summaries of these self-reports and not as independently established latent capabilities; throughout the article, GenAI literacy and research self-efficacy refer to these self-reported scores. No dimension was discarded from the measurement model, although the cognitive attitudes dimension reached a loading below the conventional criterion of 0.70; the grounds for retaining it are set out in the results section.

3.4. Procedure and Data Analysis

Responses were submitted between 8 May and 25 June 2026 at a private Peruvian university with campuses in various regions of the country. These are the dates recorded by the online form, and they correct the collection period given in earlier versions of this manuscript, which reported March to May 2026, the window declared in the ethical review certificate (Section 3.5). Because few responses had been obtained within that window, the competent academic unit of the university authorised an extension and the form remained open until 25 June 2026. The correction concerns the reporting of the fieldwork dates only: the 101 submissions and the 91 analysed records are the same in this and in the previous versions, and no additional participants, measurement occasions or data sources were incorporated. The link to the online form was distributed among students enrolled in research courses in the 2026 cycle, after reading and accepting the informed consent form. All analyses were run in R 4.3.3 with a fixed random seed (20260705) so that the simulation-based and resampling procedures are reproducible. Reliability, sampling adequacy, parallel analysis and exploratory factor analysis were computed with psych 2.4.1 and GPArotation 2024.2-1; the heteroscedasticity-consistent covariance estimator and the Breusch–Pagan test with sandwich 3.1-0 and lmtest 0.9-40; variance inflation factors with car 3.1-2; and calibration, necessity analysis, truth-table construction and Boolean minimisation with QCA 3.25.

The first phase comprised data screening and the evaluation of measurement quality. Screening was completed before the analytical dataset was assembled: of 101 submissions, all included consent and complete item responses, none contained out-of-range values or duplicated records and 10 with identical responses to all 36 items were excluded. This

screening rule is an analytical decision, documented as such: an identical response to every item carries no information for covariance-based estimation, but it is not treated as proof that the participation was invalid, and a sensitivity model that restores those ten records is reported (Table S10). All 91 retained records entered the descriptive, psychometric, correlational and configurational analyses. Analyses involving a grouping variable used the cases available for that variable: models including sex used the 90 students who declared female or male sex, and comparisons by GenAI tool used the 86 students in tool categories with at least three cases (Table S21). Descriptive statistics and level classification were then estimated for each dimension, together with the reliability and convergent validity of the constructs through Cronbach's α , McDonald's ω , composite reliability (CR) and average variance extracted (AVE); construct-level coefficients were computed from the three dimension scores of each construct, and coefficients computed from the twelve items are reported separately (Table S4). The adequacy of the correlation matrix for factor analysis was examined with the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Exploratory factor analysis with minimum residual extraction and oblimin rotation was then applied, with parallel analysis based on 1000 simulated and 1000 resampled data sets to determine the number of factors; factor-correlation matrices, estimation warnings, alternative estimators and bootstrap stability diagnostics were examined for the two-factor and three-factor solutions. Discriminant validity was assessed through the heterotrait–monotrait ratio (HTMT) with the thresholds of 0.85 and 0.90 (Henseler et al., 2015). When the HTMT revealed substantial overlap between two of the constructs, this finding was documented explicitly and carried forward as an interpretive constraint in the subsequent phases.

The second phase estimated the substantive relationships. Associations between constructs and dimensions were calculated with Spearman's coefficient, with Holm correction across the 66 pairwise tests. Differences between subgroups were assessed with Kruskal–Wallis and Mann–Whitney U tests; the fifteen contrasts (three constructs by five grouping variables) were treated as one family of exploratory tests with Holm correction, categories with fewer than three cases were described but not compared inferentially, and Dunn's pairwise tests with Holm correction within each family are reported only as supplementary detail. Attitudes toward scientific research were modelled via multiple linear regression with GenAI literacy, research self-efficacy, prior research experience (any vs. none) and sex (female = 1, male = 0) as predictors. Because the model contrasts female and male students, the participant who did not declare sex was excluded from it; models that retain this participant are reported as sensitivity analyses. Heteroscedasticity-consistent HC3 standard errors were used after a Breusch–Pagan test. Coefficient tests and 95% confidence intervals refer to Student's *t* distribution with the residual degrees of freedom of each model, and the omnibus test is a Wald *F* statistic computed from the same HC3 covariance matrix; this convention is applied to every regression in the article and supplement. Multicollinearity was checked with variance inflation factors, and standardised coefficients are reported only for the two continuous predictors, since standardising binary indicators yields coefficients without direct interpretation. Sensitivity models added age, the academic cycle and the degree programme; replaced the outcome by its affective and behavioural components; retained the participant who did not declare sex; and restored the invariant responders excluded during screening. As an additional analysis introduced during peer review, the indirect term linking GenAI literacy, research self-efficacy and attitudes was estimated with 5000 percentile-bootstrap resamples, together with the reverse ordering of the two capability scores; these estimates decompose covariance among contemporaneous, overlapping measures and are not used to infer a mechanism. Finally, fsQCA was applied as an exploratory analysis of combinations of conditions associated with high attitudes to-

ward research. The procedure comprised direct calibration with theoretically interpretable anchors, the necessity analysis of each condition and its negation, the construction of the truth table with frequency, consistency and PRI thresholds and Boolean minimisation to the complex, intermediate and parsimonious solutions, followed by robustness checks across alternative anchors, thresholds and the handling of cases at the crossover (Pappas & Woodside, 2021; Ragin, 2008). Alternative models returned via the minimisation are reported separately with their own fit statistics. The level of statistical significance was set at $p < 0.05$.

3.5. Ethical Considerations

The research was conducted in accordance with the ethical principles governing studies with human beings. Participation was voluntary, anonymous and confidential and was conditional on explicit acceptance of the informed consent form presented at the beginning of the questionnaire, which detailed the purpose of the study, the optional nature of collaboration, the guarantee of anonymity and the exclusively academic use of the information collected. No data allowing participants to be identified were requested, and the information was processed only for the declared scientific purposes, in accordance with the principles of autonomy, beneficence, non-maleficence and justice. The study was not reviewed by an independent institutional review board or by an external research ethics committee; its ethical basis is an internal institutional determination, described here in full. The protocol GCES-UID-012-A was examined by the Research Group on Education and Health Sciences (Grupo de Investigación de Educación y Ciencias de la Salud, GCES) of the Faculty of Health Sciences of the Universidad Interamericana para el Desarrollo, which issued a certificate of ethical review in Lima on 11 January 2026. The certificate classifies the study as minimal-risk educational research, on the grounds that participation consists of answering an anonymous academic questionnaire with no clinical procedure, intervention or experimental manipulation, and it makes that classification conditional on the safeguards applied here: acceptance of the consent form before the questionnaire, no direct identifiers, aggregate reporting and access to the database restricted to the research team and to ethical or editorial verification bodies. The certificate states that its determination is subject to validation by the competent institutional authority and that validation was given by the competent academic unit of the university, which is also the unit that authorised the extension of the collection period reported in Section 3.4. The absence of external review therefore rests on this internal institutional decision and not on a published exemption policy or on a ruling by an accredited ethics committee. The certificate and the informed consent form were sent to the editorial office at its request.

4. Results

4.1. Screening and Analytical Samples

Of the 101 submissions, 91 formed the analytical dataset after the exclusion of 10 invariant response patterns. Among the retained records, there were no missing item responses, out-of-range values, invalid codes or duplicated records. Descriptive, psychometric, correlational and configurational analyses used all 91 cases; the regression and indirect-effect models used the 90 students who declared female or male sex; and subgroup comparisons used 90 (sex), 86 (GenAI tool) or 91 cases (degree programme, prior research experience and academic cycle) (Table S21). As Table 1 shows, the sample was weighted toward Dentistry, Nursing, female students, students without prior research experience and users of ChatGPT, which conditions the interpretation of all subsequent results.

4.2. Descriptive Distribution of the Study Variables

Overall self-reported scores were concentrated in the moderate-to-high range of the measurement scale. Attitudes toward scientific research recorded the highest overall mean ($M = 3.50$; $SD = 0.67$), followed by generative AI literacy ($M = 3.36$; $SD = 0.75$) and research self-efficacy ($M = 3.23$; $SD = 0.82$). At the dimension level, cognitive attitudes toward research constituted the strongest component ($M = 3.82$; $SD = 0.82$), with 69.23% of students above the descriptive cut-off of 3.50. Functional knowledge of generative AI ($M = 3.41$) and critical and ethical evaluation ($M = 3.40$) were also comparatively high. By contrast, self-efficacy in scientific communication and dissemination presented the lowest mean ($M = 3.14$; $SD = 0.83$) and the smallest proportion of high scores among the research self-efficacy dimensions (39.56%) (See Table 2).

Table 2. Descriptive statistics and level classification.

Variable/Dimension	M	SD	Mdn	95% CI	High f (%)
Functional knowledge of GenAI	3.41	0.86	3.75	3.23–3.59	58 (63.7%)
Academic-research use of GenAI	3.25	0.83	3.25	3.08–3.43	42 (46.2%)
Critical and ethical evaluation of GenAI	3.40	0.84	3.50	3.23–3.58	54 (59.3%)
Generative AI literacy (overall)	3.36	0.75	3.58	3.20–3.51	51 (56.0%)
Conceptualisation and design (self-efficacy)	3.32	0.90	3.50	3.13–3.51	47 (51.6%)
Execution and analysis (self-efficacy)	3.23	0.89	3.25	3.04–3.41	41 (45.1%)
Communication and dissemination (self-efficacy)	3.14	0.83	3.25	2.97–3.31	36 (39.6%)
Research self-efficacy (overall)	3.23	0.82	3.33	3.06–3.40	40 (44.0%)
Cognitive attitudes	3.82	0.82	4.00	3.64–3.99	63 (69.2%)
Affective attitudes	3.38	0.80	3.25	3.22–3.55	44 (48.4%)
Behavioural attitudes	3.30	0.77	3.25	3.14–3.46	37 (40.7%)
Attitudes toward research (overall)	3.50	0.67	3.50	3.36–3.64	50 (54.9%)

Note. Scores ranged from 1 to 5. “High” is an operational descriptive cut-off (score ≥ 3.50), placed midway between the neutral option (3 = neither agree nor disagree) and the agreement option (4 = agree), so that it separates mean scores lying on the agreement side of the response scale. It is a reporting device for these distributions and not a validated standard of competence or attainment; no inference is drawn from the classification. M = mean; SD = standard deviation; Mdn = median; CI = confidence interval.

The dimension-level distributions were not uniform, as can be seen in Figure 1. Cognitive attitudes shifted toward the upper end of the scale, while the dimensions of research execution, communication and behavioural attitudes showed a broader concentration around the midpoint. Various low scores were observed in all constructs, although the distributions generally exhibited negative skewness, particularly in functional knowledge, scientific communication and the overall scores for GenAI literacy and research self-efficacy. Figure 2 confirms that attitudes toward research presented the most centred and comparatively symmetric overall distribution, whereas GenAI literacy and research self-efficacy showed longer lower tails, a sign that a small subgroup reported markedly lower literacy and research confidence.

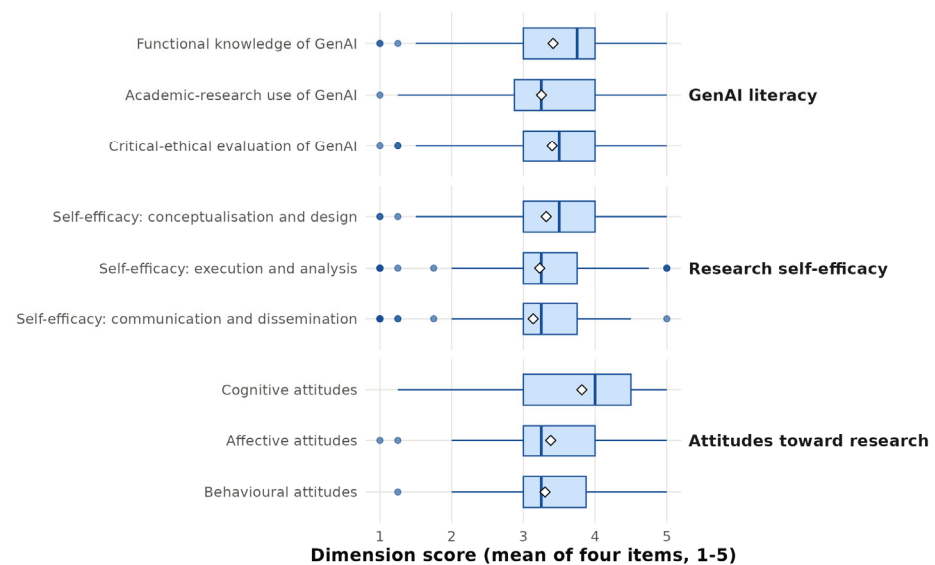


Figure 1. Distribution of the scores of the nine dimensions. Boxes represent the interquartile range, the central line corresponds to the median and points outside the whiskers indicate comparatively extreme observations; diamonds mark the means.

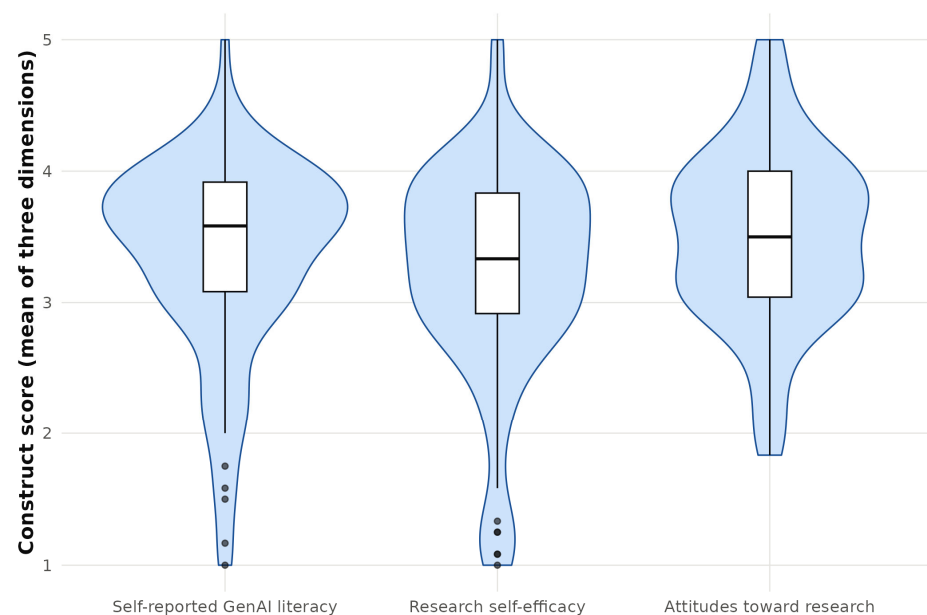


Figure 2. Distribution of the overall scores for self-reported GenAI literacy, research self-efficacy and attitudes toward scientific research (violin plots with embedded boxplots).

4.3. Construct Reliability and Exploratory Structure

The three higher-order constructs showed internal consistency ranging from acceptable to excellent at the dimension level. Research self-efficacy produced the highest reliability ($\alpha = 0.927$; $\omega = 0.928$; $CR = 0.928$; $AVE = 0.810$), followed by generative AI literacy ($\alpha = 0.861$; $\omega = 0.861$; $CR = 0.861$; $AVE = 0.675$). Attitudes toward scientific research showed lower, though still acceptable, consistency ($\alpha = 0.790$; $\omega = 0.812$; $CR = 0.812$; $AVE = 0.603$). These coefficients are computed from the three dimension scores of each construct: α and λ_6 directly from those scores, and ω , CR and AVE from a single-factor minimum-residual solution estimated for each construct separately. The loadings behind CR and AVE are therefore not the pattern coefficients of the joint exploratory solutions reported below, in which the nine dimensions are analysed together, and meeting the AVE criterion within a

construct says nothing about its separation from the other constructs. Coefficients computed from the twelve items of each construct are higher ($\alpha = 0.933, 0.959$ and 0.921 ; Table S4), but they refer to a different set of indicators and are not directly comparable with the dimension-based values (See Table 3).

Table 3. Reliability and convergent validity at the dimension level.

Construct	α	λ_6	ω	CR	AVE	Loading Range
Generative AI literacy	0.861	0.806	0.861	0.861	0.675	0.771–0.848
Research self-efficacy	0.927	0.897	0.928	0.928	0.810	0.862–0.930
Attitudes toward research	0.790	0.747	0.812	0.812	0.603	0.584–0.992

Note. Each construct was analysed separately, using the three dimension scores assigned to it: α and λ_6 were computed from those scores, and ω , CR and AVE from a single-factor minimum-residual solution estimated for that construct alone (CR from the sum of its loadings; AVE as the mean of their squares). The loading range shown is that of the same single-construct solution and differs from the pattern coefficients of the joint two-factor and three-factor solutions (Table S6). Coefficients computed from the twelve items are reported in Table S4. Convergent validity within a construct does not address the discriminant-validity problem between GenAI literacy and research self-efficacy reported in Section 4.3. α = Cronbach's α ; λ_6 = Guttman's λ_6 ; ω = McDonald's ω ; CR = composite reliability; AVE = average variance extracted.

The correlation matrix was factorable ($KMO = 0.895$; Bartlett's $\chi^2(36) = 579.73$; $p < 0.001$), but the dimensionality evidence did not match the pre-specified three-construct framework. Parallel analysis favoured two factors (Figure 3; Table S5), and the two-factor solution is therefore treated as the primary description of internal structure (Figure 4A); it is better supported than the three-factor alternative, but it is not an independently validated or estimation-stable measurement model, as the bootstrap diagnostics reported below show. In that solution, the six capability dimensions defined one broad factor (pattern coefficients 0.683 to 0.910) and the three attitudinal dimensions defined a second factor (cognitive 0.432, affective 1.009, behavioural 0.671), with an inter-factor correlation of 0.575; GenAI literacy and research self-efficacy were not separated. The three-factor solution, retained only as a theoretically motivated comparison (Figure 4B), did not separate them either: the three self-efficacy dimensions, functional knowledge (0.697) and critical and ethical evaluation (0.770), defined the first factor, and academic-research use formed a factor of its own (0.966). Both solutions contained near-boundary estimates: the uniqueness of affective attitudes was 0.002 in the two-factor and 0.004 in the three-factor solution, and that of academic-research use was 0.004 in the three-factor solution. The minimum-residual estimator issued no warning, but principal-axis extraction returned negative uniqueness for affective attitudes (an ultra-Heywood case) and maximum likelihood held it at its lower bound (0.005). Across 1000 bootstrap resamples, the two-factor pattern was recovered closely (median Tucker congruence 0.994 and 0.980), whereas the three-factor pattern was unstable: all three factors reached a congruence of at least 0.95 in only 33.7% of resamples, and Heywood-type estimates occurred in 74.3% of resamples, compared with 48.2% for the two-factor solution (Table S20). The very low residual indices of the three-factor solution ($RMSR = 0.019$; $TLI = 1.012$; $RMSEA = 0.000$) therefore reflect a nearly saturated model for nine indicators rather than support for the theoretical structure, and the Bayesian information criterion favoured the two-factor solution ($BIC = -56.9$ vs. -44.2).

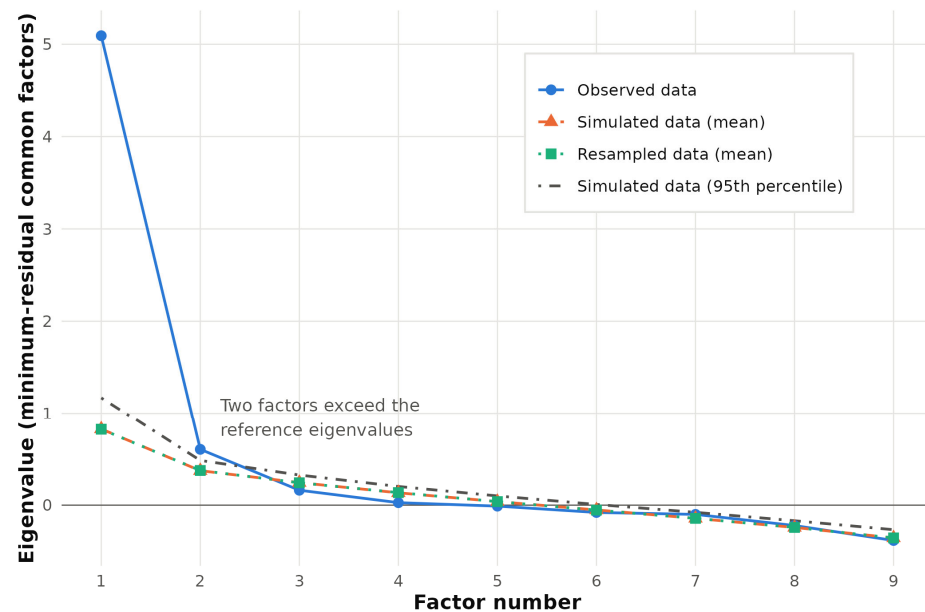


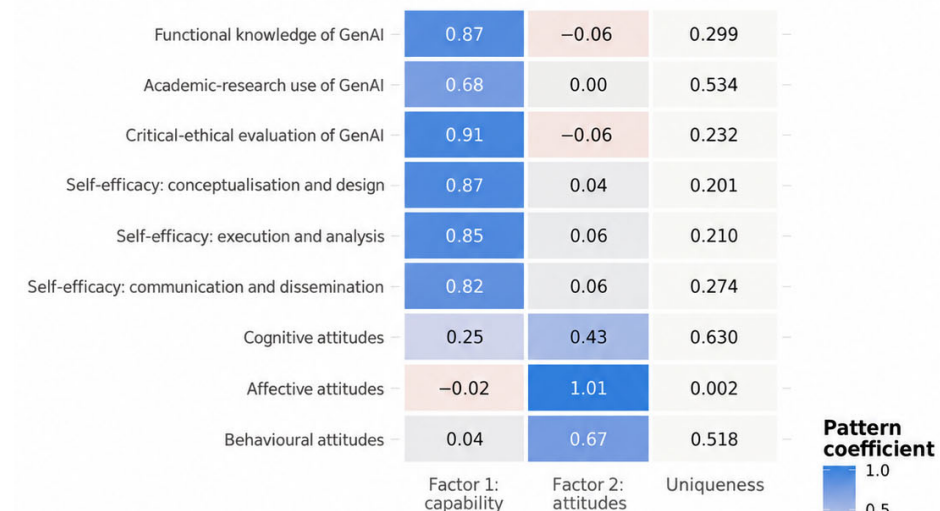
Figure 3. Parallel analysis of the nine dimension scores (minimum-residual common-factor eigenvalues; 1000 simulated and 1000 resampled data sets). Observed eigenvalues exceeded the mean and 95th-percentile reference values for the first two factors only.

The cognitive attitudes dimension was retained despite its weaker pattern coefficient (0.432) and high uniqueness (0.630). The tripartite model treats the cognitive, affective and behavioural components as constitutive of attitude, so removing the dimension would redefine the outcome rather than refine its measurement, and the average variance extracted of the attitude construct remained above 0.50 with the dimension included ($AVE = 0.603$). Heywood-type estimates arose in 48.2% of the two-factor resamples as well, so the broad capability factor is described as the structure that best accounts for these nine dimension scores in an exploratory analysis and not as a validated replacement for the theoretical three-construct model. The pattern coefficients should not be confused with scoring weights. The attitude score is the unweighted mean of its three dimensions, so each dimension contributes equally to the observed composite; the factor solution indicates only that the affective and behavioural dimensions share more variance with the common attitude factor than the cognitive dimension does. Because the near-zero uniqueness of the affective dimension is a boundary estimate, it is not interpreted as evidence that this dimension is a perfect indicator. A sensitivity check re-estimated the primary regression based on an attitude score restricted to the affective and behavioural dimensions ($r = 0.938$ with the full score): research self-efficacy retained its adjusted association ($b = 0.410$; $p = 0.005$), GenAI literacy did not ($b = -0.004$; $p = 0.981$) and R^2 was 0.392, compared with 0.405 for the complete score (Table S10).

HTMT was acceptable between attitudes and GenAI literacy (0.623) and between attitudes and research self-efficacy (0.671), but the value between GenAI literacy and research self-efficacy reached 0.912, a figure exceeding both the strict criterion of 0.85 and the liberal criterion of 0.90. Attitudes were therefore empirically distinguishable from the two capability-related constructs, whereas discriminant validity between generative AI literacy and research self-efficacy was not established in this sample. Two explanations remain open and the present design cannot arbitrate between them. The first is conceptual: students with intensive exposure to generative tools may have integrated the perception of knowing how to use them for research into their broader research-confidence judgement. The second is a measurement artefact, since overlapping item wording, self-efficacy language embedded in the GenAI-literacy items, common-method variance arising from a single self-report

administration and the aggregation of items into dimension scores may all contribute to the ratio, in amounts that this design cannot estimate. This result is treated as a psychometric limitation that constrains the interpretation of the regression and configurational analyses and not primarily as a substantive discovery: where two constructs cannot be separated empirically, any statement about which of them weighs more heavily describes how shared variance is allocated within a model rather than a difference between distinct capabilities.

A. Two factors (favoured by parallel analysis)



B. Three factors (theoretical model)

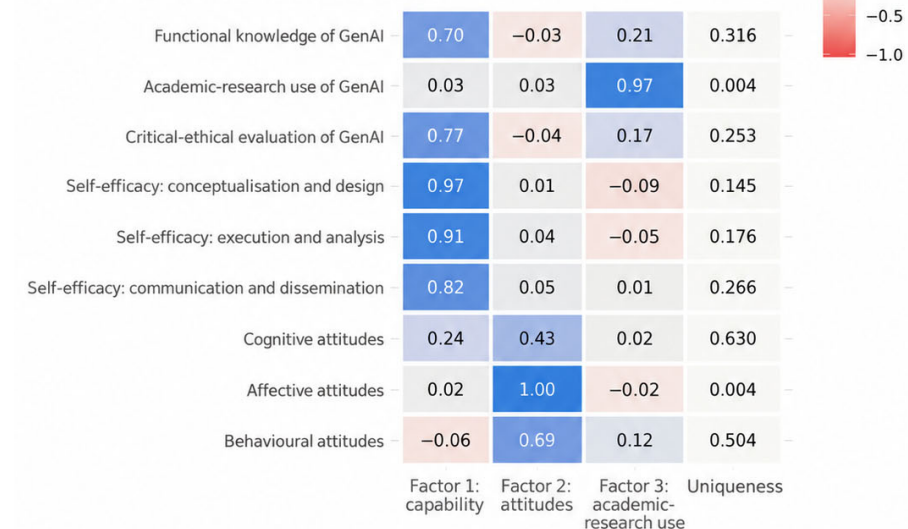


Figure 4. Pattern coefficients and uniquenesses of the exploratory factor analysis of the nine dimension scores (minimum residual extraction, oblimin rotation). (A) Two-factor solution favoured by parallel analysis; (B) three-factor solution estimated for comparison with the theoretical model. The uniquenesses of affective attitudes (both solutions) and of academic-research use (three-factor solution) are near-boundary estimates (Table S20).

4.4. Associations, Subgroup Contrasts and Multivariable Results

The three overall self-reported scores were positively and statistically significantly associated with one another. The strongest relationship at the construct level was observed between GenAI literacy and research self-efficacy (Spearman's $\rho = 0.735$; Holm-adjusted $p < 0.001$), followed by the association between research self-efficacy and attitudes ($\rho = 0.568$; adjusted $p < 0.001$) and that between GenAI literacy and attitudes ($\rho = 0.475$; adjusted $p < 0.001$). At the dimension level, a critical and ethical evaluation of generative AI showed

particularly strong associations with research conceptualisation and design ($p = 0.720$) and with execution and analysis ($p = 0.749$). As can be seen in Figure 5, the correlation pattern was uniformly positive, although the capability-related dimensions formed a denser cluster than the attitudinal dimensions, which reiterates that GenAI literacy and research self-efficacy were closely connected rather than empirically distinct.

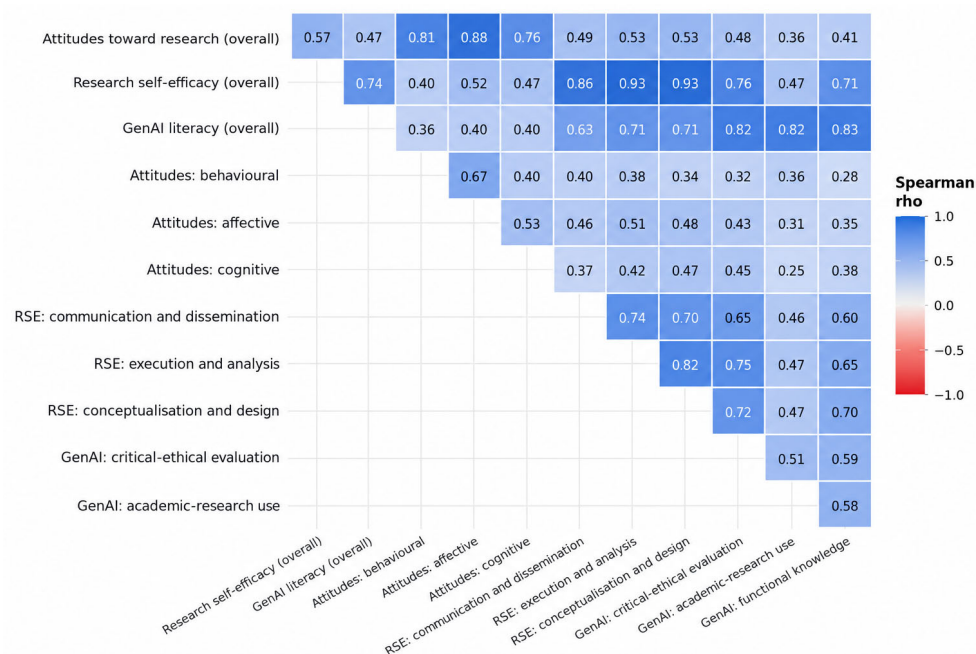


Figure 5. Spearman correlation matrix between the scores of the nine dimensions and the three overall construct scores ($n = 91$). All coefficients remained statistically significant after Holm correction across the 66 pairs (Table S8).

Fifteen exploratory subgroup contrasts were examined as one family (Table S12). Before correction, female students reported higher GenAI literacy ($U = 1106.5$; $p = 0.038$; $r = 0.219$) and more favourable attitudes ($U = 1135.0$; $p = 0.020$; $r = 0.245$) than male students ($n = 90$), and attitudes differed by prior research experience ($H = 7.46$; $p = 0.024$; $\epsilon^2 = 0.062$). None of these three differences survived Holm correction across the family (adjusted $p = 0.415$, 0.260 and 0.288), so they are not interpreted as established differences. The only contrasts that remained significant after correction were those by academic cycle in GenAI literacy ($H = 16.27$; adjusted $p = 0.037$; $\epsilon^2 = 0.143$) and in research self-efficacy ($H = 19.24$; adjusted $p = 0.011$; $\epsilon^2 = 0.177$). In exploratory pairwise tests with Holm correction within each family, students in semesters VII–VIII ($n = 48$) reported higher GenAI literacy than those in semesters I–II and V–VI and higher research self-efficacy than those in semesters V–VI (Table S13); the other cycle groups contained between 7 and 19 students. Differences by degree programme and by most-used GenAI tool were not statistically significant (See Table 4).

The primary model explained 40.5% of the variance in attitudes toward research (adjusted $R^2 = 0.377$; robust Wald $F(4, 85) = 10.85$, $p < 0.001$). Holding the other predictors constant, research self-efficacy was positively associated with attitudes ($b = 0.353$; 95% CI 0.087 to 0.619; $p = 0.010$; $\beta = 0.43$), as was prior research experience ($b = 0.261$; 95% CI 0.031 to 0.491; $p = 0.026$). The female–male difference was not statistically significant ($b = 0.283$; 95% CI -0.005 to 0.570 ; $p = 0.054$), and GenAI literacy did not retain a statistically significant adjusted association ($b = 0.088$; 95% CI -0.214 to 0.389 ; $p = 0.564$; $\beta = 0.10$), an interval that spans negative and positive values and therefore does not establish that the adjusted association is absent. Without research self-efficacy in the model, GenAI literacy

was associated with attitudes ($b = 0.400$; $p = 0.002$), so the attenuation reflects the variance that the two capability scores share and does not indicate that self-reported GenAI literacy is unrelated to attitudes. Because discriminant validity between these two scores was not established, the comparison describes how shared variance is allocated within the model, not which capability matters more.

Table 4. Multiple regression of attitudes toward scientific research with HC3 standard errors (female and male students, $n = 90$).

Predictor	b	HC3 SE	t	p	95% CI
Intercept	1.762	0.426	4.139	<0.001	0.915 to 2.608
Generative AI literacy	0.088	0.152	0.580	0.564	−0.214 to 0.389
Research self-efficacy	0.353	0.134	2.641	0.010	0.087 to 0.619
Prior research experience (any vs. none)	0.261	0.115	2.260	0.026	0.031 to 0.491
Female (vs. male)	0.283	0.144	1.956	0.054	−0.005 to 0.570

Note. $n = 90$; the participant who did not declare sex is excluded (models with $n = 91$ are reported in Table S10). Tests and 95% CIs use HC3 standard errors and Student's t with 85 degrees of freedom. $R^2 = 0.405$; adjusted $R^2 = 0.377$; robust Wald $F(4, 85) = 10.85$, $p < 0.001$ (ordinary least-squares $F(4, 85) = 14.45$). Breusch–Pagan LM = 11.01, $p = 0.026$. Maximum VIF = 3.06. b = unstandardised coefficient; SE = standard error; CI = confidence interval. Standardised coefficients: research self-efficacy $\beta = 0.43$; GenAI literacy $\beta = 0.10$. Binary indicators are reported in their original metric as adjusted mean differences in scale points.

The sensitivity models in Table S10 support the direction and approximate size of the research self-efficacy coefficient and also show which associations are fragile. Retaining the undeclared participant with an indicator of female vs. all other responses ($n = 91$) gave $b = 0.356$ ($p = 0.009$) for research self-efficacy and $b = 0.287$ ($p = 0.042$) for that indicator, which is not a female–male contrast. Adding age, academic cycle and five programme indicators ($n = 90$; 11 predictors) left research self-efficacy associated with attitudes ($b = 0.345$; 95% CI 0.027 to 0.663; $p = 0.034$), whereas prior research experience ($p = 0.295$) and the female indicator ($p = 0.064$) were not; this model estimates programme coefficients from as few as three or four students, so it is reported as a sensitivity analysis and not as evidence that programme-related confounding has been removed. Restoring the ten invariant responders ($n = 100$) gave $b = 0.388$ (95% CI 0.128 to 0.649; $p = 0.004$) for research self-efficacy and $b = 0.147$ (95% CI −0.144 to 0.438; $p = 0.318$) for GenAI literacy, and removing the five near-invariant responders (response SD < 0.25; $n = 85$) gave $b = 0.341$ (95% CI 0.070 to 0.613; $p = 0.014$) and $b = 0.042$ (95% CI −0.266 to 0.350; $p = 0.787$), respectively. Coefficients, standard errors and 95% intervals for every predictor of each sensitivity model, including both capability scores, are reported in Table S10.

An indirect-effect model, added during peer review to examine the attenuation formally, returned an indirect term of 0.313 for GenAI literacy through research self-efficacy (95% percentile bootstrap CI 0.092 to 0.536; 5000 resamples; $n = 90$) and 0.064 (95% CI −0.149 to 0.261) for the reverse ordering (Table S11). Both scores were measured at the same moment and were not empirically distinguishable, so neither ordering is privileged, and the term is reported only as a decomposition of shared variance, subordinate to the correlational and adjusted results above.

4.5. Fuzzy-Set Calibration and Necessity Analysis

Direct fuzzy-set calibration employed theoretically interpretable raw-score anchors: 2 for full non-membership, 3 for the crossover point and 4 for full membership (Figure 6). Because dimension scores are the means of four items, many cases scored exactly 3.00,

the neutral midpoint, and therefore received a membership of exactly 0.50: 10 cases for functional knowledge, 18 for academic-research use, 12 for critical and ethical evaluation, 16 for conceptualisation and design, 19 for execution and analysis, 24 for communication and dissemination and 9 for the outcome; 46 of the 91 cases had at least one condition at the crossover (Table S22). Cases with a membership of exactly 0.50 cannot be allocated to a truth-table row, so these memberships were set to 0.501 in the primary analysis. This displacement is a computational convention rather than a substantive judgement, since a score of 3.00 corresponds to the neutral response option; the analysis was therefore repeated with the opposite displacement (0.499), which is equivalent to placing the crossover just above the neutral midpoint (Section 4.7). As the observed medians lay above the crossover in most dimensions, calibrated memberships were concentrated toward higher values (Figure 7), whereas membership in the negated outcome was concentrated near zero.

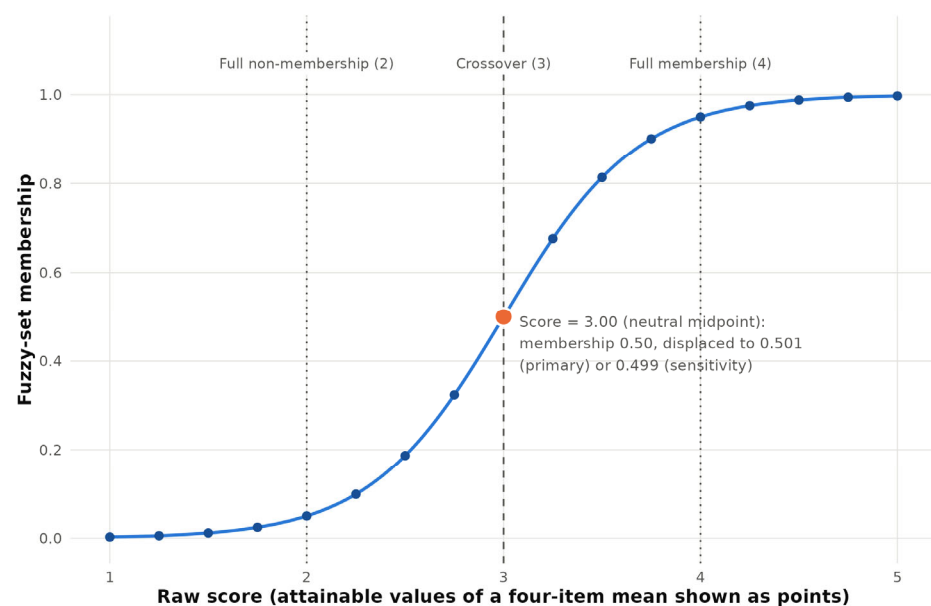


Figure 6. Direct calibration function with anchors 2 (full non-membership), 3 (crossover) and 4 (full membership). Points mark the attainable values of a four-item mean; scores of exactly 3.00 receive a membership of 0.50 and were displaced to 0.501 (primary analysis) or 0.499 (sensitivity analysis).

No individual condition was necessary for high attitudes toward research (See Table 5). Functional knowledge ($\text{inclN} = 0.841$) and critical and ethical evaluation ($\text{inclN} = 0.841$) produced the highest consistency values among the positive conditions, although both remained below the 0.90 criterion. Research execution and scientific communication exhibited high necessity coverage (0.916 and 0.921, respectively) without sufficient consistency, denoting broad empirical relevance but not necessity. The same conclusion applied to the absence of high attitudes, which is the negation of the outcome set and not a measure of unfavourable attitudes: the strongest candidates were the absence of scientific communication ($\text{inclN} = 0.832$) and the absence of research execution ($\text{inclN} = 0.815$), again below the accepted threshold. Figure 8 confirms that the outcome set was not consistently contained within any isolated condition set. Since the necessity threshold was met by no condition, the recurrence of functional knowledge and critical and ethical evaluation in the sufficient configurations reported below does not make them indispensable ingredients of high attitudes.

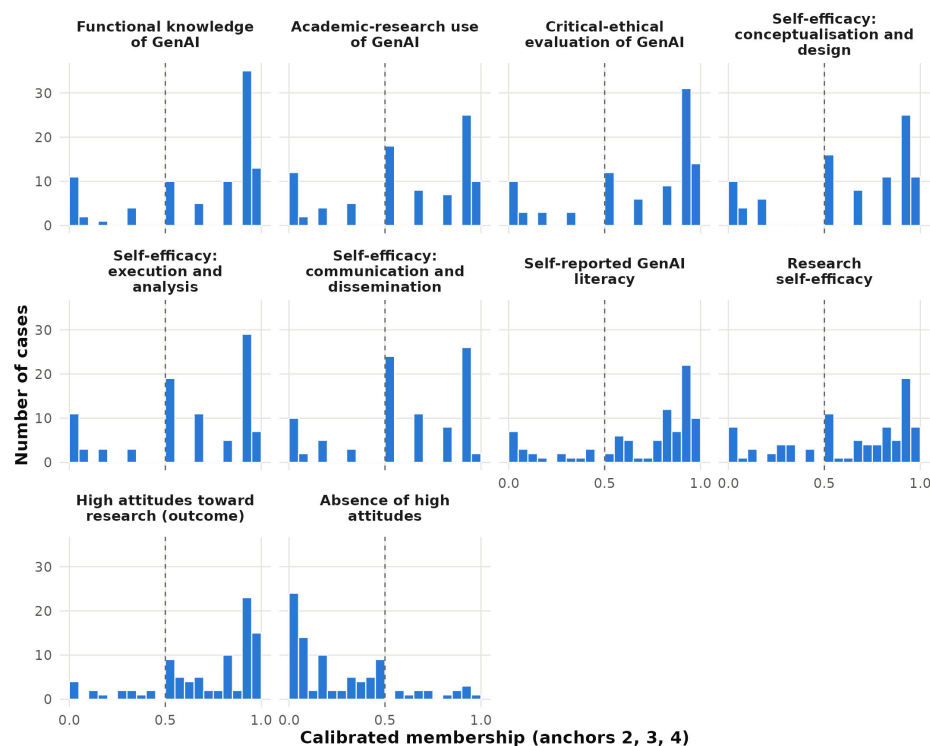


Figure 7. Distribution of calibrated memberships (anchors 2, 3 and 4) for the six dimensional conditions, the overall GenAI literacy and research self-efficacy sets, high attitudes toward research and the absence of high attitudes. The accumulation just above 0.50 corresponds to scores of exactly 3.00 displaced to 0.501.

Table 5. Necessity analysis for high attitudes toward research and for the absence of high attitudes.

Condition	High Attitudes inclN	High Attitudes covN	Absence of High Attitudes inclN	Absence of High Attitudes covN
FK	0.841	0.866	0.644	0.260
ARU	0.745	0.865	0.636	0.289
CEE	0.841	0.884	0.654	0.269
RCD	0.805	0.900	0.599	0.262
REA	0.797	0.916	0.648	0.292
SCD	0.767	0.921	0.649	0.305
~FK	0.281	0.668	0.669	0.623
~ARU	0.388	0.731	0.703	0.519
~CEE	0.305	0.692	0.718	0.638
~RCD	0.340	0.684	0.771	0.608
~REA	0.385	0.736	0.815	0.611
~SCD	0.421	0.754	0.832	0.583

Note. A condition was considered necessary only when consistency reached at least 0.90. No condition or negated condition reached that threshold. inclN = necessity consistency; covN = necessity coverage; ~ = absence of the condition. The absence of high attitudes is the negation of the outcome set and should not be read as unfavourable attitudes. FK = functional knowledge; ARU = academic-research use; CEE = critical and ethical evaluation; RCD = research conceptualisation and design; REA = research execution and analysis; SCD = scientific communication and dissemination.

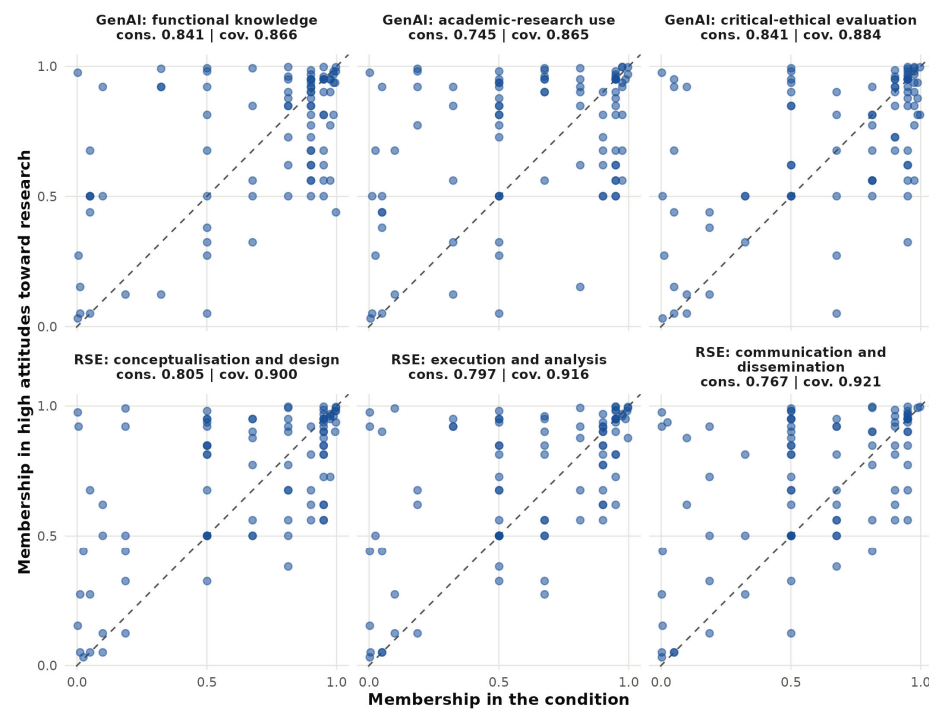


Figure 8. Necessity plots for high attitudes toward scientific research (primary calibration). The diagonal line represents equal membership in the condition and in the outcome; necessity consistency and coverage are shown in each panel.

4.6. Truth Table Analysis and Sufficient Configurations

The primary truth table (frequency threshold 2, consistency threshold 0.80, PRI threshold 0.50) contained 22 empirically observed configurations out of 64 logically possible ones. Six observed configurations reached the frequency threshold: five were coded as sufficient for high attitudes and one, with all conditions absent, as not sufficient (nine cases; consistency = 0.657); no row was contradictory (Figure 9). The remaining 58 configurations were logical remainders, 42 of them without cases and 16 observed in a single case each (Table S17). Remainders are excluded from the set of rows coded as positive or negative evidence, but the parsimonious and intermediate solutions may use some of them as simplifying assumptions, which are counted in Table 6. The distribution was highly concentrated: the configuration with all six conditions present contained 52 of the 91 cases (consistency = 0.977; PRI = 0.966), and every positive row contained both functional knowledge and critical and ethical evaluation. This concentration partly reflects the crossover convention: with the opposite displacement (0.499), the same configuration contained 27 cases and the configuration with all conditions absent 14 (Section 4.7). With so few observed patterns and so many remainders, the solutions below are exploratory.

The complex solution, which uses no simplifying assumptions, comprised four terms with an overall consistency of 0.935, a PRI of 0.910 and a coverage of 0.708. Three terms combined functional knowledge and critical and ethical evaluation with at least two research self-efficacy dimensions. The fourth combined the three GenAI-literacy dimensions with the absence of all three self-efficacy dimensions; it rests on a single configuration of two cases (raw coverage = 0.181) and is reported descriptively, not as a compensatory route.

The intermediate solution comprised two terms, $FK*ARU*CEE$ (consistency = 0.918; PRI = 0.886; raw coverage = 0.675) and $FK*CEE*RCD*REA*SCD$ (consistency = 0.964; PRI = 0.949; raw coverage = 0.634), with a solution consistency of 0.913, a PRI of 0.882 and a coverage of 0.741. The two terms overlap heavily, since both cover the 52-case configuration in which all conditions are present, so they are not interpreted as distinct

pathways. Functional knowledge and critical and ethical evaluation appear in both terms. This is a regularity of the observed configurations under this calibration, not evidence of stable core conditions, since neither condition reached the necessity threshold and the result changed under the robustness checks reported below.

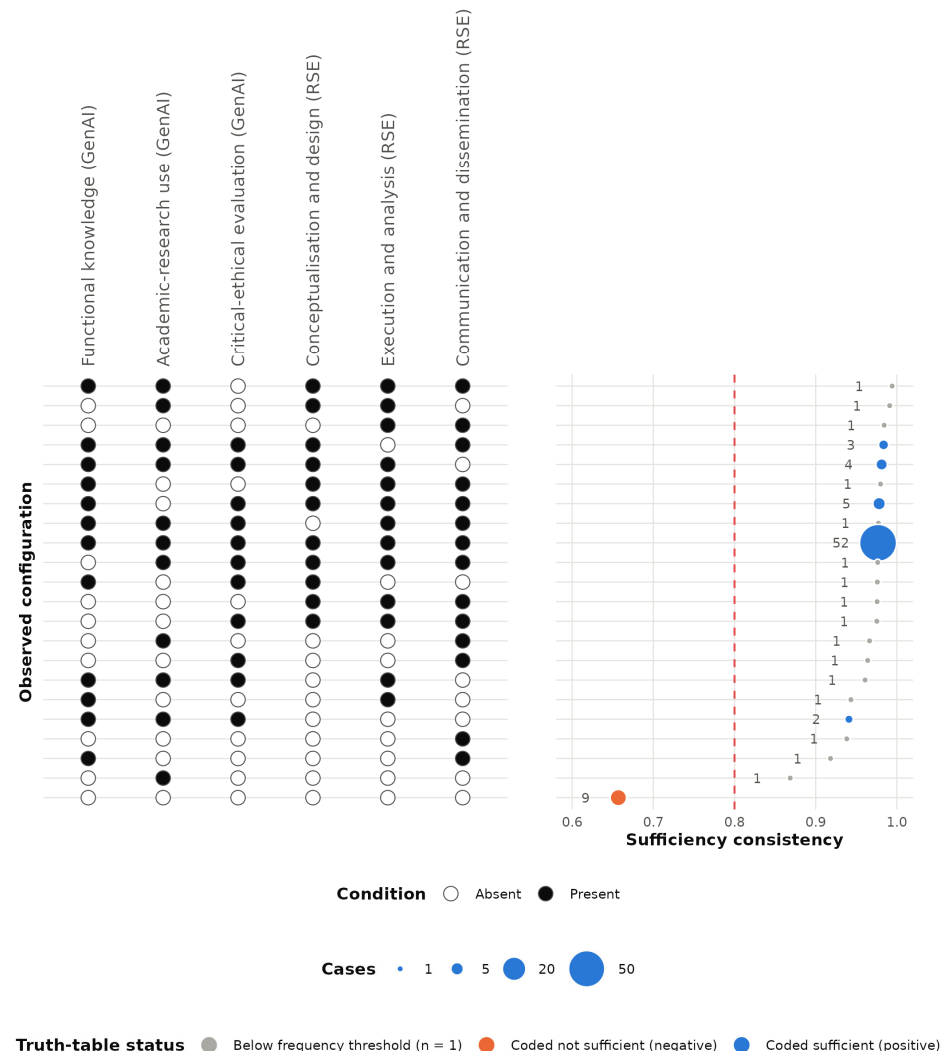


Figure 9. Observed truth-table configurations for high attitudes toward research (primary calibration). Left: presence (filled circles) or absence (open circles) of each condition. Right: sufficiency consistency; bubble size and the adjacent number indicate the number of cases in each configuration, while colour denotes truth-table status. The red dashed vertical line indicates the predefined sufficiency consistency threshold of 0.80; configurations located to the right of this line meet or exceed the consistency criterion for sufficiency, whereas those to the left do not. Configurations observed in a single case are shown for contextual purposes; they fall below the frequency threshold and are therefore treated as logical remainders.

The parsimonious analysis did not yield a single expression but two alternative minimal models, M1: FK (consistency = 0.866; coverage = 0.841) and M2: CEE (consistency = 0.884; coverage = 0.841), each resting on 27 simplifying assumptions. Because all five positive rows contain both conditions and the only negative row lacks both, either condition alone separates the coded rows; the data do not determine a choice between the two models, and neither is selected. These single-condition models depend heavily on counterfactual assumptions and are not read as evidence that either condition is sufficient on its own.

Table 6. Complex, intermediate and parsimonious solutions for high attitudes toward research (primary calibration).

Solution/Term	Configuration	Cons.	PRI	Raw Cov.	Unique Cov.
Complex C1	FK*ARU*CEE*RCD*REA	0.958	0.941	0.609	0.032
Complex C2	FK*ARU*CEE*RCD*SCD	0.970	0.957	0.584	0.008
Complex C3	FK*CEE*RCD*REA*SCD	0.964	0.949	0.634	0.066
Complex C4	FK*ARU*CEE*~RCD*~REA*~SCD	0.941	0.850	0.181	0.017
Complex solution (SA = 0)	Overall	0.935	0.910	0.708	n.a.
Intermediate I1	FK*ARU*CEE	0.918	0.886	0.675	0.108
Intermediate I2	FK*CEE*RCD*REA*SCD	0.964	0.949	0.634	0.066
Intermediate solution (EC = 4)	Overall	0.913	0.882	0.741	n.a.
Parsimonious model M1 (SA = 27)	FK	0.866	0.826	0.841	—
Parsimonious model M2 (SA = 27)	CEE	0.884	0.846	0.841	—

Note. * denotes logical conjunction, + logical disjunction and ~ absence. FK = functional knowledge; ARU = academic-research use; CEE = critical and ethical evaluation of GenAI; RCD, REA and SCD = research self-efficacy in conceptualisation and design, execution and analysis and communication and dissemination. Cons. = consistency; Raw cov. = raw coverage; Unique cov. = unique coverage within the model; SA = simplifying assumptions (remainders used by the minimisation); EC = easy counterfactuals. The intermediate solution used directional expectations of presence for all conditions and was identical whichever parsimonious model it was derived from. M1 and M2 are alternative parsimonious models of equal complexity; each covers every positive row without covering the negative row, and they are reported separately rather than combined into one expression.

4.7. Robustness, Crossover Handling and Absence of the Outcome

Table 7 reports the intermediate and parsimonious solutions obtained under each specification of the robustness grid; complete complex, intermediate and parsimonious expressions, model identifiers and fit statistics are given in Table S19. Under the theoretical anchors with the primary crossover convention, raising the consistency threshold to 0.85 or the PRI threshold to 0.60 left all solutions unchanged. A frequency threshold of three removed the two-case configuration, so the intermediate solution was reduced to the three complex terms that contain research self-efficacy dimensions (consistency = 0.944; coverage = 0.692), and the parsimonious analysis returned three alternative single-condition models (FK, CEE or RCD). Reversing the crossover displacement (0.499) altered the truth table substantially: 13 rows were coded as positive, the complex solution grew to eight terms, and the intermediate and parsimonious solutions reduced to FK + ARU + CEE (consistency = 0.830; coverage = 0.926). Under the empirical anchors, whose crossovers are the observed medians, the three research self-efficacy dimensions appeared together in every term of the intermediate solutions obtained with the 10-50-90 anchors (for example, CEE*RCD*REA*SCD + FK*ARU*RCD*REA*SCD under the primary thresholds), and solution consistencies were lower (0.777 to 0.855). The consistency threshold of 0.80 classifies individual truth-table rows, whereas the consistency reported for a minimised solution is computed for the whole expression after minimisation; the two quantities are set and computed separately, so a solution consistency below the row threshold is not an arithmetic inconsistency. Solutions in that range are nevertheless weak and are read here as specification-sensitive results rather than as comparably sufficient expressions, and the 25-50-75 anchors with the primary thresholds produced six alternative parsimonious models and eight intermediate models. Three claims should therefore be kept apart. Functional knowledge and critical and ethical evaluation were present in every raw positive configuration only under the theoretical anchors with the primary crossover convention.

Across minimised solutions, critical and ethical evaluation appeared in at least one term of every intermediate solution in the grid, but it was absent from several parsimonious solutions. No particular minimised expression was stable across specifications.

Table 7. Robustness of the configurational solutions across calibration anchors, crossover handling and truth-table thresholds.

Anchors (Crossover)	<i>n</i> /Cons./PRI	Positive Rows (Cases)	Intermediate Solution	Cons.	Cov.	Parsimonious Model(s)
Theoretical 2-3-4 (0.501)	2/0.80/0.50 2/0.85/0.50 2/0.80/0.60	5 (66)	FK*ARU*CEE + FK*CEE*RCD*REA*SCD FK*ARU*CEE*RCD*REA +	0.913	0.741	M1: FK; M2: CEE
Theoretical 2-3-4 (0.501)	3/0.80/0.50	4 (64)	FK*ARU*CEE*RCD*SCD + FK*CEE*RCD*REA*SCD	0.944	0.692	M1: FK; M2: CEE; M3: RCD
Theoretical 2-3-4 (0.499)	2/0.80/0.50 2/0.85/0.50	13 (66)	FK + ARU + CEE	0.830	0.926	FK + ARU + CEE
Theoretical 2-3-4 (0.499)	2/0.80/0.60	12 (64)	FK + CEE	0.848	0.911	FK + CEE
Theoretical 2-3-4 (0.499)	3/0.80/0.50	7 (54)	FK + CEE	0.848	0.911	FK + CEE
Empirical 10-50-90 (0.501)	2/0.80/0.50	5 (36)	CEE*RCD*REA*SCD + FK*ARU*RCD*REA*SCD	0.823	0.653	RCD*SCD
Empirical 10-50-90 (0.501)	2/0.85/0.50 2/0.80/0.60	4 (33)	CEE*RCD*REA*SCD FK*ARU*RCD*REA*SCD +	0.828	0.637	CEE*RCD*SCD
Empirical 10-50-90 (0.501)	3/0.80/0.50	4 (34)	FK*CEE*RCD*REA*SCD +	0.845	0.616	SCD
Empirical 10-50-90 (0.499)	2/0.80/0.50	5 (23)	ARU*CEE*RCD*REA*SCD FK*RCD*REA*SCD + CEE*RCD*REA*SCD	0.817	0.658	RCD*SCD
Empirical 25-50-75 (0.501)	2/0.80/0.50	6 (37)	8 alternative models, e.g., FK*~ARU + FK*CEE*REA*SCD + CEE*RCD*REA*SCD	0.777– 0.791	0.596–0.622	6 alternative models, e.g., M1: FK*~ARU + CEE*REA*SCD
Empirical 25-50-75 (0.501)	2/0.85/0.50	5 (35)	CEE*RCD*REA*SCD + FK*ARU*CEE*REA*SCD	0.829	0.513	CEE*REA*SCD
Empirical 25-50-75 (0.501)	2/0.80/0.60	6 (37)	8 alternative models, e.g., FK*~ARU + FK*CEE*REA*SCD + CEE*RCD*REA*SCD	0.777– 0.791	0.596–0.622	6 alternative models, e.g., M1: FK*~ARU + CEE*REA*SCD
Empirical 25-50-75 (0.501)	3/0.80/0.50	3 (31)	FK*CEE*RCD*REA*SCD +	0.855	0.446	CEE*SCD
Empirical 25-50-75 (0.499)	2/0.80/0.50	6 (25)	ARU*CEE*RCD*REA*SCD 4 alternative models, e.g., ~ARU*CEE*REA + FK*RCD*REA*SCD + CEE*RCD*REA*SCD	0.795– 0.814	0.552–0.589	4 alternative models, e.g., M1: RCD*SCD + ~ARU*CEE*REA

Note. Crossover = membership assigned to cases lying exactly at the crossover. *n*/cons./PRI = frequency, consistency and PRI thresholds. Positive rows = truth-table rows coded as sufficient, with the number of cases in those rows in parentheses. Intermediate solutions use directional expectations of presence for every condition; Cons. and Cov. are the consistency and coverage of the minimised expression shown. Specifications that returned identical solutions are merged into one row. The consistency threshold applies to the coding of individual rows; the consistency of a minimised solution is a separate quantity computed for the whole expression, so values below the row threshold (0.777 to 0.791 in three specifications) are possible and identify weak, specification-sensitive solutions. Complete complex, intermediate and parsimonious solutions for every specification, with model identifiers, simplifying assumptions and, separately labelled, the consistency and coverage of the union of unminimised positive rows, are reported in Table S19.

The truth table for the absence of high attitudes contained no row reaching the consistency and PRI thresholds (six negative rows, 58 remainders and no contradictions), so no solution could be minimised. This reflects the low membership in the negated outcome. The absence of high attitudes is not equivalent to unfavourable attitudes, and the result does not show that low attitudes lack configurational structure. In sum, research self-efficacy was the only capability score with an adjusted association with attitudes in the regression models, whereas the exploratory configurational results depended on the calibration anchors and on the handling of cases at the crossover.

5. Discussion

This study examined how self-reported GenAI literacy and research self-efficacy relate to attitudes toward scientific research among Health Sciences undergraduates. Three bounded findings emerge. First, the three self-report composites were positively associated. Second, research self-efficacy retained an adjusted association with attitudes in the primary regression model and in every sensitivity model, whereas GenAI literacy did not once research self-efficacy was included. Third, the measurement evidence did not distinguish GenAI literacy from research self-efficacy, which limits any comparison between them. The configurational results are secondary and exploratory. The attenuation of the GenAI-literacy coefficient does not indicate that GenAI literacy is irrelevant to research disposition: its bivariate association with attitudes was moderate, and the formal indirect-effect estimate describes how the variance shared by two overlapping, contemporaneously measured scores is distributed, not a process unfolding over time.

5.1. Correlational, Multivariable and Configurational Results

The three analytical approaches answer different questions. Spearman correlations describe bivariate monotonic association, the regression model estimates the association of each score with attitudes while holding the others constant and fsQCA describes which combinations of calibrated conditions are consistently accompanied by high attitudes. They are complementary descriptions of the same self-report data and do not independently correct for self-report bias, selection, construct overlap or limited configurational diversity. Read together, they are consistent with a simple pattern: GenAI literacy is associated with attitudes, but the part of that association not shared with research self-efficacy is small in these data. The configurational analysis adds that, under the primary calibration (theoretical anchors with crossover memberships assigned to 0.501), functional knowledge and critical and ethical evaluation of GenAI were present in the configurations accompanying high attitudes, although that result changed with the calibration anchors and the handling of crossover cases. [Hou et al. \(2026\)](#) argue that the productive use of GenAI depends less on the frequency of use than on the critical competencies accompanying it; the present data are compatible with that premise but do not test it.

[Zhu and Yang \(2026\)](#) describe a model in which GenAI use relates to research competence through critical thinking, with research self-efficacy as a moderator. The present results concern attitudes rather than competence, were obtained via self-report in a single Health Sciences sample and did not estimate that mediation and moderation structure, so they are at most consistent with that model rather than a replication or extension of it.

5.2. The Blurred Boundary Between GenAI Literacy and Research Self-Efficacy

The overlap observed between GenAI literacy and research self-efficacy admits two readings that this study cannot separate. The heterotrait-monotrait value exceeded the conventional threshold, and parallel analysis favoured a single capability factor, which means that the two constructs were not clearly differentiated in this sample. A conceptual

explanation is available: in students who use generative tools to search for literature and write and understand methods, the perception of knowing how to use AI for research and the perception of being capable of doing research may have begun to converge into a single competence belief. Consistent with what Li et al. (2026) set out, describing a pathway in which GenAI literacy, self-efficacy and growth mindset converge to explain creative identity, GenAI would have been incorporated into the repertoire of resources with which students appraise their own capability, and from Bandura (1997)'s self-efficacy theory, tools that broaden mastery experiences end up being integrated into the judgement a person makes about what they can achieve. A measurement explanation is at least as plausible on the present evidence: items belonging to the two constructs share self-efficacy phrasing, both were answered in a single self-report administration, and the analysis operated on aggregated dimension scores, three conditions that may contribute to the observed association, in shares this design cannot estimate. Deciding between conceptual convergence and measurement contamination requires instruments designed to separate the constructs and administration procedures that break the common-method structure, neither of which was available here.

This finding introduces a caveat for future research on GenAI literacy. The proliferation of scales aimed at measuring generative competence, among them the one proposed by Xia et al. (2026) for teachers and researchers, risks capturing variance that actually belongs to general self-efficacy if it is not subjected to strict discriminant validity tests. In young populations with high exposure to GenAI, the two constructs require instruments capable of separating them empirically or else explicit treatment as facets of a higher-order capability construct. The asymmetry observed here, with a clear distinction from attitudes and none between the two capability dimensions, is a question that measurement work in this field will need to settle and not a demonstration that students' competence beliefs have already merged.

5.3. Research Self-Efficacy, Research Experience and Attitudes Toward Research

Once shared variance was taken into account, research self-efficacy was the capability score that retained an adjusted association with attitudes toward research, and the association was stable across the sensitivity models. The result is consistent with studies reporting that self-efficacy and attitudes are jointly associated with research intention (Pfundt & Peterson, 2024) and that self-efficacy is linked to research competence and attitudes in nursing students (Almarwani, 2025). Given the overlap between the two capability measures, the present data do not show that research self-efficacy matters more than GenAI literacy; they show that, in this sample, the self-efficacy score carries most of the association that the two scores share with attitudes. Whether raising research confidence would improve attitudes cannot be answered with this design and would require intervention or longitudinal evidence.

Prior research experience was associated with attitudes in the primary model ($b = 0.261$; $p = 0.026$), but not after an adjustment for age, academic cycle and programme ($p = 0.295$), and the corresponding subgroup difference did not survive family-wise correction; it is therefore treated as a tentative association. It would be consistent with evidence that formative research experiences accompany more favourable research attitudes and confidence (Gros-Navés et al., 2022; Pavlova et al., 2021; Falola et al., 2025), but the present data cannot establish the order among experience, confidence and attitudes. The subgroup result that did survive correction, higher GenAI literacy and research self-efficacy in semesters VII–VIII than in some earlier semesters, is likewise descriptive: the academic cycle is confounded by age, progression through the programme and research coursework, and the groups outside semesters VII–VIII were small; the contrast describes an association between cycle and the

scores and does not show that progressing through the programme raises GenAI literacy or research confidence.

5.4. Configurational Results Under Alternative Specifications

Under the primary calibration (theoretical anchors 2-3-4 with crossover memberships assigned to 0.501), functional knowledge and the critical and ethical evaluation of GenAI appeared in every configuration coded as sufficient for high attitudes and in both terms of the intermediate solution. This qualifies the regression result, in which the overall literacy score did not retain a statistically significant adjusted association: specific literacy dimensions co-occurred with high attitudes in the observed configurations. The finding is, however, the most specification-dependent in the study. No condition met the necessity threshold, one configuration contained more than half of the cases, the parsimonious analysis returned two equally minimal alternative models, reversing the crossover convention changed the intermediate solution to the presence of any GenAI-literacy dimension, and the empirical anchors brought research self-efficacy dimensions to the fore. The configurational evidence therefore does not identify stable recipes or distinct developmental pathways. In that critical and ethical evaluation co-occurred with, rather than stood in tension with, high attitudes, the pattern is compatible with the concerns about reliability and academic integrity raised by [Giray et al. \(2026\)](#) and [Athanassopoulos et al. \(2026\)](#), but it does not test them.

5.5. Differences by Sex

Before correction, female students reported higher GenAI literacy and more favourable attitudes than male students, with small effects ($r = 0.219$ and $r = 0.245$). These differences did not survive family-wise correction, and in the primary regression model, the female–male difference in attitudes was not statistically significant ($b = 0.283$; $p = 0.054$). The sample was predominantly female and concentrated in Nursing and Dentistry, so sex and programme composition could not be separated. These results therefore do not establish a sex difference and do not call for an explanation; whether the gender gap in GenAI adoption reported internationally ([Freeman, 2025](#)) extends to the self-reported critical use of GenAI would need to be examined in balanced samples.

5.6. Implications for Research Training

Because the design is observational and cross-sectional, the following are educational practices consistent with the rationale of the study, not interventions whose effectiveness this survey has established. Since the self-efficacy and GenAI-literacy scores overlapped substantially, programmes that wish to strengthen research dispositions could consider developing confidence in research tasks and the critical use of generative tools within the same formative sequence rather than as separate initiatives. In a research course, such practices might include contrasting AI-suggested literature with the original sources, detecting fabricated references and unsupported claims, checking citation accuracy, distinguishing assistance from authorship, disclosing the extent of AI involvement in a manuscript and rehearsing scientific communication without delegating the argument to the tool. Work on the institutional integration of AI capability into the curriculum, pedagogy and assessment offers a framework for organising such practices at the programme level ([Che, 2026a, 2026b, 2026c](#)). Whether these practices improve research attitudes and whether solid GenAI literacy can compensate for low research confidence would need to be evaluated in designs built for that purpose.

6. Limitations

Four sets of constraints bound the reading of these results. The first concerns the design and the sample. Measurement at a single point in time prevents any statement about the order in which the variables operate, and non-probabilistic convenience sampling restricts statistical generalisation to the reference population. These features do not affect external validity alone: with every construct measured simultaneously via self-report, the reported associations are also open to common-method variance and to social desirability, which the anonymity of responses attenuates without eliminating. The 91 participants came from a single private university and were concentrated in two degree programmes and in the female category, so the composition of the sample and the characteristics examined are partly confounded.

The second set concerns measurement. Item-level descriptive statistics, item-total correlations and reliability within each first-order dimension are reported as Supplementary Material, and reliability computed directly on the twelve items of each construct is high, but the internal structure was modelled on the nine dimension scores rather than on the 36 items, so the evidence does not establish the first-order dimensional structure or the factorial invariance of the EAIAAIC-ECS; a confirmatory model of the complete instrument would require a substantially larger sample. No pilot administration preceded fieldwork, and content-related evidence rests on the review of three judges. Parallel analysis favoured two factors rather than the three of the theoretical model, and the heterotrait–monotrait ratio between GenAI literacy and research self-efficacy reached 0.912. Both results point in the same direction: the two capability constructs were not empirically separable here, and every comparison between them, including the contrast between their adjusted regression coefficients and the indirect-effect model, inherits that limitation. The attitude composite adds a further constraint: its cognitive dimension loaded weakly (0.432) and with high uniqueness (0.630), so the common attitude factor is defined mainly by the affective and behavioural dimensions even though the observed score weights the three dimensions equally, and the affective dimension produced near-boundary uniqueness estimates. The three-factor solution was also unstable across bootstrap resamples.

The third set concerns the scope of the inferences. The indirect–effect model reported above is statistical: it decomposes covariance among variables measured simultaneously and cannot establish that GenAI literacy precedes research confidence, still less that it produces it. Its interpretation is further constrained by the incomplete separation between the two capability constructs, since an indirect effect estimated between measures that are not empirically distinct may reflect the internal structure of a single belief. Categories with fewer than three cases were not compared inferentially, categories of three or four cases (Obstetrics and other Health Sciences programmes) yielded imprecise estimates and the sensitivity model adjusting for age, academic cycle and degree programme, although it preserves the association of research self-efficacy with attitudes, estimates several programme coefficients on very few cases. The subgroup contrasts, including those by sex and by prior research experience, do not survive a family-wise correction, and the female–male coefficient in the primary regression model was not statistically significant; these contrasts require replication before being read as established differences.

The fourth set concerns the configurational analysis. Fifty-eight of the sixty-four logically possible configurations were logical remainders (42 without cases and 16 with a single case), and a single configuration gathered 52 of the 91 cases under the primary crossover convention, a degree of limited diversity that makes minimisation dependent on few observed patterns and many counterfactuals. Half of the cases (46 of 91) had at least one condition exactly at the crossover, and reversing the displacement of those memberships changed the truth table and the solutions. No condition reached the necessity threshold, the

parsimonious analysis returned alternative models that rest heavily on remainders and the minimised solutions changed under alternative calibration anchors. The configurational results are therefore exploratory and specification-dependent.

Addressing these constraints calls for larger and more diverse samples, item-level validation of the instrument in independent groups, measurement designs that separate perceived GenAI capability from research confidence and longitudinal or intervention studies capable of testing the direction of the relationships described here.

7. Conclusions

Among undergraduate Health Sciences students at one Peruvian university, self-reported GenAI literacy, research self-efficacy and attitudes toward scientific research were positively associated. In the primary regression model, and in each of the sensitivity models reported in Table S10, research self-efficacy retained an adjusted association with attitudes, whereas GenAI literacy, although associated with attitudes at the bivariate level, did not retain a statistically significant adjusted association once research self-efficacy was included.

GenAI literacy and research self-efficacy were not sufficiently distinguished by the present measurement evidence (HTMT = 0.912; a single capability factor in the solution favoured by parallel analysis). Whether this reflects a convergence of competence beliefs or the overlap of item content and common-method variance cannot be settled with these data, and it limits any statement about which of the two matters more. The bootstrapped indirect term, through research self-efficacy, is a statistical decomposition of this shared variance, not evidence of a mechanism.

The configurational analysis is secondary and exploratory. Under the primary calibration (theoretical anchors 2-3-4 with crossover memberships assigned to 0.501), functional knowledge and the critical and ethical evaluation of GenAI appeared in every configuration coded as sufficient for high attitudes, but the minimised solutions changed with the calibration anchors and with the handling of cases at the crossover, so they do not identify stable recipes or distinct pathways.

Larger and more diverse samples, item-level confirmatory validation of the instrument, measurement designs that separate perceived GenAI capability from research confidence and longitudinal or intervention studies would be needed to establish the direction of these relationships and to evaluate whether developing both capabilities jointly improves attitudes toward research.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/publications14040066/s1>, Supplementary File S1 (Tables S1–S23): the complete wording of the 36 items in Spanish and English; item-level descriptive statistics, item-total correlations and reliability; reliability computed from items and from dimension scores; parallel analysis; the two-factor and three-factor solutions with factor correlations and fit indices; the heterotrait–monotrait matrix; the Spearman correlation matrix with Holm-adjusted *p*-values; the primary regression model with diagnostics; the sensitivity models; the indirect–effect models; the family of subgroup contrasts and exploratory pairwise tests; calibration anchors; calibrated set descriptives; necessity analysis; the complete truth table; the complex, intermediate and parsimonious solutions with model identifiers; the full robustness grid; factor-solution stability diagnostics; analytical samples; crossover counts; and the truth table under the alternative crossover convention.

Author Contributions: Conceptualisation, C.R.G.D. and A.F.H.S.; methodology, C.R.G.D., A.F.H.S. and P.V.Z.; software, A.F.H.S.; validation, P.V.Z., J.A.T.C. and M.I.H.F.; formal analysis, A.F.H.S. and J.R.I.E.; investigation, C.R.G.D., P.V.Z. and J.A.T.C.; resources, J.R.I.E. and M.I.H.F.; data curation, A.F.H.S. and J.A.T.C.; writing-original draft preparation, C.R.G.D., P.V.Z. and A.F.H.S.; writing-review and editing, J.A.T.C., J.R.I.E. and M.I.H.F.; visualisation, A.F.H.S.; supervision, C.R.G.D. and M.I.H.F.;

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Institutional Review Board Statement: The study was conducted in accordance with the ethical principles for research involving human participants set out in the Declaration of Helsinki. It was not reviewed by an independent institutional review board or external ethics committee. The protocol GCES-UID-012-A received a certificate of ethical review issued in Lima on 11 January 2026 by the Research Group on Education and Health Sciences (GCES) of the Faculty of Health Sciences, Universidad Interamericana para el Desarrollo, which classified the study as minimal-risk educational research subject to validation by the competent institutional authority.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study. Consent was implemented within the survey itself as a branched question preceding the instrument, in accordance with the Declaration of Helsinki: participants were informed of the purpose of the study, the voluntary nature of their collaboration, the guarantee of anonymity and confidentiality and the exclusively academic use of the data, and only those who explicitly accepted were able to continue to the questionnaire.

Data Availability Statement: The analysis scripts, statistical models and source code used to reproduce the reported results are available from the corresponding author upon justified request. The item-level dataset, stripped of identifying information, has not been made public; however, access may also be requested from the corresponding author, subject to applicable ethical and confidentiality requirements. No personally identifiable information was collected or retained.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Definition
GenAI	Generative artificial intelligence
AI	Artificial intelligence
AVE	Average variance extracted
CR	Composite reliability
HTMT	Heterotrait–monotrait ratio
KMO	Kaiser-Meyer-Olkin measure
EFA	Exploratory factor analysis
fsQCA	Fuzzy-set qualitative comparative analysis
PRI	Proportional reduction in inconsistency
VIF	Variance inflation factor
HC3	Heteroscedasticity-consistent covariance estimator, type 3
EAIAAIC-ECS	Scale of Generative AI Literacy, Research Self-Efficacy and Attitudes Toward Scientific Research in Health Sciences Students
FK	Functional knowledge of generative AI
ARU	Academic-research use of generative AI
CEE	Critical and ethical evaluation of generative AI
RCD	Research conceptualisation and design
REA	Research execution and analysis

SCD	Scientific communication and dissemination
ATSR	Attitudes toward scientific research
GAIL	Generative AI literacy (overall score)
RSE	Research self-efficacy

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