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Message from the Editor-in-Chief

Editor's Message

It is our pleasure to present Volume 25, Issue 4 (October 2026) of The Turkish Online Journal of Educational Technology (TOJET). This issue brings together thirteen scholarly contributions addressing artificial intelligence, digital competence, educational innovation, psychological well-being, and the evolving relationship between technology and human learning. Collectively, these studies reflect the interdisciplinary nature of educational technology and emphasize the importance of integrating technological advancement with pedagogical effectiveness and human-centered educational practices.

The article *The Impact of the Digital Environment on Human Psychology* by Adilkhanov Aydin Ziyadkhan oglu examines the psychological implications of digital environments and their influence on human experiences and behavior, drawing attention to the importance of understanding the relationship between technological engagement and psychological well-being.

In *From Technical Literacy to AI-Integrated Pedagogy: A Scoping Review of Digital Competence Frameworks for Higher Education (2000–2026)*, Muhammad Tayyab Ilyas, Cristina Mercader, and Alejandra Bosco explore the evolution of digital competence frameworks in higher education, highlighting the transition from technical literacy toward AI-integrated pedagogical approaches and the changing competencies required in contemporary educational environments.

The article *Beyond the Myths: Exploring Pre-Service Teachers' Beliefs About Giftedness Across Gender and Educational Fields* by Gülşah Batdal Karaduman and Handan Ürek investigates pre-service teachers' beliefs about giftedness across gender and educational disciplines, contributing to a broader understanding of teacher perceptions and their relevance to inclusive educational practices.

In *Role and Applications of Artificial Intelligence in Higher Education*, Jabrayilova Susan Eyvaz gizi discusses the expanding role of artificial intelligence in higher education and its potential applications in teaching, learning, and institutional practices, reflecting the growing significance of AI in educational transformation.

The study *The Influence of Textbook Policy on Teaching Quality in Higher Education in Azerbaijan* by Kazimli Farida Elchin gizi examines the relationship between textbook policies and teaching quality, emphasizing the role of educational resources and policy decisions in shaping higher education practices in Azerbaijan.

In *Psychological Resilience and Post-Traumatic Growth in Young Adults: A Multidimensional Analysis of Cognitive, Emotional, and Social Recovery Mechanisms*, Mehdiyeva Kubra Nazim explores psychological resilience and post-traumatic growth through cognitive, emotional, and social dimensions, offering perspectives on recovery mechanisms and young adults' psychological development.

The article *AI-Enabled Corporate Learning and Human Capital Development: An Educational Technology-Economic Value Framework from Azerbaijan* by Narmin Vuqar Isayeva examines the integration of artificial intelligence into corporate learning and human capital development, focusing on its implications for educational technology and economic value creation.

In *Exploring the Relationship Between Digital Literacy and Students' Preferences for E-Learning Platforms*, Sasmita Pagal and Swayam Prava Mishra investigate the relationship between students' digital literacy and their preferences for e-learning platforms, highlighting the relevance of digital competencies to technology-supported learning experiences.

The study *The Impact of Ensuring Psychological Well-Being in the Learning Environment on Educational Quality: A Systematic Approach* by Simnarə Heydərova addresses the relationship between psychological well-being and educational quality, emphasizing the importance of supportive learning environments in promoting educational effectiveness.

In *From Principles to Practice: A Systematic Review of Generative AI-Responsive Assessment Interventions in Higher Education*, Zafer Yuca and Fahme Dabaj review assessment interventions designed in response to generative artificial intelligence, examining emerging approaches to assessment and their implications for higher education.

The article *Measuring Cognitive Engagement in AI-Supported Writing: Introducing the Revision Responsiveness Index (RRI) as a Process-Based Assessment Model* by Traci C. Eshelman introduces the Revision Responsiveness Index as a process-based assessment model for examining cognitive engagement in AI-supported writing, contributing to ongoing discussions about evaluating learning processes in technology-enhanced education.

In *Japanese University Students' Pre-Course Perceptions of American Society, Group Formation, and Discrimination: Implications for Needs Analysis in Intercultural Teaching*, Yuki Amaki explores Japanese university students' perceptions of American society, group formation, and discrimination, highlighting their relevance to needs analysis and intercultural teaching practices.

Finally, *The Use of Modern Teaching Technologies in Pedagogical Staff Training as a Key Factor in the Quality Indicators of University Instructors* by Zeynalli Aysel Shahin examines the role of modern teaching technologies in academic staff development and their relationship to teaching quality in higher education.

Concluding Remarks

The contributions presented in this issue demonstrate the growing influence of artificial intelligence and digital technologies on contemporary education. They address the development of digital competencies, innovative teaching and assessment approaches, academic staff training, and the psychological and social dimensions of learning. Together, these studies emphasize that educational transformation requires more than technological adoption; it also depends on pedagogical competence, ethical responsibility, learner engagement, and supportive educational environments.

The findings and perspectives represented in this issue are also relevant to higher education quality assurance and accreditation. The integration of educational technologies into teaching practices, assessment strategies, institutional development, and continuous improvement processes remains an important consideration for universities seeking to enhance educational effectiveness and sustainability.

On behalf of the editorial team, I would like to express my sincere appreciation to all authors for their scholarly contributions, to our reviewers for their valuable expertise, and to our international readership for its continued interest in TOJET. We hope that this issue will stimulate further research, encourage international academic collaboration, and contribute to the advancement of educational technology and quality in higher education.

October 1, 2026

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AI-Enabled Corporate Learning and Human Capital Development: An Educational Technology-Economic Value Framework from Azerbaijan

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ABSTRACT

Digital learning systems can be treated as investments in human capital only when educational outcomes can be distinguished from business performance and measured over time. This article develops a framework linking artificial intelligence (AI)-supported corporate learning, digital skill acquisition, workforce adaptability, and economic value creation. A document-based case analysis uses publicly reported information from Azercell Telecom LLC to illustrate the institutional context and data limitations. The case shows an 18.52% increase in permanent employment between 2021 and 2023, a rise in the professional staff share from 55.18% to 61.42%, and an increase in reported employee engagement from 77 to 84 between 2022 and 2023. These trends are descriptive; they do not establish that AI-supported learning produced the changes. The proposed research model specifies learning participation, skill transfer, verified AI use, and subsequent productivity as distinct measurement layers. It includes an editable interaction equation and a prospective difference-in-differences evaluation design for a training pilot. The article contributes a practical bridge between educational technology evaluation and human-capital economics while making explicit the ethical requirements for employee learning analytics.

Keywords: educational technology; artificial intelligence; corporate learning; human capital; digital competencies; learning analytics; economic performance

INTRODUCTION

Artificial intelligence has intensified a long-standing question in human-capital economics: how does an organization transform expenditure on learning into a durable productive capability? In digital enterprises, formal qualifications alone do not describe whether employees can interpret data, use intelligent tools, respond to changing technologies, or transfer newly acquired skills to daily tasks. This makes workplace education more than an auxiliary human-resource activity. It is a potential mechanism through which digital investment becomes economically meaningful.

Yet a recurring weakness in studies of AI and human capital is the tendency to equate access to technological tools with learning, learning with productivity, and coincident company growth with a causal training effect. These are different processes. A learning management system records participation but not necessarily mastery; an AI chatbot can offer support without improving transfer; company revenue may increase while employee competencies remain unchanged. A credible educational-technology study must separate these levels of analysis.

The article asks: (1) through which mechanisms can AI-supported corporate learning contribute to measurable human-capital development? (2) What educational and economic indicators are required to evaluate that contribution? (3) What can be established from public company reporting, and what requires a prospective intervention? The purpose is to develop an integrated but empirically cautious model, illustrated through Azerbaijani telecommunications-sector evidence. The principal contribution is a testable architecture rather than a claim that an unavailable training experiment has already been conducted.

LITERATURE REVIEW AND THEORETICAL ARGUMENT

Educational technology as a human-capital investment

Human-capital theory regards education and training as investments that can expand capabilities and raise future productive potential. Organizational value, however, depends on the match between acquired competencies and the tasks employees actually perform. In a rapidly changing digital workplace, that match must be reviewed repeatedly. A useful distinction is between learning inputs (expenditure, access, instructional time), educational processes (feedback, practice, completion), learning outcomes (demonstrated competence), transfer outcomes (application at work), and economic consequences (quality, time, innovation, or output).

This sequence prevents a purely financial interpretation of workplace education. Cost reductions cannot substitute for evidence that learning occurred. Conversely, immediate accounting returns may underestimate the value of capacities such as adaptability and innovation readiness. The relevant outcome horizon may be longer than the training programme itself, especially where new technical skills enable subsequent changes in work design.

AI-enabled personalisation and the limits of learning analytics

AI-based recommendations can in principle tailor content to prior knowledge, skill gaps, task requirements, and preferred pacing. Conversational feedback may increase opportunities for practice, while learning analytics can signal disengagement or difficulties early. Such functions are educationally important only when they are aligned with explicit objectives and verified assessments. A personalised recommendation is not evidence of effective instruction; engagement indicators must not be mistaken for competency acquisition.

Generative AI research identifies productivity effects for certain tasks (Noy & Zhang, 2023; Brynjolfsson et al., 2025), but translating those results to corporate education requires separate tests of learning durability, transfer and fairness. The use of employee data for adaptive learning also raises risks of opaque inferences, biased skill labels, and inappropriate use of educational records in personnel decisions (Budhwar et al., 2023; Dima et al., 2024). Responsible educational technology should allow human review and meaningful learner control.

The economic mechanism

An AI-supported learning ecosystem can create value through a chain of linked but non-identical mechanisms: better diagnosis of skill gaps, better targeted instruction, improvement in demonstrated competence, workplace transfer, and finally operational impact. Complementarity matters because the same AI tool may have different effects depending on baseline human capital, managerial support, and job design. The resulting economic hypothesis is not that AI replaces human expertise, but that verified AI use and acquired expertise may jointly contribute to work performance (Babina et al., 2024; Rammer et al., 2022).

METHODOLOGY

Research design and evidence boundary

The study combines a conceptual synthesis with documentary case analysis. The empirical illustration is based on the Azercell Telecom LLC audited financial statements for 2021-2022 and Sustainability Report 2023, as identified in the source manuscript. Publicly reported figures concerning employment structure, engagement, and training infrastructure are treated as descriptive company-level evidence. No individual-level training records, pre/post skill tests, AI-use logs, counterfactual groups, or measured causal education outcomes are available in the source material. Accordingly, no regression coefficients or statistical significance tests are presented as observed findings.

Table 1. Distinct levels of evaluation in AI-supported workplace learning

Analytical layer	Example indicator	Interpretation
Learning access	Enrolment and completion	Participation, not mastery
Learning outcome	Pre/post competency assessment	Observed skill gain
Workplace transfer	Verified task application	Behavioral change
AI exposure	Logged educational tool use	Intensity and timing of AI support
Economic outcome	Quality-adjusted output / task time	Potential value after controls

Source: author-developed analytical framework

Measurement model

For employee or team i at time t , a digital learning human-capital index (DL-HCI) may aggregate independently validated dimensions, such as digital literacy, task-relevant AI literacy, problem solving and verified application. The weights should be justified through a documented procedure and examined for sensitivity; the index itself is not an AI algorithm.

$$DLHCI_{it} = \sum_{j=1}^J w_j z_{jit}; \sum_{j=1}^J w_j = 1 \quad (1)$$

Here z represents normalised skill indicators and w the nonnegative weights. Normalisation should rely on a fixed baseline or reference distribution to avoid misleading comparisons over time. A basic measure of learning gain can be defined as the difference between a post-training and pre-training score.

$$LearningGain_i = Score_{post,i} - Score_{pre,i} \quad (2)$$

To express the complementarity hypothesis, a future employee-, team- or department-level panel can include validated human capital, verified use of AI-supported learning, their interaction, time-varying controls, and unit and period effects.

$$Y_{it} = \beta_0 + \beta_1 HC_{it} + \beta_2 AI_{it} + \beta_3 (HC_{it} \times AI_{it}) + \gamma Z_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

Y denotes a pre-specified economic or work-quality outcome; HC indicates measured competencies; AI represents substantiated instructional use; Z captures confounders. β_3 is an association parameter unless stronger identification assumptions are met. Because the public reports do not contain the required individual-level series, Equation (3) is a prospective estimation plan, not an empirical result.

Pilot impact-evaluation design

A feasible institutional pilot would compare a group offered AI-assisted adaptive modules with a matched or randomly assigned group receiving the standard learning programme. Both groups should complete equivalent pre- and post-tests; workplace transfer should be assessed at a delayed follow-up. Where the design permits, the difference-in-differences estimator is:

$$DID = (Y_{treated,post} - Y_{treated,pre}) - (Y_{comparison,post} - Y_{comparison,pre}) \quad (4)$$

Random allocation is preferable where practical. In nonrandom designs the parallel-trends assumption requires investigation. The study must predefine educational outcomes, report attrition, and record compliance and access differences. Economic effects should be interpreted only after training transfer and the timing of relevant operational outcomes have been established.

DOCUMENTARY CASE FINDINGS

Azercell's published company reports offer a useful contextual illustration because they describe both an expanding professional workforce and digital HR initiatives. They do not, however, report the employee-level educational measures required to attribute those outcomes to any AI learning intervention. The original case document reports the following changes.

Table 2. Selected documented developments at Azercell

Indicator	Earlier value	Later value	Descriptive change
Permanent employment	2021 baseline	2023 value	+18.52%
Professional-category share	55.18% (2021)	61.42% (2023)	+6.24 percentage points
Employee engagement	77 (2022)	84 (2023)	+7 points
Customer base	2021 baseline	2023 value	+7.89%
Revenue	2021 baseline	2022 value	+8.07%
Operating profit	2021 baseline	2022 value	+14.11%

Source: source manuscript based on Azercell audited financial statements and Sustainability Report 2023; growth values reproduced from source analysis

The professional-category increase can be relevant to learning-system design: it suggests that a larger portion of the organisation's workforce occupies roles for which specialised knowledge and continual skill updating are potentially important. It cannot demonstrate that workers obtained those skills through AI tools. Likewise, rising employee engagement may coexist with investments in learning or better managerial practices, but the reporting does not isolate their contribution.

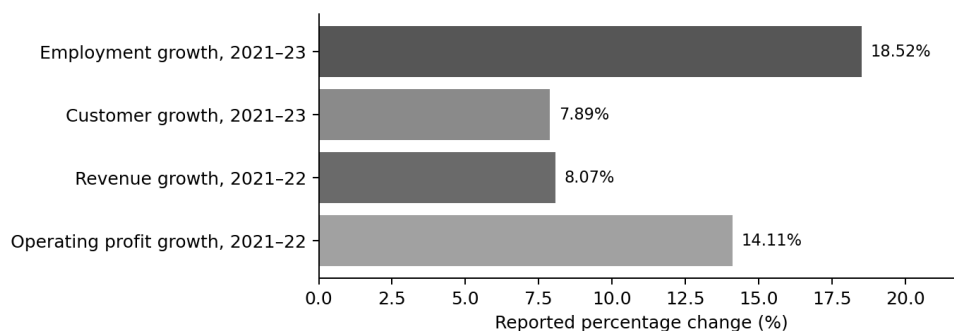


Figure 1. Descriptive trends reported for different periods; the figures must not be interpreted as treatment effects. Source: source manuscript and referenced Azercell reports.

The existing corporate evidence includes employee development initiatives, Azercell Academy, internal internship opportunities, professional development assessments, and digital HR infrastructure, including SAP SuccessFactors. These initiatives provide a plausible organisational setting for research on digital learning. A credible study of AI-enabled instruction nevertheless needs verified implementation dates, detailed instructional functions, programme participants, and learning results. Without those records, the case can support institutional plausibility but not measured educational effectiveness.

INTEGRATED EDUCATIONAL TECHNOLOGY-ECONOMIC VALUE FRAMEWORK

The framework below positions pedagogical design ahead of economic attribution. A diagnostic assessment identifies skill gaps and relevant job tasks. A governed educational AI layer may recommend instructional content and structured feedback. Learning outcomes are verified through independent measures, then workplace transfer is monitored through concrete task evidence. Only after these stages should economic indicators be used to assess potential return on investment.

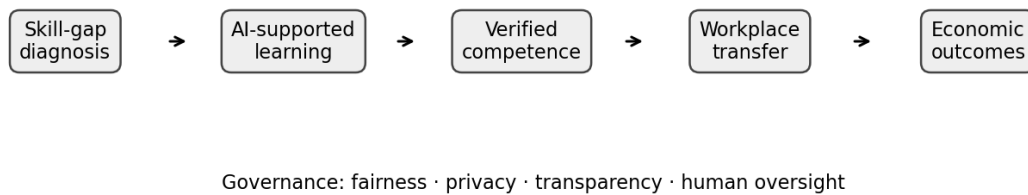


Figure 2. Proposed sequential pathway from AI-supported learning to economic value (conceptual, not an observed causal relationship). Source: author-developed framework.

Table 3. Proposed evidence requirements for enterprise implementation

Stage	Educational evidence required	Economic or governance check
Diagnosis	Competency map and baseline tests	Relevance to task demand
Instruction	Content validity and exposure logs	Access and cost
Assessment	Comparable pre/post skill test	Fairness across employee groups
Transfer	Observed application after 4-12 weeks	Quality and time measures
Evaluation	Comparison group and follow-up	Net benefit and uncertainty

Source: author-developed evaluation protocol

Interpreting investment returns

Simple benefit-cost analysis is valuable for decision making but should not erase attribution uncertainty. For a pre-specified observation period, a transparent accounting measure can be written as follows:

$$ROI_{learning} = [(AttributedBenefit - ProgrammeCost) / ProgrammeCost] \times 100 \quad (5)$$

“Attributed benefit” is not identical to the company’s total sales increase; it requires an explicit counterfactual, documented valuation rules and sensitivity tests. Programme costs should include licences, instructional design, employee learning time, support, assessment and governance. A defensible report should present learning achievement and equity outcomes beside financial returns, avoiding the claim that profitability alone measures educational success.

DISCUSSION

The resulting synthesis links two literatures frequently kept apart. Educational technology research asks whether a learning intervention produces appropriate knowledge or skill gains; human-capital economics asks whether developed capabilities contribute to economic performance. A complete research design must connect these questions without assuming the second follows automatically from the first. Measured competence is an intermediate outcome, while productivity is a distal outcome affected by organizational conditions and market dynamics.

For Azerbaijan, this perspective has practical significance for universities, corporate academies and continuing professional development providers. Universities can collaborate with employers on skills taxonomies and

competency-based modules, whereas employers can provide aggregated evidence on changes in task requirements. Joint design would allow educational programmes to respond to economic needs while retaining independent standards of learner assessment. AI systems should support, not determine, career opportunities and performance judgments.

There are also constraints. Algorithmic recommendations may reproduce historical inequalities if training data reflect unequal access to promotions or challenging assignments. Employee monitoring can undermine trust if learning logs are repurposed for disciplinary surveillance. Any pilot should therefore establish purpose limitation, data minimisation, opt-out and appeal processes where applicable, as well as routine review by educators and employee representatives. These are operational prerequisites rather than peripheral ethical declarations.

The case evidence illustrates why methodological restraint matters. Public reports establish business and workforce changes, but provide no evidence of the counterfactual educational outcomes that a causal conclusion needs. The proposed equations, design and implementation table should be read as a transparent research agenda that can be evaluated once suitable data become available, not as results of an intervention already completed.

CONCLUSION

AI-supported corporate learning is a promising link between educational technology and the economics of human-capital development, but its value must be demonstrated stage by stage. This article differentiates access, verified learning, workplace transfer and business performance; proposes measures suitable for a future panel or controlled pilot; and illustrates evidence boundaries using Azercell's public reports. The observed increases in workforce scale, professional composition and engagement do not demonstrate that AI education caused the changes. The core practical implication is that firms should evaluate AI-enabled learning first as an educational intervention and only subsequently as an economic investment. This approach supports more reproducible scholarship, better training decisions and fairer governance of workplace learning technologies.

DECLARATIONS

Ethics: This article uses publicly available aggregate secondary data and proposes, but does not conduct, an employee intervention. Data availability: Corporate documents cited in the source manuscript; no new employee-level dataset was collected. Competing interests: None declared in the supplied source manuscript.

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Beyond the Myths: Exploring Pre-Service Teachers' Beliefs About Giftedness Across Gender and Educational Fields

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ABSTRACT

This study aims to identify myths held by pre-service teachers regarding giftedness, considering their gender and educational field. We administered a survey to 235 third-year pre-service teachers from five educational fields. Data were collected using an eight-item test reflecting common myths about giftedness identified in the literature. Participants indicated agreement or disagreement with each item and explained their responses. Descriptive analyses revealed general trends for each item, and Chi-square tests assessed the influence of gender and educational field on responses. Results showed that approximately half of the participants endorsed myths related to the first item, while about one third held myths concerning the second, sixth, and seventh items. In contrast, most participants demonstrated scientifically accurate understandings for the fourth and fifth items. Gender was not a significant factor for any item except the seventh, and educational field did not significantly affect responses to any item. Overall, pre-service teachers exhibited similar beliefs about giftedness. Incorporating real-life case studies into faculty courses may help replace these myths with evidence-based understandings.

Keywords: *Gifted students, giftedness, pre-service teachers, myths.*

1. INTRODUCTION

1.1 Conceptual Framework and the Nature of Giftedness

The construct of giftedness and human intelligence remains both central and contentious within special education, developmental psychology, and educational policy (Callahan et al., 2018). Recent scholarship frames giftedness as a dynamic, asynchronous, and multidimensional phenomenon, rather than a fixed, singular IQ score. This perspective emphasizes the interplay of high domain-specific or general intellectual capability, creative productivity, task commitment, and supportive environmental factors (Cross & Coleman, 2014; Renzulli, 1977; Winner, 1996). Although empirical research has established the domain-specific, heterogeneous, and developmental characteristics of high ability (Gardner, 1983; Reis & Renzulli, 2009), both popular and professional perceptions remain influenced by persistent fallacies, folklore, and dogmas (Clark, 1997; Treffinger, 1982). Tannenbaum (1983) described societal attitudes toward intellectual precocity as a 'tradition of ambivalence,' characterized by ongoing tension between public admiration for high achievement and egalitarian suspicion of intellectual difference.

Within educational contexts, a 'myth' refers to an unsubstantiated belief, dogma, or overgeneralization concerning the nature, identification, social-emotional development, or educational needs of high-ability learners (Kaplan, 2009; Treffinger, 1982). Kaplan (2009) notes that myths persist because they offer plausible, simplified explanations for complex educational issues or seem to justify ambiguous instructional practices. Such misconceptions are perpetuated by popular media, personal educational experiences, and lay theories of intelligence (Baccassino & Pinnelli, 2022; Sak, 2011). When left unchallenged, these myths become embedded in educators' social representations, thereby restricting the learning opportunities available to gifted students (Pérez et al., 2020; Tavani et al., 2014).

1.2 Taxonomy of Prevalent Misconceptions in Gifted Education

International literature in gifted education has categorized common myths into several distinct clusters:

1. Entity and Genetic Determinism Myths (The 'Born-Gifted' Fallacy): This misconception posits that individuals are born gifted and that high ability is an immutable, fixed trait that cannot be developed later in life

through effort, instruction, or environmental enrichment (Cross, 2002; Sak, 2011). This entity view stands in opposition to growth mindset frameworks (Dweck, 2016; Sheffield, 2017) and neuroplasticity research, which emphasize the dynamic interaction between biological potential and environmental stimulation (Clark, 1997).

2. Social-Emotional Maladjustment and 'Mad Genius' Myths (The Disharmony Hypothesis): Originating from clinical case studies, this myth asserts a mandatory connection between high intellect and psychological distress, social awkwardness, anxiety, or psychopathology (Cross, 2002; Peterson, 2009). While profoundly gifted individuals or those in unsupportive environments may experience heightened sensitivity or social isolation (Columbus Group, 1991; Silverman, 2002), extensive epidemiological research demonstrates that gifted children as a group display social-emotional adjustment equivalent or superior to their non-gifted peers (Bain & Bell, 2004; Frances et al., 2015; Neihart, 1999).

3. Behavioral and Physical Stereotypes: Common lay perceptions associate giftedness with specific physical or behavioral markers, such as wearing thick glasses, having larger heads, or exhibiting constant hyperactivity, restlessness, and sharp-tongued verbal behaviors (Neumeister et al., 2007; Treffert, 2013). These superficial stereotypes distort teacher observations and lead to misdiagnoses or missed identifications.

4. The 'Self-Sufficiency' Myth (The 'Sink or Swim' Fallacy): This widespread fallacy asserts that truly gifted students possess sufficient autonomy and cognitive power to succeed in any educational setting without specialized support, differentiation, or extra instruction (Baccassino & Pinnelli, 2022; Clark, 1997; NAGC, 2008). In reality, unchallenging learning environments lead to chronic boredom, underachievement, poor study habits, and school dropout (Feldhusen & Wyman, 1980; Marland, 1972; Whitmore, 1980).

5. The Omniscience and Homogeneity Myth (Global Giftedness): This myth assumes that gifted students form a uniform group possessing exceptional talent across all academic subject areas (Bain et al., 2006; Reis & Renzulli, 2009). Modern research decisively falsifies this 'omniscient' view, confirming that cognitive profiles are asynchronous and domain-specific (Benbow & Minor, 1990; Winner, 1996), and that twice-exceptional learners combine high ability with specific learning disabilities (Baum et al., 2021; Trail, 2021).

Taken together, the literature indicates that misconceptions about giftedness extend beyond isolated stereotypes and reflect broader assumptions concerning the origins of giftedness, psychological adjustment, social functioning, achievement, educational needs, and the heterogeneity of gifted learners. Table 1 synthesizes the major myths most relevant to the present investigation and contrasts them with corresponding research-based understandings. This synthesis also provides the conceptual basis for the specific misconceptions examined in the present study.

Table 1. Major Myths About Giftedness and Corresponding Research-Based Understandings

Myth domain	Common misconception	Research-based understanding	Selected sources
Fixed and innate giftedness	Giftedness is determined at birth and represents a fixed characteristic that cannot meaningfully develop through education, effort, or environmental opportunities.	Contemporary conceptions regard giftedness as developmental and multidimensional rather than as an immutable entity. Although individual potential has biological foundations, the expression and development of high ability are influenced by educational opportunities, environmental conditions, motivation, and sustained engagement.	Clark (1997); Cross (2002); Cross and Coleman (2014); Sak (2011)
Psychological maladjustment and mental-health vulnerability	Gifted individuals are inherently more psychologically troubled and are especially prone to depression, anxiety, or other forms of psychopathology.	Giftedness itself does not imply psychological maladjustment. Research comparing gifted and nongifted populations does not support a generalized assumption of greater psychopathology or depression among gifted learners. Social and emotional outcomes vary according to individual characteristics and environmental circumstances.	Frances et al. (2015); Martin et al. (2010); Neihart (1999)

Myth domain	Common misconception	Research-based understanding	Selected sources
Social isolation and poor peer relationships	Gifted students are socially inept, have difficulty forming friendships, prefer isolation, and are poorly adjusted among same-age peers.	Gifted students are not inherently deficient in social competence or friendship formation. Research indicates that many gifted learners demonstrate healthy peer relationships and social functioning, although the availability of intellectual peers and the quality of the educational environment may influence their social experiences.	Bain and Bell (2004); Reis and Renzulli (2004)
Perfectionism as an inevitable pathology	Gifted students are invariably perfectionistic, and their perfectionism necessarily produces emotional distress or maladjustment.	Perfectionism among gifted learners should not be treated as uniformly maladaptive. Perfectionistic tendencies may have both adaptive and maladaptive manifestations; high standards can contribute to persistence and accomplishment rather than necessarily producing psychological dysfunction.	Reis and Renzulli (2004)
Self-sufficiency and lack of need for specialized education	Gifted students are sufficiently capable to succeed in any educational environment and therefore do not require differentiation, enrichment, acceleration, or specialized educational support.	High ability does not eliminate the need for appropriately challenging instruction. A lack of differentiated educational opportunities may contribute to boredom, disengagement, weak study habits, and underachievement. Gifted learners therefore require educational experiences responsive to their readiness and learning needs.	Fiedler et al. (1993); National Association for Gifted Children [NAGC] (2008); Whitmore (1980)
Giftedness as synonymous with consistently high achievement	Gifted students are always high achievers; therefore, poor grades or low classroom performance indicate that a student cannot be gifted.	Giftedness and achievement are related but distinct constructs. Gifted learners may underachieve, and discrepancies between ability and performance may occur in response to motivational, instructional, contextual, or personal factors. Consequently, current academic performance alone is insufficient for determining giftedness.	Reis and McCoach (2000); Whitmore (1980)
Global giftedness and homogeneous ability	A gifted student should demonstrate exceptional ability across virtually all academic domains and should therefore perform at a similarly high level in every area.	Gifted learners constitute a heterogeneous population. High ability may be domain-specific, and cognitive and academic profiles can be markedly uneven. Exceptional ability in one domain does not imply equivalent performance in all other domains.	Benbow and Minor (1990); Reis and Renzulli (2009); Winner (1996)
Giftedness and disability as mutually exclusive	A learner cannot simultaneously be gifted and have a learning disability, ADHD, ASD, or another disability.	Giftedness and disability can coexist. Twice-exceptional learners may display advanced ability together with specific disabilities, and one characteristic may mask the other, complicating identification. Educational provision must therefore address both advanced potential and areas requiring support.	Baum et al. (2021); Trail (2021)

Note. The table synthesizes recurrent misconceptions and corresponding research-based perspectives represented in the literature used in the present study and in the supplementary myth-research materials reviewed for this manuscript. “Research-based understanding” refers to the broader empirical position represented by the cited sources rather than to an assertion that every gifted learner displays the same developmental, psychological, or educational profile.

1.3 Pre-Service Teachers' Beliefs, Identification Biases, and Demographic Variables

Teachers serve as the primary gatekeepers of talent development, responsible for identifying gifted students and implementing classroom adaptations (Biber et al., 2021; Cuban, 2002). The implicit beliefs held by prospective teachers directly influence their instructional decisions, expectations, and nomination accuracy (Pajares, 1992). When pre-service teachers endorse myths, they exhibit systematic identification biases—such as nominating only high-achieving, compliant, or male students while overlooking underachieving, culturally diverse, or twice-exceptional learners (Biber et al., 2021; McBee, 2006; Siegle & Powell, 2004).

Despite the critical role of teachers, undergraduate teacher preparation programs in Turkey and internationally provide minimal coursework in gifted education (Hafenstein et al., 2021). In Turkey, teacher education curricula typically include only a single general special education course covering diverse populations, leaving prospective teachers reliant on popular culture and societal dogmas (Kaya et al., 2023). Research shows that teacher self-efficacy and positive attitudes toward gifted programming are strongly linked to formal training (Vatansever Bayraktar et al., 2019). In the absence of specialized preparation, pre-service teachers across different discipline areas remain susceptible to widespread myths.

Demographic variables such as gender and academic discipline (educational field) have been examined as potential moderators of educator beliefs. While gender biases favoring male students frequently emerge in teacher nomination studies (Biber et al., 2021; Gagné, 1993), empirical evidence regarding whether male and female prospective teachers differ in their endorsement of giftedness myths remains mixed. Similarly, while candidates in distinct fields (e.g., Computer Education, Classroom Teaching, English Language Teaching, Music Teaching, Science Teaching) encounter varying subject-matter pedagogies, the baseline lack of formal gifted education training across departments may yield similar susceptibility to societal misconceptions.

1.4 Purpose and Research Questions of the Present Study

To address these gaps in the literature, the present survey research investigated the prevalence of myths about giftedness among third-year pre-service teachers in Turkey and examined whether these beliefs differ significantly across gender and educational fields. Specifically, this study addressed three main research questions:

1. What is the overall percentage distribution of myths versus scientific constructions among pre-service teachers across individual survey items?
2. Do pre-service teachers' endorsements of giftedness myths differ significantly as a function of their gender?
3. Do pre-service teachers' endorsements of giftedness myths differ significantly across their educational fields of study?

2. METHODOLOGY

2.1 Research Design

This investigation utilized a descriptive survey research design. Survey research collects data from a sample of individuals through their responses to structured questions, enabling the quantitative and qualitative evaluation of beliefs, attitudes, and trends within a target population (Check & Schutt, 2012; Ponto, 2015).

2.2 Participants and Sampling Framework

The study group comprised 235 third-year pre-service teachers enrolled in the faculty of education at a state university in western Turkey. Participants were selected across five distinct educational fields using stratified random sampling: Computer Education and Instructional Technologies (CEIT; $n = 27$, 11.5%), Classroom Teaching (CT; $n = 69$, 29.4%), English Language Teaching (ELT; $n = 45$, 19.1%), Music Teaching (MT; $n = 44$, 18.7%), and Science Teaching (ST; $n = 50$, 21.3%). The sample included 86 male students (36.6%) and 149 female students (63.4%), with ages ranging from 21 to 24 years ($M_{age} = 22.1$). Table 2 details the demographic distribution across fields and gender.

Table 2. Distribution of Participants by Educational Field and Gender

Educational Field	Male n (%)	Female n (%)	Total n (%)
CEIT	19 (8.1%)	8 (3.4%)	27 (11.5%)
CT	13 (5.5%)	56 (23.8%)	69 (29.4%)
ELT	16 (6.8%)	29 (12.3%)	45 (19.1%)
MT	25 (10.6%)	19 (8.1%)	44 (18.7%)

Educational Field	Male n (%)	Female n (%)	Total n (%)
ST	13 (5.5%)	37 (15.7%)	50 (21.3%)
Total	86 (36.6%)	149 (63.4%)	235 (100.0%)

The study group was formed via stratified sampling which is one of the probability sampling techniques. Stratified sampling is used when the population is divided into sub-groups and a random sample is taken from each sub-group (Taherdoost, 2016). In this research, the population consisted of pre-service teachers who study at different fields. Hence, the study group involved sub-groups. So, individuals who were selected randomly from those sub-groups comprised the study group.

2.3 Data Collection Instrument and Procedure

Data were gathered using an 8-item survey test reflecting common societal myths about gifted learners established in the literature. For each item, participants indicated whether they agreed or disagreed with the statement and provided qualitative open-ended explanations for their choices. This open-ended justification allowed the researchers to verify whether an agreement/disagreement reflected a myth or a scientific construction. Table 3 presents the survey items and their theoretical sources.

Table 3. Survey Items and Underlying Literature Sources

Item No	Statement	Research Source
1	People are born gifted; they cannot become gifted later in their life.	Cross (2002); Sak (2011)
2	Most gifted people have psychological problems.	Sak (2011)
3	Gifted children are smarty by giving ripostes.	Neumeister et al. (2007)
4	Gifted children can improve themselves in every setting without taking extra education.	Fiedler et al. (1993); NAGC (2008)
5	The appearances of gifted children are different from those of other children.	Carman (2011)
6	Gifted children are bustling individuals who cannot stay in the same place.	Neumeister et al. (2007)
7	Gifted children are not well adjusted in the society.	Neumeister et al. (2007)
8	Gifted children have a general intellectual capacity which makes them special talented in all subject areas.	Sak (2011)

Before conducting the research, several validation studies were carried out on data collection instrument. Validity indicates the degree to which test scores precisely measure the proposed idea (Kaur et al., 2020). For this reason, content and literature validation and expert validation were used in the study. In terms of the content and literature validation, the items in the test were based on the literature as can be seen in Table 3. In terms of expert validation, the test was reviewed by four experts studying in the field of gifted students' education. Since the study group involved Turkish pre-service teachers, the test was applied to the participants in their original language, Turkish. Hence, the test was also presented to the language experts to review its intelligibility. The items were refined according to the opinions of the experts several times. As a result, final version of the test was obtained.

The tests were applied to the participants in each educational field by one of the researchers in 50 minutes periods. The participants were also asked to provide demographic data about them. The application of the tests on the participants resulted in a Cronbach's Alpha coefficient of .72 which indicated the reliability of data analysis.

2.4 Data Analysis

Collected instruments were firstly coded with letters and numbers to indicate each participant in different fields. For example, MT-5 indicated number 5 student in Music Teaching field. Then, the participants' responses were scored with '1' to show their agreements with the myths based on their explanations. Besides, their disagreements were scored with '2' to show that they held scientific constructions by referring to their explanations. Afterwards, data were transformed to computer to run statistical analyses. Descriptive statistics were utilized to indicate the frequency and percentage distributions of their myths and scientific constructions. Findings were visualized in the form of a bar graph.

The normality of the distribution of the scores obtained for each item in the test was analyzed with Kolmogorov-Smirnov Test (K-S Test). The results of K-S Test indicated that data sets did not show a normal distribution, $p < .05$. Hence, non-parametric statistics tests were utilized to analyze data. At this respect, Chi-square tests were conducted to investigate whether different group pre-service teachers' myths differentiated in a statistically significant manner with respect to the gender or educational field as they were measured on a nominal level. The test results give Pearson's Chi square scores to remark whether there is an association between two categorical variables. When the results of Pearson's Chi square test are violated (0 cells [0%] should have an expected value less than 5), Fischer's exact test is used (Chan, 2003) or data is interpreted by making comments on the percentages (Büyükoztürk et al., 2010). Such cases were indicated with different letters on the tables which demonstrated study findings.

3. RESULTS

3.1 Overall Prevalence of Myths and Scientific Constructions

Figure 1 provides the percentage distribution of pre-service teachers' myths and scientific constructions for each item in test. According to Figure 1, more than half of the participants possessed myths related to the first item. In addition, about one third of the participants had myths related to the second, sixth and seventh items. On the other hand, majority of the participants possessed scientific constructions related to the fourth and fifth items.

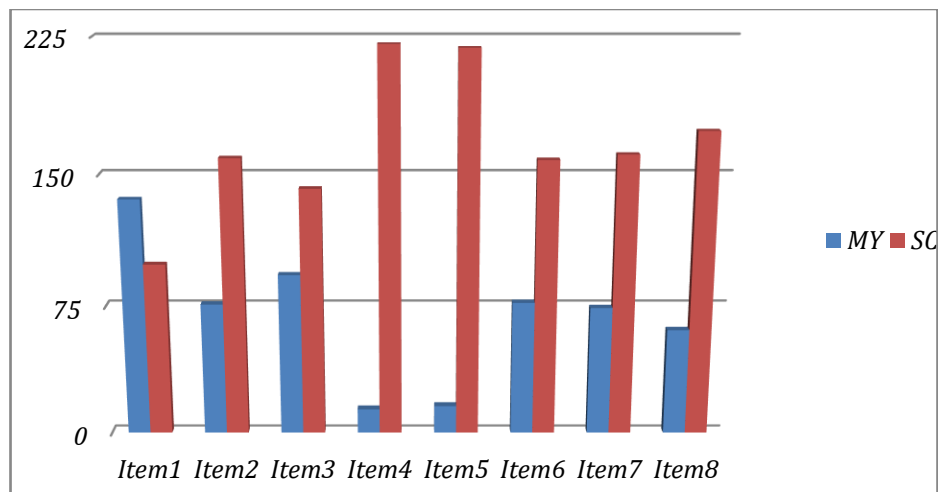


Figure 1. Percentage distribution of students' myths and scientific constructions

Descriptive analysis revealed varying rates of myth endorsement across the eight items. More than half of the participants (57.9%) possessed the myth in Item 1 (Entity belief). Approximately one-third endorsed myths in Item 2 (Psychological problems; 32.3%), Item 3 (Ripostes/Smarty responses; 39.6%), Item 6 (Hyperactivity/Bustling behavior; 32.8%), Item 7 (Social maladjustment; 31.5%), and Item 8 (Omniscience/Global giftedness; 26.0%). Conversely, a vast majority held scientific constructions for Item 4 (Self-sufficiency fallacy; 94.0% scientific construction, 6.0% myth) and Item 5 (Physical appearance stereotype; 93.2% scientific construction, 6.8% myth).

Figure 1 provided a general look for the appearance of pre-service teachers' myths on gifted students. Examples from students' responses asserting myths are presented in Table 4 below. Table 4 presents illustrative participant statements representing myths for each item.

Table 4. Exemplary Participant Qualitative Explanations Indicating Myths

Item	Code	Qualitative Explanation
1	CT-3	<i>"I believe that giftedness forms in pre-natal period and is influenced by genetic factors. Hence, I do not think people who were not gifted can be as successful as those individuals by working hard."</i>
2	CEIT-8	<i>"Gifted children might have problems such as anxiety and fear towards life since they try to be a perfectionist at all."</i>
3	ST-39	<i>"They are in a constant learning process since they have a deep curiosity... This makes them defend themselves against problems and give instant responses during dialogues."</i>
4	ELT-29	<i>"Because they know themselves very well. They know how to learn. They can improve themselves intellectually at home with the help of a computer."</i>
5	CEIT-27	<i>"According to my observations, they get tired of mental activities... That's why they are different than other children, such as wearing thick glasses, larger heads, and so on."</i>
6	MT-36	<i>"Those children have more energy than other people. So, they reflect their energy on their behavior."</i>
7	ELT-20	<i>"Because they tend to be independent and against authority. That's why they experience problems in adapting to society."</i>
8	ST-40	<i>"Gifted students are very good at constructing cause-effect relationships. Hence, they have an intellectual capacity in all fields."</i>

3.2 Evaluation of Myths Across Gender

Chi-square analyses demonstrated that endorsement of myths did not differ significantly between male and female pre-service teachers for seven of the eight items. However, a statistically significant difference emerged for Item 7 (Social maladjustment; $\chi^2 = 18.921$, $p = .0001$), with male pre-service teachers (48.8%) endorsing the social maladjustment myth at a significantly higher rate than female pre-service teachers (21.5%). Table 5 summarizes the gender comparisons.

Table 5. Pre-Service Teachers' Myths by Gender (* Statistically significant at $p < .05$)

Item No	Male n (%)	Female n (%)	χ^2	p-value
1	50 (58.1%)	86 (57.7%)	0.004	.950
2	31 (36.0%)	45 (30.2%)	0.851	.356
3	38 (44.2%)	55 (36.9%)	1.206	.272
4	7 (8.1%)	7 (4.7%)	1.153	.283
5	9 (10.5%)	9 (4.7%)	2.858	.091
6	26 (30.2%)	51 (34.2%)	0.395	.530
7	42 (48.8%)	32 (21.5%)	18.921	.0001*
8	28 (32.6%)	33 (22.1%)	3.075	.080

3.3 Evaluation of Myths Across Educational Fields

As shown in Table 6, pre-service teachers' endorsement of myths did not differ significantly across educational fields for any of the survey items. In another words, the participants in different educational fields tended to have similar percentages of myths at this respect. Besides, it is not appropriate to consider Pearson Chi Square test score and the significance value for the fourth and fifth items due to the low frequency values in the cells (5 cells [50.0%] have expected count less than 5). Hence, the frequency and percentage values were interpreted among the fields for those items. For the fourth item, ELT participants were found to possess more myths than the other participants. For the fifth item, CEIT participants were determined to carry more myths than the other participants. Across all five departments (CEIT, CT, ELT, MT, ST), participants displayed comparable percentages of

misconceptions. For Items 4 and 5, Fisher's exact test percentages were interpreted due to low cell counts; ELT participants showed slightly higher myth endorsement for Item 4 (15.6%), while CEIT participants showed slightly higher endorsement for Item 5 (18.5%).

Table 6. Pre-Service Teachers' Myths Across Educational Fields ($b = 50\%$ cells expected count < 5 ; interpreted descriptively)

Item	CEIT	CT	ELT	MT	ST	χ^2	p-value
1	15 (55.6%)	46 (66.7%)	26 (57.8%)	25 (56.8%)	24 (48.0%)	4.267	.371
2	13 (48.1%)	26 (37.7%)	12 (26.7%)	13 (29.5%)	12 (24.0%)	6.391	.172
3	15 (55.6%)	27 (39.1%)	17 (37.8%)	15 (34.1%)	19 (38.0%)	3.555	.470
4	2 (7.4%)	2 (2.9%)	7 (15.6%)	2 (4.5%)	1 (2.0%)	10.207	.037b
5	5 (18.5%)	4 (5.8%)	3 (6.7%)	3 (6.8%)	1 (2.0%)	7.770	.100b
6	10 (37.0%)	25 (36.2%)	13 (28.9%)	16 (36.4%)	13 (26.0%)	2.204	.698
7	12 (44.4%)	18 (26.1%)	15 (33.3%)	16 (36.4%)	13 (26.0%)	4.288	.368
8	12 (44.4%)	18 (26.1%)	10 (22.2%)	12 (27.3%)	9 (18.0%)	6.815	.146

4. DISCUSSION AND CONCLUSION

4.1 Co-existence of Scientific Constructions and Persistent Myths

The empirical findings of this study demonstrate that pre-service teachers hold a contradictory mixture of scientifically sound constructions and persistent misconceptions regarding giftedness. The high endorsement rate for Item 1 (57.9% myth endorsement) indicates that more than half of prospective teachers adhere to an entity view of giftedness, believing that high ability is fixed at birth and cannot be developed later. This finding aligns with Sak's (2011) survey of Turkish laypeople and Yazgan-Sağ's (2022) study on prospective mathematics teachers, which noted that candidates frequently view mathematical talent as an innate, fixed trait. When prospective educators believe intelligence is immutable, they are less likely to adopt growth mindset practices or recognize talent potential in non-traditional learners (Boaler, 2016; Dweck, 2016; Sheffield, 2017).

In contrast, the vast majority of participants possessed scientific constructions for Item 4 (94.0% scientific construction) and Item 5 (93.2% scientific construction). Unlike findings in some international samples where the 'self-sufficiency' myth is widely held (Baccassino & Pinnelli, 2022; Portešová et al., 2014), pre-service teachers in this sample overwhelmingly recognized that gifted students require specialized educational support and cannot improve on their own in every setting. Furthermore, participants rejected the physical appearance stereotype, recognizing that gifted children do not possess distinct physical anomalies.

However, moderate myth endorsement persisted for Item 2 (32.3%), Item 3 (39.6%), Item 6 (32.8%), Item 7 (31.5%), and Item 8 (26.0%). Approximately one-third of prospective teachers believed that gifted children inherently suffer from psychological problems and social maladjustment. This reflects the enduring influence of the 'disharmony hypothesis' and 'mad genius' stereotype identified in prior studies (Bain et al., 2006; Cross, 2002; Peterson, 2009; Porter, 2005). Furthermore, 26.0% endorsed the 'omniscience' myth (Item 8), assuming that giftedness implies superior talent across all subject areas, which contradicts empirical evidence on domain-specific talent profiles (Gardner, 1983; Reis & Renzulli, 2009; Winner, 1996).

4.2 Invariance Across Gender and Educational Fields: Systemic Implications

A key finding of this study is that endorsement of myths remained consistent across educational fields ($p > .05$ for all items) and was also consistent across gender for seven of the eight items. Pre-service teachers in Computer Education, Classroom Teaching, English Teaching, Music Teaching, and Science Teaching exhibited statistically similar rates of misconceptions. This discipline-invariance indicates a systemic issue in teacher preparation; without explicit, specialized coursework in gifted education, candidates from all departments tend to internalize prevailing societal representations (Hafenstein et al., 2021; Troxclair, 2013).

Regarding gender, male pre-service teachers endorsed the social maladjustment myth (Item 7) at a significantly higher rate than females (48.8% vs. 21.5%, $p = .0001$). This gender difference suggests that male prospective teachers may be particularly prone to viewing gifted students as socially oppositional or anti-authoritarian.

Nevertheless, for all other items, gender did not exert a significant effect, supporting prior research showing that teacher candidate beliefs are primarily shaped by information deficits rather than demographic identity (Biber et al., 2021; Kaya et al., 2023; Vatansever Bayraktar et al., 2019).

4.3 Pedagogical, Curricular, and Policy Recommendations

Based on the empirical results of this study and the broader literature in gifted education, several actionable recommendations are proposed:

1. Case-Based Instruction and Real-Life Exemplars in Faculty Courses: To directly counter persistent myths, teacher education curricula should incorporate real-life case studies, narrative vignettes, and diagnostic profiles of gifted learners—including underachievers, twice-exceptional students, and diverse talent profiles (Bain et al., 2007; Pérez et al., 2020). Exposing pre-service teachers to authentic cases helps replace intuitive stereotypes with nuanced scientific constructions.

2. Integration of Evidence-Based Differentiation Models: Education faculties must equip teacher candidates with practical formational training in validated curricular models:

- Schoolwide Enrichment Model (SEM): Focuses on Type I, II, and III enrichments and curriculum compacting (Renzulli & Reis, 1985).
- Integrated Curriculum Model (ICM): Emphasizes advanced content, higher-order process skills, and overarching concepts (VanTassel-Baska, 2009, 2011).
- CLEAR Curriculum Model: Combines continual formative assessment, clear learning goals, data-driven learning experiences, authentic products, and rich curriculum (Azano et al., 2014).
- Parallel Curriculum Model (PCM): Uses Core, Connections, Practice, and Identity parallels to escalate intellectual challenge (Leppien, 2011; Tomlinson et al., 2002).
- Depth and Complexity Model: Employs specific prompts to foster abstract reasoning and critical thinking (Kaplan, 2013).
- Multiple Menu Model: Guides content selection and instructional strategies through structured menus (Renzulli, 2000).

3. Addressing Social-Emotional Stereotypes: Teacher educators should explicitly address the disharmony myth, providing empirical evidence that high-ability students generally exhibit healthy social-emotional adjustment when provided with supportive learning environments (Cross, 2002; Neihart, 1999). Male pre-service teachers, in particular, may benefit from targeted discussions on social adjustment and classroom management.

4. Future Empirical Research: Future investigations should examine the efficacy of specific instructional interventions (e.g., pre-post experimental designs following a dedicated gifted education course) in changing pre-service teacher beliefs. Additionally, longitudinal studies tracking candidates into their early teaching years could assess how implicit beliefs translate into classroom nomination behaviors and instructional adaptations.

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Exploring the Relationship Between Digital Literacy and Students' Preferences For E-Learning Platforms

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ABSTRACT

Education has a vital role in forming an individual's personality. The COVID-19 pandemic drove the Indian education sector to transition from physical to online learning. The purpose of this study is to identify students' digital literacy about online educational platforms in secondary education institutions, as well as their preferences for E-learning. It is based on primary data that has been collected from the Balasore district of Odisha by using a well-structured schedule, with a sample size of 128 respondents. For objective one, five characteristics are utilized to determine the level of digital literacy among students: availability, accessibility, affordability, usage and awareness and objective two was addressed using a logistic regression model to find out the preferences for E-learning in secondary education institutions. However, the majority of the students were using smartphones to attend online classes through various online educational platforms, indicating that they are digitally literate and have a strong preference towards e-learning.

Keywords: Covid-19 Pandemic, Digital Literacy, Government Initiatives, Online Educational Platforms, Preferences for E-learning, Secondary Educational Institutions.

JEL Classification: I21, I22, I28

INTRODUCTION

Digital literacy is identified as a core competency necessary for effective participation in online learning, encompassing technical skills, cognitive and social skills (Alanoglu et al., 2026). It serves as a significant predictor of e-learning success and directly impacts online learning readiness (Ahooie et al., 2026; Alanoglu et al., 2026). Student with higher digital literacy levels demonstrate superior self directed learning skills, allowing them to manage schedules and assignments more effectively (Alanoglu et al., 2026). Furthermore, digital literacy acts as a moderator, strengthening the impact of system use and computer self-efficacy on overall learning engagement (Seraj and Sundram, 2025). However, a lack of formal digital training often forces students into self-learning, leading to inconsistent skill levels (Ahammad and Islam, 2025).

Digital literacy defines the use of computers and other digital devices, the ability to understand and use online applications and information in multiple formats from a wide range of digital resources (Shopova, 2014; Gallardo-Echenique et al., 2015; Olszewski & Crompton, 2020). It is broadly defined as a range of competencies that enable individuals to effectively access, evaluate and utilize information from digital sources (Ahammad and Islam, 2025). It is the capacity to use information and communication technologies (ICT) to locate, assess, produce and share information, combining technical proficiency with cognitive understanding (Chigbundu and Oluwabiye, 2023; Ai et al., 2025). The study aims to determine how well students can effectively use, understand, and interact with online learning platforms used in schools. Specifically, students' digital skills such as ability to use computers, smartphones, and the internet and to navigate online learning platforms, students' knowledge of online educational platforms, students' competence in using digital tools for learning, and students' awareness of digital safety and responsible use. However, to know students' level of digital literacy so that schools can improve online learning, provide necessary training, and ensure that students can successfully use the modern educational technologies.

E-learning is a notion that has existed since the 1960s but became popular with the emergence of the internet and the web (Bezovski & Poorani, 2016). Observing the expansion of E-learning from the early 2000s, there has been an increase in research on internet technology, which serves as its base (Elango et al., 2008). Since then,

scholars around the world have been assessing and evaluating the E-learning systems and giving recommendations that will optimize the process (Singh et al., 2021). At the beginning of 2020, 1.6 billion children and teenagers in 190 nations were pulled out of school, which had various consequences on their academic advancement after that (UNICEF, 2020). Most Governments used Digital Education as a backup response to ensure learning continuity at all levels of education (Lennox et al., 2021). However, the existing digital divide revealed that digital education was underdeveloped, and individuals with fewer technical resources had a more difficult time learning because more than two-thirds of kids aged three to seventeen worldwide did not have access to the internet at home (UNICEF, 2020).

Education is one of the most important factors responsible for shaping an individual's personality and has manifold functions. It is a potent source for material and human development. Especially, "Secondary Education" is an indispensable passport to life upon which the quality of further education and life depends. Secondary education is considered the minimum level of attainment for the survival of the people. It leads to several jobs, pre-job training courses and self-employment. But the COVID-19 pandemic briefly disrupted the school education system in India. Due to the global spread of the deadly new corona virus, the most severe consequences have lately been observed. The COVID-19 outbreak put the learners, teachers and other stakeholders in danger since it forced the suspension of physical classes and shifted them to online learning platforms to continue the classes (Agarwal, 2021; Gopal et al., 2021; Muthuprasad et al., 2021; Singh et al., 2021). In these situations, electronic learning (E-learning), and the application of information and communication technology (ICT) tools were useful because they aided students in the communication of ideas, the delivery of online instruction, the creation of online discussion forums, and the taking of online tests (Sar & Misra, 2020; Agarwal, 2021; Singh et al., 2021).

The Digital Education System in India represents the future of studying and gaining information via the use of technology and digital gadgets. To overcome this situation, the Government of India, the Government of Odisha, and the Odisha School Education Programme Authority (OSEPA) have also taken some initiatives, which include; the Odisha Shiksha Sanjog WhatsApp Platform, Telecast of video lessons in Doordarshan (Odia), DIKSHA Portal, E-Pathshala, Madhu App, E-class through Microsoft Team/ ZOOM/ Google Meet Platforms, etc. (Samagra Shiksha Odisha, Annual Report- 2020-21). So these are the digital measures being used to ensure continuity in students' education in Odisha. However, online education gained prominence during the COVID-19 pandemic. Although in developed countries it was present earlier, in developing nations, the shift from a traditional mode of teaching and learning to an online platform has not been smooth yet. In the state of Odisha, the teachers as well as students faced a lot of problems in this regard at all educational levels. Furthermore the National Education Policy 2020 focuses on the use of technology for education in order to reap long-term benefits. So this motivated to evaluate online educational platforms, particularly in the case of secondary educational institutions in Odisha.

REVIEW OF LITERATURE

In March 2020, India issued a warning, which was followed by the immediate closure of schools and other educational institutions due to the spread of the new corona virus named COVID-19. So, the closure of the educational institutions and the confinement of the students to their homes made it necessary for schools to investigate the most opted alternative way of teaching and learning methods, such as online learning. However, this immediate change from traditional classroom-based learning to online learning gave neither teachers nor students much time to get ready (Bhaumik & Priyadarshini, 2020; Selvaraj et al., 2021). So, this emancipation is possible to be literate digitally when both teachers, as well as students, are digitally learned and aware of it.

Role of Technology and Digital Literacy in Online Education

As new technologies are used more frequently to support and deliver education, new concerns about the efficacy of conventional educational approaches in non-traditional learning environments are emerging (Ahern & Repman, 1994; Benta et al., 2014; Guri-Rosenblit, 2018). With a minuscule part of the budget devoted toward education, the technological divide is now even more apparent. States like Kerala and Tamil Nadu are better off since technological enhancements are significant, whereas Bihar and Odisha are the flip sides of the coin. The New Education Policy of 2020 in India has suggested for spending up to 6 per cent of the GDP on education. Some of the studies suggest that technology-supported courses have a positive relationship with students' performance (Harasim, 2000; Brown et al., 2009). So, technological support in education is needed the most and the idea of educational technology will be effective by not only having access to technology but rather, how one uses technology matters for providing an innovative educational experience with the availability of technology for students and teachers (Olszewski & Crompton, 2020) and most importantly one should be able to afford it (Joshi et al., 2020; Kapasia et al., 2020).

For e-learning to become a leading learning pattern, technology alone will not suffice (Ahoovie et al., 2026). The integration of “Internet and Education” models enhances educational experiences by providing various resources and fostering collaborative learning using technology (Ahammad and Islam, 2025). Furthermore, both teachers and students need to be digitally literate in academics. But the implementation of digital technologies in higher education settings focuses mainly on students’ learning rather than on professors’ teaching. So, teachers should get appropriate training and use technologies in the academic world that enhance their digital literacy (Harasim, 2000; Guri-Rosenblit, 2018; Joshi, 2020). The increasing digital literacy of students and their growing proficiency in using ICTs is a necessary condition for effective performance and improved learning outcomes (Shopova, 2014).

Perception and Preferences for Online Education

The Indian Government has always given preference to the use of ICT as a means of mass education, so the CLASS (Computer Literacy and Studies in Schools) project was launched as far back as 1984 by the INDIAN government to make computer literacy a compulsory project for class IX and XII (Singh et al., 2021). Most interestingly, both teachers and students prefer to use WhatsApp, Telegram, Email, Zoom, Google Meet, YouTube, Swayam Prava educational DTH channels, e-Pathshala, DIKSHA portal, etc., as tools and sources of online education (Kapasia et al., 2020; Mishra et al., 2020; Agarwal, 2021; Singh et al., 2021). There is a notable preference for student-centered methodologies, where learners increasingly gravitate towards informal, socially embedded spaces like WhatsApp and Telegram for engagement, finding traditional Learning Management Systems (LMS) rigid (Cardona-Acevedo et al., 2025; Zwane and Mudau, 2026).

Some studies were done on faculty, some on students, and some on both, but most of them found that regular classes were better in terms of efficiency, interaction and overall understanding (Ray, 2009; Bhaumik & Priyadarshini, 2020; Selvaraj et al., 2021). Some of the students agreed that online learning was helpful for them, even though it was their first time taking an online class during the Covid-19 pandemic (Agarwal & Kaushik, 2020; Mishra et al., 2020; Rajabalee & Santally, 2020; Gopal et al., 2021; Muthuprasad et al., 2021). The majority of contemporary learners displayed low or no positive contentment with the present e-learning systems in use, although most of them were comfortable using smartphones, the internet and the web for learning purposes (Ngampornchai & Adams, 2016; Sunkara & Kurra, 2017). Generally students hold a positive perception of online education due to its flexibility and accessibility (Ahoovie et al., 2026; Siregar & Bendo, 2026). In a study of German language students, 57.8 percent preferred online or hybrid formats, with 91 percent expressing high satisfaction with instructor communication (Ahoovie et al., 2026). Preferred platforms for regular interaction include ZOOM and Microsoft Teams, while institutional platforms like Blackboard often see lower daily usage (Aldosari, 2025). Students preferred well-structured content with recorded videos uploaded on university websites (Mishra et al., 2020; Muthuprasad et al., 2021). They also prefer to use the smartphone to attend online classes (Saxena et al., 2018), but they do not prefer it as a future replacement for online classes because of certain limitations and issues (Al-Amin et al., 2021; Singh et al., 2021). But students using broadband connections have a more positive perception towards online classes than students using mobile networks to attend online learning (Sarkar et al., 2021). Further, some students adopt e-learning because it will be beneficial for future job preparation (Park, 2009). However, there is a greater preference for face-to-face learning as compared to e-learning from the student's perspective, so one thing is certain, face-to-face interaction cannot be excluded from the educational process (Paechter & Maier, 2010; Gherhes et al., 2021).

The teachers or faculty members preferably use a laptop or desktop to conduct online classes through Google Meet, followed by Zoom, CISCO Webex, Classdojo, etc., and the success of online education depends on the digital proficiency of the participants (Kapasia et al., 2020; Agarwal, 2021; Singh et al., 2021). So, it is noted that teachers traditionally have extensive knowledge in the field of their subjects and much less knowledge in the field of information technology and electronic pedagogy, which is a major obstacle to effective online teaching (Almazova et al., 2020). Wherever a study found that teachers have a positive attitude towards the adoption of technologies and are ready to integrate ICTs into teaching and learning, but they lacked the requisite ICT skills (Chisango et al., 2019). So, most of the teachers desired prior training to develop their knowledge of technology and online learning at their institutions (Ray, 2009; Chisango et al., 2019; Mishra et al., 2020; Sar & Misra, 2020; Rahman, 2021).

Factors Affecting Online Learning and Teaching

Various factors affect positively or negatively on the online education, like the course content, the choice possibilities of the course, class size, the teacher’s support and performance are some of the factors that strongly influence students’ satisfaction with the course (Barbera et al., 2013; Gopal et al., 2021). But several factors influenced positively online classes such as time efficiency, convenience, flexibility and accessing courses anytime, while some factors influenced negatively, such as harder to learn, fewer explanations given during

classes, lack of practical implications, technical problems and lack of interaction (Agarwal, 2021; Gherhes et al., 2021; Muthuprasad et al., 2021;). Demand side factors like fluctuating internet and electricity connections, lack of attention, no separate reading room, technical skills, and understanding lessons through online platforms (Mishra et al., 2020; Al- Amin et al., 2021; Rahman, 2021; Sarkar et al., 2021) and lack of technological literacy and competencies are the major constraints of online learning in developing country (Barrot et al., 2021). Additional issues that affect teachers' participation in online teaching and assessment include their lack of digital literacy, technical challenges, academic staff preparedness, and students' readiness for online learning. Institutional barriers also exist, such as funding for technology purchases, inadequate training, and unavailability of technical support (Almazova et al., 2020; Joshi, 2020; Muthuprasad et al., 2021). But fluctuating network connectivity, slow speeds and high costs affect rural and low income students are the major challenges of online learning (Mishra et al., 2020; Chigbundu and Oluwabiye, 2023; Aldosari, 2025; Ahammad and Islam, 2025; Siregar & Bendo, 2026). Furthermore a study indicate that students' perceived usefulness, critical thinking in the 21st-century skills, and behavioral intention to utilize e-learning indicate a positive effect on their academic achievement in higher education institutions (Aldraiweesh and Alturki, 2023).

Students' Satisfaction and Experiences in an E-learning Environment

Online education, with its authentic qualities, has revolutionized the way students engage in learning processes. So, online education has been approached to focus on the teaching and learning processes to ensure children may obtain the abilities that are required for a future workforce (Kong et al., 2014; Martin & Ramos, 2022). Student satisfaction is heavily influenced by perceived usefulness that technology enhances learning efficiency (Ai et al., 2026). Interactive features, such as real-time feedback, online forums, and multimedia resources (videos and simulations), significantly enhances engagement and the clarification of difficult topics (Rafiq et al., 2024; Quraishi et al., 2024). While many students report high satisfaction with the flexibility of managing their own schedules, challenges such as social isolation, and reduced academic focus due to digital distractions remain prevalent (Ahammad and Islam, 2025; Aldosari, 2025). During the COVID-19 lockdown, this open-ended question provided valuable insights into the attitudes and perceptions of students regarding the caliber of their online education (Bhaumik & Priyadarshini, 2020; Kapasia et al., 2020; Barrot et al., 2021). However, several colleges employed online learning technologies such as Idea Web and Moodle as their e-learning platforms, which provided an excellent teaching and learning experience for both teachers and students. However, it is quite effective and enhances students' enthusiasm in laboratory tasks and assignments (Ahern & Repman, 1994; Benta et al., 2014). The Odisha government has taken steps to integrate technology into the teaching and learning process through ICT, creating an ICT-enabled environment that improves the learning experience for both students and teachers and allows them to make intensive use of the time spent in ICT labs for knowledge acquisition (Sar & Misra, 2020). Barbera et al. (2013) discovered that in a correlation analysis of students in higher education social sciences online courses, learner satisfaction was positively and highly connected with social presence, direct instructions, learning content, and course design. However, the characteristics identified as critical - notably, course design and learning content - remained opaque in this investigation.

RESEARCH GAP

Various studies have sought to analyze the problems and challenges that students face when taking online classes, as well as the tools and sources of online education. However, in the rural areas' there were few studies (only one in the case of Odisha). This study wanted to assess the level of digital literacy among rural students' in the district of Balasore regarding government provided online educational platforms.

OBJECTIVES OF THE STUDY

1. To study the level of digital literacy among students regarding the online educational platforms in secondary education institutions in the study area.
2. To find out the preferences for E-learning in secondary education institutions in the sample area.

MATERIALS AND METHODS

This study is based on primary data. Primary data has been collected from the Balasore district of Odisha by using a well-structured schedule which has been developed on the basis of a pilot survey. Here the sample consists of 128 respondents for the primary survey in the year 2022. Both quantitative and qualitative data have been collected for this study from the Government Secondary Schools. Quantitative data about the number of students, applications used for online classes, availability of digital devices, electricity connection, internet facility, hours of study, and number of classes will be collected from the concerned government secondary schools. Similarly, qualitative data will be collected about access, awareness about cyber privacy and safety issues, uses of digital devices, online educational platforms, etc. One district in Odisha has been chosen purposively to collect the primary data. So, Balasore has been chosen as our research region. Then, a simple

random sampling method is used to choose one block, i.e., Baliapal and Ratai GP (Gram Panchayat), which has been chosen for this study. There is only one government secondary schools in this GP and from this school, all students from class IX to class X are selected for this study.

For the data analysis, Descriptive statistics, percentages, averages, bar diagrams and charts have been used for both objectives. For objective one in this study, there are five parameters used to find out the level of digital literacy among the students about the online educational platforms in secondary education institutions, such as Availability, Accessibility, Affordability, Usage (Joshi et al., 2020; Kapasia et al., 2020; Olszewski & Crompton, 2020; Akintola & Bello, 2021; Dadhe & Kuthe, 2021; Oni, 2024) and Awareness (Zakariah et al., 2012; Nafrees et al., 2020), and a binary logistic regression model has been used for objective two because the dependent variable was binary in nature in this study.

The Logistic regression model is specified as follows

$$Li = \log (Pi / 1 - Pi) = \beta_0 + \beta_i X_i + u_i$$

Where,

Pi = Probability of an event occurring

1-Pi = Probability of an event not occurring

β_0 = Constant or intercept term

β_i = Beta coefficient in respect of variables X_i

X_i = Characteristics of the respondents (Discriminating variables)

u_i = Error term

The explicit Logistic regression model was expressed as;

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + u_i$$

Where,

Y_i = Preferences for e-learning (If Yes, 1, Otherwise, 0)

X_1 = Age of the students

X_2 = Parents' Annual Income

X_3 = Monthly expenditure on digital devices

X_4 = Having multiple digital devices (If Yes, 1, Otherwise, 0)

X_5 = Number of online classes per day

X_6 = Hours of online study per day

u_i = Error term

DATA ANALYSIS

Level of Digital Literacy Among Students Regarding the Online Educational Platforms

The ability to obtain information from the internet utilizing a variety of digital devices, technical know-how, and familiarity with numerous online platforms for online work, study, communication, etc., are all considered aspects of digital literacy. Digital literacy is crucial for both teachers and students in educational institutions. However, in the case of instructors, the government provides them with training on how to use various digital devices, technical skills, and online platforms for online instruction, internet access, recharges, etc. Teachers and students who possess digital literacy will feel more at ease and secure using the current online learning environments, while those who do not may find their progress hindered by a lack of confidence or an inability to use the relevant technology. The availability of digital infrastructure, accessibility, affordability, use of online learning platforms through various digital devices, and most importantly, awareness of cyber security and safety policies are the five factors that determine students' level of digital literacy.

Having digital devices such as a smartphone, tablet, laptop, desktop computer, etc. is defined as availability in this context. In order to participate in online learning, one must be able to access the internet or the data pack on digital devices. Then, affordability demonstrates the ability to purchase digital gadgets for online learning, as well as the reason(s) if they are unable to do so. The use of digital devices for online learning through online educational platforms is the most significant factor in determining the degree of digital literacy among educators and learners. Finally, an understanding that illustrates the security of online learning, worries about online safety and privacy, etc.

Availability

The availability of technology for students including the types of devices and connection of internet at home (Dadhe & Kuthe, 2021). Figure 1 shows that out of 128 students, 71.09 percent possess digital devices, while 28.90 percent lack any kind of device for online learning. Additionally, 67.97 percent of students have data packs or Wi-Fi connections in their devices, and 32.03 percent do not have any data packs in their devices. 100 percent of the pupils have an electricity connection at home in the study area (Table 1).

Table 1: Availability of digital infrastructure

Availability of digital infrastructure	Yes (% of the respondents)	No (% of the respondents)
Electricity connection	100	0
Data pack/ Wi-Fi connection	67.97	32.03

Source: Primary Survey

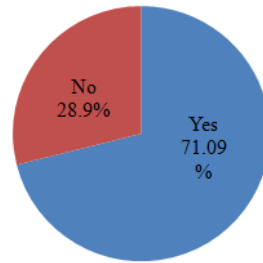


Figure 1: Availability
Source: Primary Survey

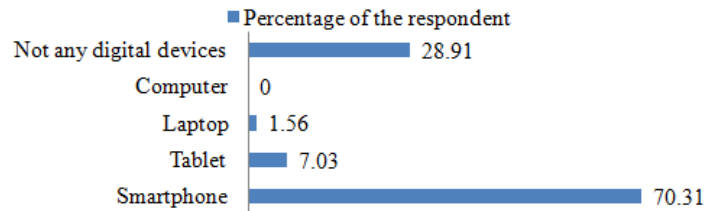


Figure 2: Having any form of electronic gadgets
Source: Primary Survey

The varieties of electronic devices that students utilized to continue their studies during lockdown are depicted in figure 2. Out of the 91 participants, 70.31 percent of pupils possess smartphones, 7.03 percent have tablets, and only 1.56 percent have laptops. Hence, none of the pupils are using computers here, and the majority of them have smartphones. Similar result were found by Dadhe & Kuthe (2021).

Accessibility

Figure 3 shows that accessibility of digital devices, there are 87 number of students (i.e. 67.97%) said that they have accessed and allowed to use digital devices at their homes but 41 (i.e. 32.03%) number of students are not accessing and allowed to use these devices for learning online at their homes due to unavailability of digital devices, data pack or Wi-Fi connection and also there are some parents feel that it is not the appropriate age for children to use digital devices (i.e., 7 out of 41 number of the respondents). However, majority of the students access the internet at home through their own device. Dadhe & Kuthe (2021), found the same.

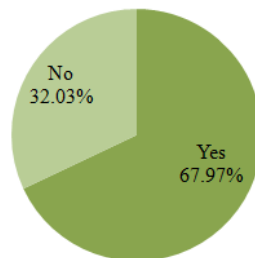


Fig: 3 Accessibility
Source: Primary Survey

Affordability

Figure 4 shows that out of 128 students, 64.84 percent of the students said that they can afford these digital devices, and 35.16 percent of students said that they cannot afford them. However, majority of the student can afford digital devices. This result was contradicting the study of M. B. Oni (2024). According to M. B. Oni (2024), affordability and stability of internet access have posed challenges for e-learning.

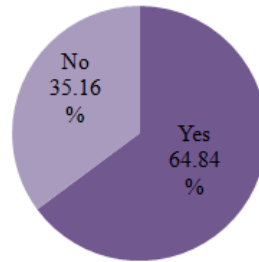


Figure 4: Affordability
Source: Primary Survey

Table 2: Reasons for not being able to afford digital devices

Reasons for not being able to afford digital devices	Percentage of the respondents
High price	24.44
High-price and Low-income	57.78
Low income of parents' annual income	17.78

Source: Primary Survey

Table 2 explains the reasons why students are not able to afford digital devices for learning. Out of 45 students (i.e. 35.16 %), 24.44percent of students are not able to afford it because of the high price of digital devices, while 57.78percent of students are unable to afford it because of the high price of the digital devices and the low income of their parents. 17.78percent of students said that due to the low income of their parents, they are not able to afford it.

Uses of digital devices

Figure 5 shows the uses of these digital devices for online learning through online educational platforms. So, out of 128 students, 67.97percent of students are using digital devices for learning through online educational platforms, while 32.03percent of students are not using these digital devices because of the unavailability of digital devices in their homes due to high prices and low income. Figure 6 shows that there are various types of online educational platforms that are used by students in the study area. Here, nobody is using the e-pathshala portal for learning. Most of the students are using YouTube and WhatsApp for online learning, i.e., 67.97 per cent, while 25percent of students are using the Madhu app, and 16.41percent of the students are using the Diksha app for online learning.

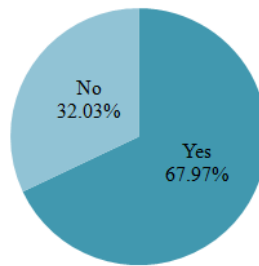


Fig: 5 Uses of digital devices
Source: Primary Survey

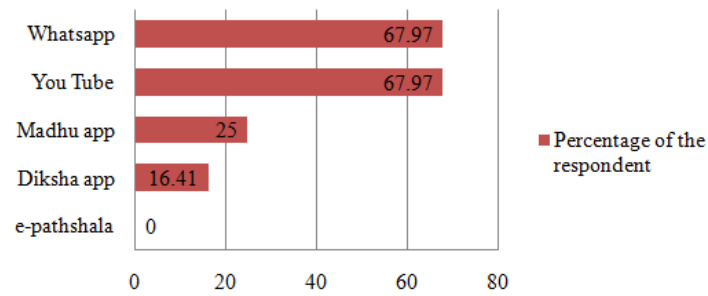


Figure 6: Name of the online educational platforms
Source: Primary Survey

Awareness

Figure 7 shows that the awareness among students regarding e-learning, out of 128 students, regarding cyber safety and privacy, 52.34percent of students raised their concerns, while 12.5percent of students didn't express any such concern towards their privacy and safety policies on the internet. 35.16percent of the students are neutral about privacy and safety policies on the internet.

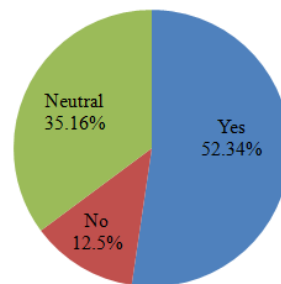


Fig: 7 Awareness
Source: Primary Survey

PREFERENCES FOR E-LEARNING IN THE SECONDARY EDUCATION INSTITUTIONS

E-learning promotes active and independent learning through the internet. It saves time, money and energy because, with online learning (e-learning), learners can access content anywhere and anytime, students can interact with their peers from all around the world through group discussions and charts using various online platforms, etc., so that students can explore their knowledge. In this study, the preferences for e-learning are based on their preferences to attend the classes through online mode, preferences for various digital devices and tools for online learning, issues during online classes and online learning experience.

Preferences to attend the class through online mode

Figure 8 represents the preferences to attend the classes through online mode. The majority of the students preferred to attend classes through online mode, i.e., 58.59percent (i.e., 75 number of respondents) and 41.4percent of the respondents did not prefer to deliver the classes through online mode.

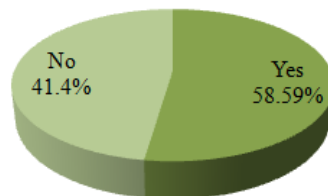


Figure 8: Preferences for online class
Source: Primary Survey

Table 3: Reasons for preferring online classes

Reasons for preferring online classes	Number of respondents	Percentage of the respondents
Comfortable	67	89.33
Easy to access the digital devices	67	89.33
Learning from anywhere at anytime	67	89.33

Online classes are more interesting than offline classes	56	74.67
Students are more attentive than in offline classes	35	46.67
Easy to share the study materials	64	85.33
Easy to understand the concept	41	54.67
It is more flexible than offline classes	63	84
Time efficiency	65	86.67

Source: Primary Survey

Table 3 shows the reasons for preferring online classes. Out of the 75 respondents, 89.33percent of the respondents said that online classes are better than offline classes because it is comfortable and easy to access digital devices and learn from anywhere at any time. 74.67percent of the respondents said that online classes are more interesting than offline classes, and 46.67percent of the respondents like online classes because students are more attentive in online classes than in offline classes. 85.33percentof the respondents said that online classes are better because, through the online educational platform, it is easy to share the study materials. 54.67percent of the respondents said that in online classes, it is very easy to understand the concepts through the use of technology, and we can see scientific experiments with the help of various online educational platforms like YouTube. 84percent of the respondents preferred online classes because online classes are more flexible than offline classes, and the most important thing is that these are time-efficient, preferred by 86.67percent of the respondents, because during online classes, we can do some other work simultaneously.

Table 4: Reasons for not preferring online classes

Reasons for not preferring online classes	Number of respondents	Percentage of respondents
Student and teacher interaction is less	53	100
Lack of knowledge of technology	40	75.47
Question-answer discussion is not easy	50	94.34
Not easy to understand the topic	53	100
Find many problems like network issues, electricity issues, data pack, etc.	44	83.02
It is not affordable for the school students	52	98.11
Compulsory to have digital devices	53	100
Not comfortable	40	75.47

Source: Primary Survey

Table 4 shows the reasons for not preferring online classes. So, out of 53 students, 100percent of the respondents have not preferred online classes because here both teacher and student interaction is less than in offline classes, while 75.47percent of the students lacked knowledge of technology. 94.34percent of the students said that here the question-answer discussion is not easy, and 100percent of the students said that it is not very easy to understand the topic in the online class. 83.02percent of the students said that in online classes, they found many types of problems like network issues, electricity fluctuations, limited data pack, etc. during e-learning, and the most important thing is that online learning is not affordable for the government secondary school students, said 98.11percent of the respondents. 100percent of the respondents do not prefer online classes because it is compulsory to have digital devices for online learning. 75.47percent of the respondents are not comfortable with online classes.

This study also uses the logistic regression approach. It's a mathematical modeling method for representing the relationship between a dichotomous or limited dependent variable and several independent factors. Here, the dependent variable is dichotomous (i.e., preferences for e-learning or not preferences for e-learning), and the suggested covariates are a combination of continuous and categorical random variables, which are discussed below Table 5.

Table 5: Binary Logistic Regression Model Output

Sl. No	Variables	Coefficient	P values (Significance)	Odds Ratio (Probability)
1	Age of the students	.278	.580	1.321
2	Parents' Annual Income	.000	.647	1.000
3	Monthly expenditure on digital devices	.004**	.027	1.005

4	Having multiple digital devices	-.225**	.032	.799
5	Number of online classes	.557*	.009	1.745
6	Hours of online study	.026*	.000	1.026
7	Constant	-9.176	.270	.000
-2 log-likelihood = 65.998 ^a Cox & Snell R ² = .571 Nagelkerke R ² = .768				

Note: * indicates significance at 1% level, ** significance at 5% level

Sources: Authors' Computation using SPSS

Table 5 shows the coefficients of the variables show the preferences for e-learning in secondary school students in the study area. It can be seen that the age of the students and parents' annual income are the explanatory variables which are statistically insignificant and positively related to the preferences for e-learning in secondary school students, while the monthly expenditure on digital devices, availability of digital devices, number of online classes per day, and hours of online study are significantly related.

Based on the odds ratio (i.e., 1.321), which implies the probability of falling into the target group, i.e., the preferences for e-learning, is greater than 1, meaning the probability of an event occurring increases, as opposed to not having the preferences for e-learning. It means the probability of the preference for e-learning is positively related to age. Similarly, based on the odds ratio (i.e., 1), which implies the probability of falling into the target group, i.e., the preferences for e-learning is exactly equal to 1, means the probability of an event occurring is equal to that against not having the preferences for e-learning. Also, the probability of the preference for e-learning is positively related to parents' annual income.

Here we can see that the monthly expenditure on digital devices for online learning was found to be statistically significant (at a 5per cent level) and positively related to the preferences for e-learning based on the odds ratio (i.e., 1.005) which implies the probability of falling into the target group i.e., the preferences for e-learning is greater than 1, means the probability of an event occurring increase as against not having the preferences for e-learning. So, this implies that the increase in the monthly expenditure on digital devices leads to an increase in the preferences for e-learning. Similarly, we can see that having multiple digital devices for online learning was found to have a statistically significant (at 5per cent level) but negatively related to the preferences for e-learning based on the odds ratio (i.e., .799). So, this implies that the increase in the availability of digital devices leads to a decrease in the preferences for e-learning, because they use it for many other purposes like social media, entertainment, playing video games, etc.

The probability of preferring e-learning was positively and significantly related to the number of online classes at a 1per cent level of significance. Hence, the number of online classes per day under online educational platforms increases the probability of students' preferences for e-learning by 1.745 times. As in the table, the hours of online study were significantly associated with the probability of students' preferences for e-learning at a 1per cent level of significance and based on the odds ratio (i.e., 1.026) which implies the probability of falling into the target group i.e., the preferences for e-learning is greater than 1, means the probability of an event occurring increases, as against not having the preferences for e-learning. It means the probability of the preference for e-learning is positively related to the hours of online study.

Lastly, from the above table, we found that the Nagelkerke R Square on this model is 0.768. The value of 0.768 means that the independent variable is able to explain the variability of the dependent variable by 76.8per cent while the rest is explained by other variables not included in the model.

Preference for various digital devices and tools for online learning

Table 6: Preference for digital devices to attend the classes

Preferred digital devices to attend the class	Number of respondents	Percentage of respondents
Smartphone	125	97.66
Tablet	7	5.47
Laptop	2	1.56
Computer	0	0
No answer	3	25.78

Source: Primary Survey

Table 6 shows the digital devices they preferred to attend the classes. Out of 128 respondents, 97.66% of the respondents preferred a Smartphone to attend classes through online mode, while only 5.47% of respondents preferred a tablet. There is a very small percentage of respondents who preferred the laptop to attend the classes through online mode, i.e., 1.56% while nobody preferred the computer.

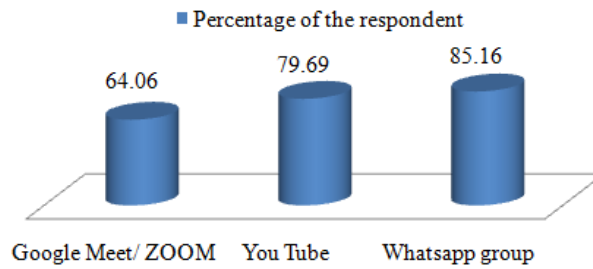


Figure 9: Preferred online tools for e-learning
Source: Primary Survey

Figure 9 shows, 64.06% of the respondents preferred to use Google Meet/ZOOM for e-learning, and 79.69% of the respondents preferred YouTube. The majority of the respondents preferred to use WhatsApp for e-learning, i.e., 85.16%.

Table 7: Causes to prefer Google Meet/Zoom

Causes to prefer Google Meet/Zoom	Number of respondents	Percentage of respondents
Audio-visual learning is possible	81	98.78
Asking doubts/questions easily	82	100
Face-to-face interaction with the teacher/students	82	100
Clearing concepts easily	77	93.90

Source: Primary Survey

Table 7 shows the reasons why they prefer Google Meet/ZOOM for e-learning. 98.78% of the respondents preferred Google Meet/ZOOM because through these applications, audio-visual learning is possible. 100% of the respondents preferred this because they can ask doubts/questions easily through these applications and also have face-to-face interaction with the teachers as well as students. 93.90% of the respondents preferred these applications for e-learning because, with the help of these applications, they can clear their concepts easily. WhatsApp is the most preferred platform, i.e., 100% because through WhatsApp they can easily share and get all the study materials, while 98.04% of the respondents prefer YouTube because it keeps all the recordings (Table 8).

Table 8: Causes to prefer YouTube and WhatsApp

Causes to prefer YouTube and WhatsApp	Number of respondents	Percentage of respondents
Because YouTube keeps all the recordings	100	98.04
Easily share and get all the study materials through the WhatsApp group	109	100

Source: Primary Survey

Figure (10) shows the preferred languages for online classes. Here, all of the respondents preferred English and Odia as the most preferred languages during the classes in the study area, i.e., 100%. But there are only 24.22% of the respondents who preferred Hindi, and 75% of the respondents preferred the Sanskrit language for online classes because they have optional subjects in Hindi and Sanskrit in the sample school. But all of the respondents preferred English and Odia as the most preferred languages during the classes in the study area, i.e., 100%.

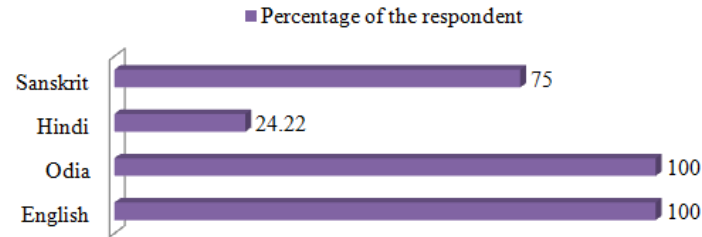


Figure 10: Preferred languages for e-learning
Source: Primary Survey

Issues during online classes

When the students were asked if online learning affected their health, the responses show that only 33.59% of the students said yes, 48.43% of the students said no, and that there were no health issues, and 17.97% of the respondents did not answer this question because they may have attended very few online classes during the lockdown (Table 9).

Table 9: Health issues during online class

Health issues during online class	Number of respondents	Percentage of respondents
Yes	43	33.59
No	62	48.44
No answer	23	17.97

Source: Primary Survey

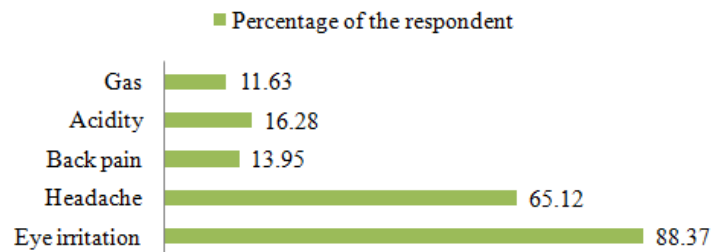


Figure 11: Health issues related to online class
Source: Primary Survey

Figure 11 shows that out of 43 students, 88.37% of the students had eye irritation, 65.12% of the students had a headache during the online classes, and only 13.95% of the students had back pain. 16.27% of the students said that they had severe acidity problems because of the classes, and 11.62% of the students had a gastric problem due to the online classes. The majority of the students had eye irritation during the classes, i.e., 88.37%.

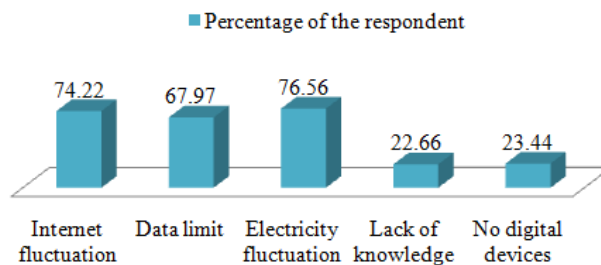


Figure 12: Other issues during online class
Source: Primary Survey

Figure 12, shows the challenges during online classes. Here, 74.22% of the students said that the most serious issues are internet fluctuation, and 67.97% of the students faced issues like limited data packs in their smartphones. 76.56% of the students said that electricity fluctuation is another issue during online classes. 22.66% of the students said that the lack of knowledge on the use of digital devices is also a challenge for

attending the online class, while 23.44% of the students said that they couldn't attend any classes due to the unavailability of digital devices for learning online. The major issues during online classes are internet fluctuation, data limit and electricity fluctuation, i.e., 74.22%, 67.97% and 76.56% respectively, which are similar to the teachers' side as well. But the issues like lack of knowledge and not having any digital learning devices are different from the teachers' side.

DISCUSSION

Out of the 128 students who responded, 71.09% had availability, 67.97% had accessibility, 64.84% had affordability, 67.97% had used digital devices for online learning, and 52.34% had worried about online privacy and safety policies, i.e., awareness. The fact that they were using these electronic devices to attend online courses via different online learning environments, however, was crucial since it proved that they were digitally literate. Additionally, it was shown that the vast majority of pupils utilized smartphones to access online learning resources like YouTube and WhatsApp, which is similar to the findings of Saxena et al. (2018).

The majority of students, or 58.59%, preferred to attend classes online. After all, they felt comfortable doing so, because it was convenient to access digital devices, because they could learn at any time and from any location, because it was time-efficient, etc. Similar result was found by Mohsin, et.al (2025). In contrast, 41.4% of students preferred to attend classes offline because they didn't have to deal with issues like internet problems, fluctuating electricity, limited data packs, etc. Other writers with similar reasons, such as Mishra et al. (2020), Agarwal (2021) and Muthuprasad et al. (2021), also discovered this. Nonetheless, regular classes are superior in terms of effectiveness, interaction, and general comprehension, according to Ray (2009), Bhaumik & Priyadarshini (2020) and Selvaraj et al. (2021). In order to participate in the online course, students preferred using numerous digital devices. In this survey, the majority of students preferred smartphones, as well as a variety of online learning resources and applications like Google Meet, Zoom, YouTube and WhatsApp. In addition to these, Kapasia et al. (2020), Mishra et al. (2020), Agarwal (2021), and Singh et al. (2021) discovered other online learning resources and tools, such as Telegram, Email, Swayam Prava educational DTH channels, e-Pathshala, and the DIKSHA portal. Figure 10 shows that 100% of the students preferred English and Odia languages during the online classes.

The logistic regression model (Table 5) revealed that while monthly spending on digital devices, the number of online classes taken each day, and the number of hours spent studying online were significant and positively correlated with the dependent variable, the annual income of the parents was statistically insignificant but positively correlated with the secondary school students' preferences for e-learning. Similarly, the age of the students was statistically insignificant but positively correlated with the dependent variable, which is contrary to the findings of the Glazier & Harris study in 2021. However, because students used their digital devices for a variety of other purposes, such as social networking, entertainment, and playing video games, having multiple digital devices was significant and negatively associated with their preferences for e-learning in this study.

Additionally, this study discovered that out of 43 students, some experienced a variety of health problems during online classes, such as headaches (65.12%), irritation of the eyes (88.37%), and acidity (16.28%) (Figure 11). Other significant problems with online learning included inconsistent internet, limited data pack, power outages, lack of knowledge on technology and the unavailability of electronic gadgets. In addition to these concerns, Mishra et al. (2020), Rahman (2021), and Sarkar et al. (2021) discovered other challenges, such as inattention during online classes, a lack of a dedicated reading area and comprehension of teachings delivered via online platforms. Similar to this, Barrot et al. (2021) discovered that the main obstacle to online learning in developing nations is a lack of technological literacy and competencies. Nevertheless, most respondents said that they liked and enjoyed the online courses, but they would like to see some changes made to a few things, such as network problems, data limitations, electricity fluctuations, the issue of digital device unavailability, student training programs on online education, etc.

CONCLUSION

A survey was conducted to get students' insights about online learning. Some outcomes were satisfactory and some were not, where most of the respondents favoured online learning and found these initiatives to be a major step in maintaining the continuity of the study in the era of COVID-19, but some of the respondents were not in favour of online learning due to some limitations and issues. Issues like network/internet connectivity, electricity fluctuation, lack of knowledge of technology, limited data pack, and health-related issues were highlighted by the conducted study. Hence, this study provided insights into the learners' perspective towards the government's initiatives and online learning, and the students studied with the government initiatives such as the Diksha app, Madhu app, Shiksha Sanjog WhatsApp group and OSEPA YouTube channel. A mixed set of

opinions (positive, negative, and neutral) was seen in the responses of the students, and the majority of the students had a positive preference for e-learning.

This paper makes two primary recommendations: to help students become more proficient with technology, there should be a variety of awareness and training initiatives that enable them to participate in online courses in the field of study, and according to the student responders, the study area's institutions ought to offer a minimum of two online courses every week. There were some of the study's limitations, like the study's conclusions were restricted to the local schools that were polled, and only secondary school students enrolled in government schools were considered in the study.

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From Principles to Practice: A Systematic Review of Generative AI-Responsive Assessment Interventions in Higher Education

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Abstract

Generative artificial intelligence (GenAI) challenges higher education assessment because a polished submitted artefact may no longer provide transparent evidence of the learner's knowledge, reasoning, or competence. This systematic review examines empirical studies in which assessment practices were deliberately configured in response to GenAI and implemented with higher education students. It synthesizes evidence concerning assessment design, the role assigned to GenAI, evidence of student learning, educational outcomes, and implementation conditions. Five recurring functional responses are identified: regulating AI use, structuring human-AI collaboration, requiring critical evaluation of AI-generated material, making the human learning process visible, and verifying competence through oral or performance-based evidence. Across these approaches, the central design issue is not simply whether GenAI is permitted, but how cognitive responsibility is distributed between learner and technology and how the learner's contribution is evidenced. The review therefore proposes an AI-Human Assessment Responsibility Model linking AI delegation, human cognitive responsibility, and evidentiary mechanisms. Sustainable GenAI-responsive assessment should be designed from intended learning outcomes and evaluated in relation to learning, validity, integrity, equity, workload, accessibility, and scalability rather than seeking a universally 'AI-proof' format.

Keywords: generative artificial intelligence; GenAI; higher education; assessment; assessment redesign; academic integrity; assessment validity; AI literacy

1. Introduction

The rapid development and widespread accessibility of generative artificial intelligence (GenAI) have introduced a significant transition in higher education. Since the public release of ChatGPT in late 2022, generative AI systems have become increasingly capable of producing sophisticated text, code, images, analyses, and other academic artefacts in response to natural-language prompts. Their growing integration into students' academic practices has created opportunities for personalized learning, feedback, idea generation, writing support, and problem solving, while simultaneously challenging established assumptions about how student learning is demonstrated and assessed (Kasneci et al., 2023; Xia et al., 2024). Consequently, the educational debate surrounding GenAI has progressively shifted from whether students will use these technologies toward how higher education should design learning and assessment in environments where AI assistance is readily available.

Assessment represents one of the areas most directly affected by this transformation. Higher education assessment serves several interconnected purposes: it supports learning, provides feedback, evaluates achievement, and enables institutions to make judgments about whether students have attained intended learning outcomes. These functions depend on the capacity of assessment evidence to support defensible interpretations of students' knowledge, skills, reasoning, and competence. Generative AI complicates this relationship because the quality of an assessed artefact may no longer provide sufficient evidence of the cognitive processes or capabilities of the student who submits it. A student may use GenAI to explore alternative explanations, obtain feedback, refine an argument, or critically evaluate a draft; alternatively, the same technology may perform substantial portions of the reasoning, synthesis, writing, or problem solving that the assessment was intended to elicit. Similar-looking final products may therefore represent markedly different levels of student engagement and learning.

Emerging empirical evidence illustrates the significance of this problem. Recent research has demonstrated that AI-generated academic work can satisfy conventional assessment criteria without necessarily providing reliable evidence of the student's underlying competence.

McGroarty et al. (2026), for example, submitted AI-generated psychology coursework through an authentic university marking process and reported that the submissions received passing grades without being identified by markers as unusual. Similarly, Brattli et al. (2026), using assessment data from 1,066 undergraduate students across five years, found substantial changes in grade distributions when a course moved from an AI-permissive take-home examination to an AI-restricted supervised examination, raising questions about whether performance under different AI-access conditions represents equivalent evidence of student competence. Such findings suggest that GenAI does not merely create a new mechanism for academic misconduct; rather, it challenges the relationship between observable assessment performance and the learning that assessment is intended to represent.

Initial institutional responses to this challenge frequently emphasized prohibition, detection, and academic-integrity regulation (Cotton et al., 2024). However, reliance on these approaches alone is increasingly difficult to sustain as generative AI capabilities develop and AI functionality becomes embedded within widely used digital platforms. Moreover, treating GenAI exclusively as a threat risks overlooking its emerging role in professional and disciplinary practice. Graduates are increasingly likely to encounter environments in which the ability to work critically and responsibly with AI constitutes part of professional competence. The educational challenge is therefore not simply to create assessments that prevent AI use, but to determine when AI use is educationally appropriate, what capabilities students should demonstrate with and without AI assistance, and how assessment can generate credible evidence of those capabilities.

This challenge has stimulated growing interest in assessment redesign. Scholars have proposed a range of responses, including authentic assessment, oral examinations and viva voce, staged or multi-component tasks, process-based assessment, reflective components, portfolios, supervised performance, AI-use declarations, prompt or interaction records, and assessment designs in which students are explicitly required to use, critique, verify, or improve AI-generated outputs. These approaches reflect a broader movement away from relying exclusively on polished final products and toward assessment architectures that make aspects of students' reasoning, decision making, verification, and learning processes more visible.

Recent conceptual work has described this transition as a movement from authentic products toward "authenticated processes," emphasizing the need for assessment to provide interpretable evidence of human judgment and responsibility when AI contributes to the production of assessed work (Tsiligkiris, 2026).

The literature has consequently advanced rapidly from identifying the disruption caused by GenAI toward proposing principles and frameworks for assessment redesign. Recent scholarship has examined assessment validity, authentic assessment, academic integrity, transparency mechanisms, AI susceptibility, and approaches for distinguishing students' own understanding from AI-supported performance. For example, Ali and Maroulis (2026) critically reviewed assessment validity in AI-rich higher education, while Tsiligkiris (2026) developed a multidimensional framework emphasizing process transparency, cognitive demand, student agency, inclusion, and AI-aware validity. Other emerging approaches include assessment twins, process-focused assessment, AI-supported oral verification, and mechanisms intended to establish students' epistemic ownership of AI-mediated work.

Although the emerging literature offers increasingly sophisticated guidance concerning how assessment should respond to generative artificial intelligence (GenAI), an important distinction remains between principles for assessment redesign and evidence concerning their implementation. Conceptual recommendations may be pedagogically compelling without demonstrating how effectively they operate when translated into assessment practice. An assessment designed to increase confidence in students' authorship or understanding may, for example, increase staff workload, introduce accessibility challenges, generate student anxiety, or prove difficult to implement with large cohorts. Conversely, assessments that deliberately incorporate GenAI may strengthen AI literacy, evaluative judgement, and professional authenticity while simultaneously creating new questions concerning how individual learning should be evidenced. The educational value of GenAI-responsive assessment therefore cannot be established through conceptual plausibility alone; it also requires systematic examination of what occurs when redesigned assessment is implemented with students.

A growing body of empirical research indicates that this transition from principle to practice has begun. Researchers and educators have implemented approaches including structured AI integration, critical evaluation of AI-generated material, reflective documentation of AI use, process-oriented assessment, and oral or performance-based verification. These interventions represent substantively different responses to GenAI. Some seek to preserve opportunities for students to demonstrate unaided competence; others permit AI while making its use transparent; still others deliberately incorporate human-AI interaction into the capabilities being assessed.

Consequently, the emerging question is no longer simply whether assessment should change in response to GenAI, but which assessment responses have actually been implemented, how they have been designed, and what empirical evidence exists concerning their educational and practical consequences.

Existing research also suggests that implementation outcomes cannot be reduced to academic performance alone. GenAI-responsive assessment may influence students' critical engagement, AI literacy, evaluative judgement, perceptions of authenticity, and approaches to learning. At the same time, redesigned assessment may affect academic integrity, confidence in authorship, accessibility, educator workload, scalability, and institutional feasibility. These outcomes are particularly important because an assessment intervention that appears pedagogically desirable in a small class may not necessarily remain viable when applied across disciplines or large student cohorts. Understanding GenAI-responsive assessment therefore requires attention not only to what is designed, but also to how it is implemented and what evidence emerges from its implementation.

Despite the increasing number of empirical studies, this evidence remains distributed across disciplines, assessment formats, methodological traditions, and educational contexts. Individual studies frequently focus on a particular intervention within a specific programme or course, making it difficult to determine broader patterns across the developing evidence base. Moreover, empirical studies of implemented assessment interventions coexist with a much larger literature comprising conceptual frameworks, institutional recommendations, perception surveys, academic-integrity discussions, and studies testing GenAI performance against conventional assessments. Although each contributes to understanding the broader transformation of assessment, they answer different questions. A focused synthesis of interventions implemented with higher education students is therefore necessary to distinguish recommendations about what educators could do from evidence concerning what educators have done and what happened as a result.

Accordingly, the present study systematically reviews empirical research on GenAI-responsive assessment interventions implemented in higher education. A GenAI-responsive assessment intervention is understood as an assessment practice whose design, procedures, conditions of AI use, verification mechanisms, or evaluative activities have been deliberately configured in response to the availability or educational integration of generative AI. The review focuses specifically on interventions implemented with higher education students for which empirical evidence concerning implementation or outcomes was collected. In doing so, it distinguishes assessment interventions from studies concerned exclusively with attitudes toward GenAI, AI-detection technologies, institutional policies, or the ability of GenAI systems themselves to complete conventional assessments.

The review is guided by the following research questions:

- RQ1. What GenAI-responsive assessment strategies have been empirically implemented in higher education?
- RQ2. What pedagogical purposes, design characteristics, and approaches to GenAI use characterize these assessment strategies?
- RQ3. What educational, assessment-related, and implementation outcomes have been investigated, and what does the empirical evidence indicate about these outcomes?
- RQ4. What challenges, limitations, and contextual factors influence the implementation and effectiveness of GenAI-responsive assessment strategies?
- RQ5. What gaps in the existing empirical evidence should guide future research and the development of GenAI-responsive assessment practice in higher education?

By addressing these questions, this review seeks to move the assessment debate from principles to practice. Rather than attempting to identify a universally "AI-proof" assessment format, the study examines how higher education is beginning to negotiate different relationships between human and artificial intelligence within assessment. Through systematic comparison of assessment design, implementation, and reported outcomes, the review aims to identify patterns in the emerging evidence, clarify where empirical support remains limited, and provide an evidence-informed foundation for future assessment design and research in AI-rich higher education.

2. Method

2.1 Review Design

This study employed a systematic literature review to identify, evaluate, and synthesize empirical research on generative artificial intelligence (GenAI)-responsive assessment strategies implemented in higher education. The review was designed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al., 2021), with search reporting guided by PRISMA-S (Rethlefsen et al., 2021). PRISMA 2020 was used to support transparent reporting of the identification, screening, eligibility assessment, and inclusion of studies.

The review differed from broader reviews of artificial intelligence in educational assessment by focusing specifically on assessment practices that had been implemented and empirically investigated in higher education settings. Accordingly, conceptual papers proposing assessment redesign without implementation, policy commentaries, general discussions of academic integrity, and studies examining perceptions of GenAI without an implemented assessment component were outside the principal scope of the review.

2.2 Eligibility Criteria

Eligibility criteria were established before the final screening process to maintain consistency between the research questions, literature search, and study-selection decisions.

Studies were considered eligible when they met all of the following criteria: (a) they were conducted in a higher education context; (b) they addressed generative artificial intelligence, including systems such as ChatGPT or comparable large-language-model-based generative tools; (c) they described an assessment strategy, assessment task, assessment intervention, or assessment-related educational practice that had been implemented with students; (d) they reported empirical evidence concerning the implementation or outcomes of that practice; (e) they were published as peer-reviewed journal articles or full peer-reviewed conference papers; and (f) the full text was available in English.

An assessment strategy was considered GenAI-responsive when the design of the assessment was introduced, modified, or investigated in explicit response to the availability, use, restriction, integration, or educational implications of generative AI. This definition permitted the inclusion of strategies that intentionally integrated GenAI as well as strategies designed to verify student learning in contexts where GenAI was restricted or could otherwise influence assessment performance.

Studies were excluded when they: (a) focused exclusively on primary, secondary, or non-formal education; (b) examined artificial intelligence generally without a clear GenAI component; (c) evaluated automated grading, conventional intelligent tutoring systems, learning analytics, or predictive AI without relevance to generative AI; (d) reported only students' or educators' attitudes, intentions, acceptance, or perceptions without implementing an assessment practice; (e) focused solely on AI-detection accuracy or the detection of AI-generated text; (f) discussed academic misconduct or institutional policy without an implemented assessment strategy; (g) were conceptual articles, editorials, commentaries, opinion pieces, protocols, dissertations, book chapters, abstracts, or literature reviews; or (h) did not report original empirical data.

Existing systematic and scoping reviews were excluded from the final empirical synthesis but were retained separately for background, identification of potentially relevant primary studies, and comparison of the contribution of the present review with previous syntheses.

2.3 Information Sources and Search Strategy

The literature search was designed to capture research at the intersection of three concepts: generative artificial intelligence, higher education, and assessment. Searches were conducted in Scopus, Web of Science Core Collection, ERIC, and Education Source. These databases were selected to provide complementary coverage of educational research, multidisciplinary scholarship, and technology-enhanced learning research.

Because the contemporary educational impact of GenAI accelerated following the public release of ChatGPT in November 2022, the search period began in November 2022. The upper boundary corresponded to the date on which the final database searches were conducted.

The syntax was adapted to the indexing conventions and search fields of each database. Searches were conducted primarily in titles, abstracts, and keywords where database functionality permitted.

A deliberately broad assessment block was retained during the initial search because emerging GenAI-responsive practices may not consistently be described using terms such as “assessment redesign.” Restricting retrieval to this terminology could therefore omit relevant empirical interventions described using discipline-specific language.

Backward reference searching of included articles and relevant previous reviews was also undertaken to identify eligible studies not captured through database searching. Forward citation searching was used for particularly relevant foundational or early empirical studies where appropriate.

The complete database-specific search strings and the dates on which each search was conducted should be reported in an appendix to ensure reproducibility, consistent with PRISMA-S (Rethlefsen et al., 2021).

2.4 Study Selection

All records identified through the database searches were exported to a reference-management system and duplicates were removed before screening. Study selection then proceeded in two stages.

During the first stage, titles and abstracts were screened against the predefined eligibility criteria. Records clearly unrelated to GenAI, higher education, or assessment implementation were excluded. During the second stage, the full texts of potentially eligible studies were retrieved and evaluated against all inclusion and exclusion criteria.

Particular attention during full-text screening was given to distinguishing an implemented assessment intervention from a proposed assessment strategy. A study was not included solely because its authors recommended oral examinations, authentic assessment, reflective tasks, or other redesign strategies. Evidence that the assessment practice had actually been implemented with higher education students and investigated empirically was required.

Reasons for full-text exclusion were recorded systematically. The study-selection process and the numbers of records identified, screened, excluded, assessed for eligibility, and included in the synthesis were documented using a PRISMA 2020 flow diagram.

2.5 Data Extraction

A structured data-extraction form was developed to capture information relevant to the five research questions. For each included study, the following information was extracted:

1. bibliographic information, including author(s), publication year, and publication outlet;
2. country and institutional context;
3. academic discipline or subject area;
4. educational level and participant characteristics;
5. sample size;
6. research design and data-collection methods;
7. GenAI technology or platform used;
8. type of assessment and assessment context;
9. description of the GenAI-responsive assessment strategy;
10. whether GenAI use was prohibited, restricted, optional, permitted, required, or deliberately integrated;
11. pedagogical rationale and theoretical or conceptual framework, where reported;
12. student learning and performance outcomes;
13. assessment-validity or academic-integrity outcomes;
14. student and educator experiences or perceptions of the implemented assessment;
15. implementation challenges, workload, scalability, accessibility, and feasibility considerations; and
16. authors' reported limitations and recommendations.

The extraction framework was designed to capture both the characteristics of the interventions and the evidence reported regarding their implementation. This distinction enabled the review to move beyond identifying assessment formats toward examining what is currently known about how these formats operate in practice.

2.6 Methodological Quality Appraisal

Because empirical educational research on GenAI includes qualitative, quantitative, and mixed-methods designs, methodological quality was assessed using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). The MMAT provides design-specific criteria for evaluating qualitative studies, randomized controlled trials, non-randomized quantitative studies, quantitative descriptive studies, and mixed-methods research.

Quality appraisal was used to inform interpretation of the strength and limitations of the evidence rather than to calculate an overall numerical quality score. Studies were not automatically excluded solely because they exhibited methodological limitations; instead, appraisal findings were considered when evaluating the confidence that could be placed in particular conclusions and when identifying methodological weaknesses in the emerging evidence base.

2.7 Data Synthesis

Given the expected heterogeneity of assessment interventions, academic disciplines, research designs, and reported outcomes, a narrative and thematic synthesis was planned rather than a conventional meta-analysis.

The first stage of synthesis involved descriptive mapping of the included studies according to publication year, geographical location, discipline, research design, participant group, GenAI platform, and assessment context.

The second stage focused on developing a taxonomy of empirically implemented GenAI-responsive assessment strategies. Categories were generated inductively from the included studies rather than imposed in advance. Potentially related interventions were compared according to their underlying assessment purpose and design characteristics rather than merely their labels.

The third stage synthesized evidence concerning the reported consequences of implementation. Outcomes were organized around recurring domains emerging from the literature, with particular attention to student learning and performance, cognitive engagement, assessment validity, academic integrity, student experience, AI literacy, educator workload, scalability, accessibility, and feasibility.

Finally, relationships among assessment design, the role assigned to GenAI, implementation conditions, and reported outcomes were examined across studies. This stage was intended to identify not only which strategies had been implemented but also the conditions under which particular approaches appeared promising, problematic, or insufficiently evaluated.

2.8 Development of an Evidence-Informed Framework

Following the descriptive and thematic synthesis, findings were integrated to develop an evidence-informed framework for GenAI-responsive assessment practice. The framework was derived from recurring patterns observed across the included empirical studies rather than established a priori.

Its purpose was to connect three dimensions of the evidence: assessment design, the role of GenAI, and evidence of student learning. Particular attention was given to how assessment designs make students' reasoning, judgment, decision making, verification, reflection, or performance observable when GenAI contributes to academic work.

The resulting framework was intended as a synthesis of the available empirical evidence rather than a prescriptive model applicable to all educational contexts. Areas supported by limited or methodologically weak evidence were identified explicitly as priorities for further research.

2.9 Operational Definition of a GenAI-Responsive Assessment Intervention

For the purposes of this review, a GenAI-responsive assessment intervention was defined as an assessment practice in which the task design, assessment procedure, conditions governing AI use, student–AI interaction, verification mechanism, or evidentiary requirements were deliberately configured in response to the availability or educational use of generative artificial intelligence.

This operational definition distinguished GenAI-responsive assessment interventions from studies in which GenAI was merely present in the educational environment. Student use of GenAI during an otherwise unchanged assessment was not, by itself, considered sufficient for inclusion unless the assessment design or associated requirements explicitly addressed that use. Similarly, studies investigating students' or educators' perceptions of how GenAI might affect assessment were excluded when no assessment intervention had been implemented.

To support consistent eligibility decisions, potentially relevant studies were evaluated using four sequential questions:

1. Was the study conducted in a higher education context?
2. Did the study concern generative AI in relation to assessment?
3. Was an assessment practice, requirement, procedure, or condition deliberately designed or modified in response to GenAI?
4. Was that practice implemented with students and investigated using empirical data?

Studies meeting all four conditions were eligible for the principal synthesis. Studies failing the third condition but providing empirical evidence concerning students' naturally occurring GenAI use during assessment were retained as contextual literature but excluded from the principal intervention synthesis. Conceptual proposals and assessment frameworks that had not been implemented with students were similarly retained for theoretical comparison but excluded from the empirical corpus.

This distinction was intended to preserve the review's focus on the translation of GenAI-responsive assessment principles into educational practice.

3. Results

3.1 Emerging Characteristics of GenAI-Responsive Assessment Interventions

The emerging empirical literature indicates that higher education institutions have responded to generative artificial intelligence through substantively different forms of assessment intervention.

These interventions cannot be adequately distinguished solely according to conventional assessment formats such as essays, examinations, presentations, or oral assessments. Rather, a more meaningful distinction concerns the function that the intervention assigns to GenAI and the mechanisms through which students remain responsible for demonstrating learning.

Across the identified studies, GenAI-responsive interventions ranged from assessments that regulated or documented students' AI use to tasks in which interaction with GenAI constituted an intentional component of the assessed activity. In some interventions, students were permitted to use GenAI while being required to disclose or reflect upon their use. Other interventions structured the purposes or stages for which GenAI could be employed. A further group repositioned AI-generated content as an object of disciplinary evaluation, requiring students to identify limitations, verify claims, correct errors, or critically evaluate the quality of AI-generated work. Finally, some assessment redesigns introduced additional process, oral, or performance evidence intended to make students' own understanding more directly observable.

An important distinction therefore emerged between AI-permissive and pedagogically structured AI use. Merely allowing students to use GenAI did not necessarily result in cognitively sophisticated engagement. Evidence from postgraduate management students, for example, indicated that GenAI use was concentrated largely on writing, paraphrasing, and rephrasing activities, whereas comparatively few students demonstrated more advanced forms of critical engagement. In contrast, assessment interventions that explicitly required students to interrogate or evaluate AI-generated content repositioned critical judgement as part of the assessed performance.

This distinction suggests that the educational significance of GenAI-responsive assessment depends not simply on whether artificial intelligence is permitted, but on the cognitive responsibilities assigned to the learner when AI is present. Where GenAI performs part of the productive work associated with an assessment, redesigned tasks may require students to demonstrate responsibility through verification, critique, modification, justification, reflection, or direct performance.

The identified interventions also differed in the evidence used to represent student learning. Conventional assessment typically locates evidence predominantly in the submitted product. GenAI-responsive interventions increasingly supplement or partially replace product evidence with process records, reflective accounts, documented human–AI interactions, critical evaluations, oral explanations, or observable performance. This movement indicates an emerging concern with making the human contribution to AI-mediated work more visible to assessors.

Taken together, the developing evidence suggests that GenAI-responsive assessment may be understood through three interconnected dimensions: the functions delegated to AI, the cognitive responsibilities retained by the student, and the evidentiary mechanisms through which those responsibilities are demonstrated. These dimensions provide an initial analytical structure for comparing otherwise heterogeneous assessment interventions across disciplines and educational contexts.

3.2 Types of GenAI-Responsive Assessment Intervention

The verified empirical literature indicates at least five recurring functional responses to GenAI. First, some assessments regulate AI use by defining purpose-specific, open, restricted, or disclosure-based conditions. Quince and Faulconer (2026), for example, examined three redesigned undergraduate physics assessments operating under purpose-specific and open-use policies and found that assessment context shaped the functions for which students reported using GenAI.

Second, some interventions structure human–AI collaboration rather than merely permitting it. Martin et al. (2025) co-designed an AI-integrated postgraduate assessment in which students in a compliant condition used AI to support a blog and critically reflected on the outputs, while an unrestricted condition permitted broader AI use. Cochrane et al. (2026) similarly examined a scaffolded first-year assessment requiring students to generate, critically evaluate, revise, and reflect on GenAI-assisted outputs.

Third, a group of interventions makes AI-generated content an explicit object of disciplinary critique. Tam et al. (2026) required students to critically evaluate ChatGPT-generated scientific output. Casey (2026) required public-policy students to use ChatGPT to draft a ministerial policy brief and then reflect critically on the process and limitations of the resulting output. These designs reposition verification and evaluative judgement as part of assessed performance rather than treating AI solely as a production aid.

Fourth, some approaches attempt to evidence the human learning process through reflections, interaction records, or other process data. Fischer et al. (2024) embedded reflection on GenAI use into a postgraduate management assessment and found that students' reported uses were concentrated on writing, paraphrasing, and rephrasing, with comparatively limited evidence of advanced sensemaking. Oliveira et al. (2025) went further by evaluating 1,450 annotated GenAI interactions linked to 70 graded STEM essays; interaction quality was positively associated with essay performance, and different interaction profiles were associated with idea co-development versus text refinement.

Fifth, some redesigns emphasize direct verification of human competence through oral or performance evidence. Ogle and Jarrett (2026) replaced a written nursing case study with an oral ISBAR assessment for 740 students and reported broadly stable cohort performance, no identified integrity breaches under the oral format, greater educator confidence in authorship, and reductions in marking time and cost. Hutson et al. (2026) examined an adaptive viva layer paired with written submissions; the pilot suggests that oral explanation can reveal comprehension and authorship-related information not visible in the written artefact alone, while also underscoring the need for larger and more systematic evaluation.

These functional strategies are not mutually exclusive. A single assessment may simultaneously regulate AI use, structure interaction, require critique, collect process evidence, and include oral verification.

Table 1. Core empirical GenAI-responsive assessment studies synthesized in the manuscript

Study	Context	Participants	Assessment response	Evidence	Primary contribution
Casey (2026)	Public policy	25 students	Required ChatGPT policy brief + reflection	Reflections; focus group	Critical evaluation; AI literacy
Foung et al. (2024)	University English	74 reflections; 28 focus-group participants	Redesigned assessments using GenAI/digital tools	Reflections; focus groups	Tool choice; equity/access
Fischer et al. (2024)	Postgraduate management	118 students	Assessment plus reflection on GenAI use	Student claims; assessor evaluation	Permissive use often remained surface-level
Martin et al. (2025)	Postgraduate coursework	Implemented co-designed assessment	Structured/compliant vs unrestricted AI-use conditions	Mixed evaluation	Feasibility; integrity; structured use
Oliveira et al. (2025)	STEM writing	70 essays; 1,450 interactions	GenAI interaction as analyzable learning process	Annotated interaction traces; grades	Interaction quality and learning process
Tam et al. (2026)	Undergraduate science	Coursework participants	Critical evaluation of ChatGPT-generated scientific content	Student-perspective evidence	Critical evaluation and verification
Cochrane et al. (2026)	First-year HE	164 students	Scaffolded generate-evaluate-revise-reflect assessment	Cross-sectional survey	Evaluative engagement; perceived learning
Quince & Faulconer (2026)	Undergraduate physics	Three redesigned assessments	Purpose-specific/open AI-use conditions + disclosure	Mixed methods; performance	Policy conditions shape AI use
Ogle & Jarrett (2026)	Nursing	740 students	Written case study replaced by oral ISBAR assessment	Cohort outcomes; staff experience	Verification; scalability; workload/cost
Hutson et al. (2026)	Higher education pilot	Small pilot; student survey n=7	Adaptive viva following written submission	Pilot evaluation	Oral verification; feasibility caveat
Stratton-Maher & Kelly (2026)	First-year nursing	Large cohort; focus-group subsample	Structured ChatGPT-integrated assessment	Qualitative/student experience	Ethics; guidance; digital inequity

Table 2. Functional taxonomy of GenAI-responsive assessment strategies

Strategy	Central design question	Typical mechanisms	Illustrative studies
Regulating AI	What may AI do?	Permission levels, restrictions, purpose-specific conditions, disclosure	Quince & Faulconer, 2026
Structuring AI collaboration	How should students work with AI?	Scaffolds, staged use, specified functions, revision and reflection	Martin et al., 2025; Cochrane et al., 2026
Critiquing AI	Can students judge AI output?	Verification, correction, comparison, error identification, justification	Casey, 2026; Tam et al., 2026
Evidencing the human process	What did the student contribute?	Interaction records, prompts, drafts, annotations, reflections, decision traces	Fischer et al., 2024; Oliveira et al., 2025
Verifying human competence	Can the student demonstrate understanding?	Viva, oral defence, practical or supervised performance	Ogle & Jarrett, 2026; Hutson et al., 2026

3.3 Positioning of Generative AI Within Assessment

The studies show that the educational role of GenAI varies substantially across interventions. In some cases, GenAI is a permitted support tool; in others, it is deliberately integrated into task completion, becomes an object of critique, or contributes process data that are themselves assessed. Fount et al. (2024), for example, redesigned university English assessments to allow students to select among GenAI and other digital tools and found that students could make purpose-sensitive choices, while also identifying concerns about inequities between free and premium tools. Martin et al. (2025), Casey (2026), Tam et al. (2026), and Cochrane et al. (2026) illustrate more structured forms of integration in which students are required to evaluate, reflect on, or revise AI-supported work.

This variation supports a distinction between AI access and pedagogically structured AI use. Access alone does not establish that students are engaging in higher-order reasoning. Fischer et al. (2024) found that only a minority of students demonstrated advanced critical engagement with GenAI, whereas interventions explicitly designed around critique, verification, and revision place those activities within the assessed construct.

3.4 Evidencing Human Learning in AI-Mediated Assessment

A recurring feature of the empirical literature is the use of evidence beyond the final submitted product. Process-oriented approaches use reflective accounts, AI-interaction histories, annotated revisions, or documented decision making to make aspects of the learner's contribution visible (Casey, 2026; Fischer et al., 2024; Oliveira et al., 2025). Oral and performance-oriented approaches instead seek direct evidence that students can explain, justify, or apply the knowledge represented in submitted work (Hutson et al., 2026; Ogle & Jarrett, 2026).

The need for such evidence is reinforced by studies outside the intervention corpus. Kofinas et al. (2025) found that markers could not reliably distinguish human-authored, GenAI-modified, and GenAI-generated work and that greater assessment authenticity did not, by itself, safeguard against GenAI involvement. McGroarty et al. (2026) likewise reported that two AI-generated psychology reports received passing grades under routine university marking conditions. Brattli et al. (2026), using five years of assessment data from 1,066 students, observed a substantial change in grade distributions when a course moved from an AI-permissive take-home examination to an AI-restricted supervised examination. Although these studies do not all constitute implemented GenAI-responsive interventions, they provide contextual evidence for the concern that final-product performance and independent student competence may not be measurement-equivalent under different AI-access conditions.

3.5 Educational and Assessment-Related Outcomes

The empirical studies report outcomes at different evidentiary levels. Several studies primarily capture experience and perception, including acceptability, perceived learning, confidence, and students' views of AI integration (Casey, 2026; Fount et al., 2024; Stratton-Maher & Kelly, 2026; Tam et al., 2026). Such evidence is important for implementation but should not be interpreted as equivalent to demonstrated learning gains.

Other studies provide behavioural or process evidence. Fischer et al. (2024) compared students' claims about GenAI use with assessors' evaluations, Oliveira et al. (2025) analysed interaction traces, and Quince and Faulconer (2026) coded student declarations of GenAI use across redesigned assessments.

A smaller group provides performance or comparative outcome evidence. Ogle and Jarrett (2026) compared cohort-level outcomes before and after an oral assessment redesign, while Martin et al. (2025) compared structured and unrestricted AI-use conditions within an implemented assessment. Across this heterogeneous evidence base, the strongest conclusion is therefore not that GenAI-responsive assessment uniformly improves learning, but that outcomes depend on how AI use is structured, what students are required to do cognitively, and what evidence is collected.

3.6 Implementation, Feasibility, Equity, and Scalability

Implementation outcomes are central to judging whether promising assessment designs are sustainable. Martin et al. (2025) explicitly examined feasibility, acceptability, and perceived integrity. Ogle and Jarrett (2026) provide evidence that oral assessment can be implemented at large cohort scale under particular conditions and may reduce marking time and cost, challenging assumptions that oral verification is necessarily impractical. Conversely, Hutson et al. (2026) describe a smaller pilot and appropriately call for broader validation.

Equity also emerges as an implementation concern. Fount et al. (2024) reported student concerns about differences between free and premium AI tools, while Stratton-Maher and Kelly (2026) identified digital inequities and inconsistent institutional guidance as issues in a structured nursing assessment. These findings suggest that requiring GenAI within assessment may create new access and support obligations for institutions.

3.7 Methodological Quality and Limitations of the Evidence Base

The verified evidence base is methodologically heterogeneous. It includes qualitative case studies, mixed-methods evaluations, cross-sectional surveys, observational studies, process analyses, pilots, and cohort-level comparisons. This diversity supports the use of the MMAT for design-sensitive appraisal (Hong et al., 2018), but it also limits direct comparison across studies. Final MMAT judgments for each included study should be reported in the study-characteristics/appraisal table once the definitive corpus is locked; no overall numerical MMAT score should be calculated.

A recurring limitation is reliance on self-reported experience or perceived learning. Cochrane et al. (2026), for example, provide useful evidence concerning perceived learning, evaluative engagement, confidence, and competence, but the cross-sectional survey design does not establish causal learning effects. Casey (2026), Fount et al. (2024), Stratton-Maher and Kelly (2026), and Tam et al. (2026) similarly provide valuable evidence about student experience and critical engagement while remaining context-specific. Stronger causal claims require comparative, longitudinal, or experimental designs with objective measures of learning.

3.8 Evidence Gaps

Several gaps remain evident. First, more comparative studies are needed to establish whether structured GenAI-responsive interventions improve learning, evaluative judgement, or transfer relative to alternative assessment designs. Second, the literature needs stronger longitudinal evidence concerning whether students retain the knowledge and judgement demonstrated during AI-supported assessment. Third, workload, cost, accessibility, reliability, and equity require systematic evaluation across larger and more diverse cohorts.

Fourth, research remains concentrated in individual courses and institutions, limiting cross-disciplinary and cross-institutional generalization. Finally, the field requires more explicit validation of process evidence. Interaction logs, reflections, declarations, and oral explanations may make student contribution more visible, but future research should establish when these sources provide reliable and valid evidence of the intended learning outcomes.

4. Discussion

The rapid integration of generative artificial intelligence (GenAI) into higher education has generated extensive debate about academic integrity, assessment validity, and the continuing suitability of established assessment practices. While much of the early discussion concentrated on preventing unauthorized AI use or detecting AI-generated work, the emerging empirical literature examined in this review indicates a broader transition. Higher education assessment is increasingly moving from attempts to control the presence of GenAI toward deliberate decisions about what role AI should play, what intellectual responsibility should remain with the student, and what evidence is required to demonstrate student learning. This transition represents an important shift from reactive responses to GenAI toward the intentional redesign of assessment for environments in which AI assistance is increasingly difficult, and in some contexts undesirable, to exclude.

The findings of this review suggest that the central assessment problem created by GenAI cannot be reduced to whether students are permitted to use artificial intelligence. Rather, the more consequential issue concerns the relationship among AI delegation, human cognitive responsibility, and evidence of learning. GenAI can contribute to brainstorming, information synthesis, drafting, linguistic refinement, feedback, problem solving, and other activities traditionally performed by students. As these functions are partially delegated to AI, the quality of a final product may become a less transparent indicator of the knowledge, reasoning, judgement, and disciplinary competence possessed by the student.

GenAI-responsive assessment therefore requires educators to reconsider not only the format of assessment but

also the inferential relationship between the evidence produced by an assessment and the learning outcomes that the assessment is intended to represent.

4.1 Beyond the Binary of Prohibiting or Permitting GenAI

One of the clearest implications emerging from the reviewed literature is the inadequacy of treating GenAI use as a binary choice between prohibition and unrestricted permission. Such a distinction focuses primarily on access to technology rather than on the educational quality of students' interactions with it.

Evidence from studies in which students were permitted to use GenAI indicates that access alone does not necessarily generate sophisticated forms of learning. Fischer et al. (2024), for example, found that postgraduate students frequently used GenAI for writing-related functions such as paraphrasing and rephrasing, whereas substantially fewer demonstrated uses associated with more advanced critical thinking and sensemaking. This finding illustrates an important limitation of permissive approaches: allowing GenAI may normalize its use without ensuring that students engage with it critically, strategically, or in ways aligned with intended learning outcomes.

By contrast, interventions that deliberately structured students' interactions with GenAI appeared to reposition AI use as an object of pedagogical design. Students may be required to interrogate an AI response, identify inaccuracies, compare alternative outputs, justify whether AI-generated information should be accepted, revise inadequate responses, or reflect on the limitations of the technology. In these contexts, GenAI does not simply reduce the work required from the learner. Instead, the assessment redistributes cognitive activity by assigning some productive functions to AI while deliberately retaining evaluative and decision-making responsibilities for the student.

This distinction suggests that the educational question should move beyond whether GenAI is used toward how GenAI use is structured and what students remain responsible for doing.

Consequently, policies that classify assessment simply as "AI permitted" or "AI prohibited" may be insufficient for guiding pedagogically meaningful practice.

More useful assessment specifications may need to identify the functions that can legitimately be delegated to AI, the functions that students are expected to perform themselves, and the evidence through which those expectations will be assessed.

4.2 From Product Authenticity to Evidence of Human Learning

A second major implication concerns the status of the final assessment product. Conventional assessment frequently assumes that the submitted artefact provides meaningful evidence of the student's capabilities. Although this assumption has never been absolute, students have always had access to external resources, peers, editors, and digital tools, the generative capabilities of contemporary AI substantially increase the distance that can exist between the quality of a submitted product and the competence of the individual submitting it.

This issue explains why simply making assessment tasks more "authentic" may not be sufficient. Authentic assessment remains educationally valuable because it can connect academic learning with meaningful disciplinary and professional practice. However, authenticity does not automatically establish authorship, understanding, or intellectual ownership. Evidence showing that assessors may struggle to distinguish human-generated from AI-generated or AI-modified submissions reinforces the limitation of relying on product characteristics alone.

The reviewed interventions indicate an emerging response: shifting some assessment attention from the product of learning to evidence of the process and performance underlying that product. Several strategies reflect this movement. Students may document their interactions with GenAI, submit prompts or conversation histories, explain how outputs were evaluated and modified, reflect upon decisions made during task completion, or defend their conclusions orally. Other approaches require students to demonstrate disciplinary competence directly through oral, practical, dialogic, or supervised performance.

These approaches do not imply that final products have become irrelevant. In many disciplines, producing a high-quality artefact remains an important learning outcome. Rather, the findings suggest that AI-mediated products may need to be interpreted alongside complementary forms of evidence when educators need to make claims about individual student competence.

This distinction is especially important because a polished AI-assisted product and genuine student learning are not mutually exclusive. A student may use GenAI extensively while exercising substantial disciplinary judgement in selecting, verifying, rejecting, integrating, and improving its outputs. Conversely, a student may produce an equally polished artefact while exercising minimal understanding. Assessment therefore needs mechanisms capable of distinguishing these situations.

4.3 Human Cognitive Responsibility as a Principle for GenAI-Responsive Assessment

The synthesis supports the development of human cognitive responsibility as a useful organizing principle for GenAI-responsive assessment. Human cognitive responsibility refers to the knowledge, reasoning, judgement, verification, decision making, and disciplinary accountability that students are expected to retain when GenAI contributes to assessed work.

This concept differs from requiring students to complete all intellectual work without technological assistance. Such an expectation may be neither realistic nor educationally desirable in disciplines where responsible AI use is becoming part of professional practice. Instead, human cognitive responsibility requires assessment designers to specify what students must remain capable of understanding and doing even when some productive activities are delegated to AI.

Three questions follow from this principle:

What may be delegated to AI?

What intellectual responsibility must remain with the student?

What evidence demonstrates that the student has exercised that responsibility?

These questions provide a common analytical language for assessment strategies that otherwise appear very different. An assessment requiring students to critique AI-generated scientific explanations, for example, deliberately delegates initial content production to AI while retaining evaluation, verification, and disciplinary judgement as student responsibilities. An assessment involving an AI-generated policy brief may similarly shift content generation toward AI while requiring students to identify factual limitations, political assumptions, omissions, and inappropriate recommendations. An oral verification component takes a different approach by requiring students to demonstrate that they understand and can justify work submitted through an AI-mediated process.

Viewed in this way, GenAI-responsive assessment does not necessarily seek to minimize AI involvement. Its objective is to maintain alignment between intended learning outcomes, the responsibilities assigned to students, and the evidence used to evaluate achievement.

4.4 The AI–Human Assessment Responsibility Model

Based on the emerging synthesis, this review proposes the AI–Human Assessment Responsibility Model as a conceptual framework for interpreting and designing GenAI-responsive assessment. The model consists of three interconnected dimensions: AI delegation, human cognitive responsibility, and evidentiary mechanism.

AI delegation concerns the functions that an assessment permits or requires students to assign to GenAI. These may include idea generation, information organization, drafting, linguistic refinement, feedback, coding, problem solving, simulation, or content generation.

Human cognitive responsibility concerns the intellectual capabilities that students remain accountable for demonstrating. Depending on the learning outcomes, these may include disciplinary understanding, critical evaluation, verification, reasoning, synthesis, ethical judgement, decision making, creativity, or the ability to recognize limitations and errors in AI-generated material.

Evidentiary mechanism concerns how assessment makes those human capabilities observable. Evidence may be located in the final product but may also include process documentation, AI-interaction records, annotated revisions, reflective accounts, critical commentary, oral justification, supervised performance, or combinations of these approaches.

The central proposition of the model is that the validity of AI-mediated assessment depends less on minimizing the amount of AI used than on achieving appropriate alignment among these three dimensions. Increasing AI delegation without reconsidering human responsibility and assessment evidence may weaken the relationship between observed performance and student competence. In contrast, extensive AI use may remain compatible

with meaningful assessment when the learning outcomes legitimately involve human–AI collaboration and when students' distinctive responsibilities are clearly defined and evidenced.

This model also suggests that no single GenAI-responsive assessment strategy is likely to be universally appropriate. Appropriate delegation and evidence depend upon disciplinary expectations and intended learning outcomes. The level of unaided performance required from a nursing student demonstrating clinical judgement, for example, may differ substantially from the AI-supported capability expected of a student producing professional communication in a field where AI-assisted drafting has become routine. Assessment redesign therefore requires decisions about the educational construct being assessed rather than simply decisions about technology.

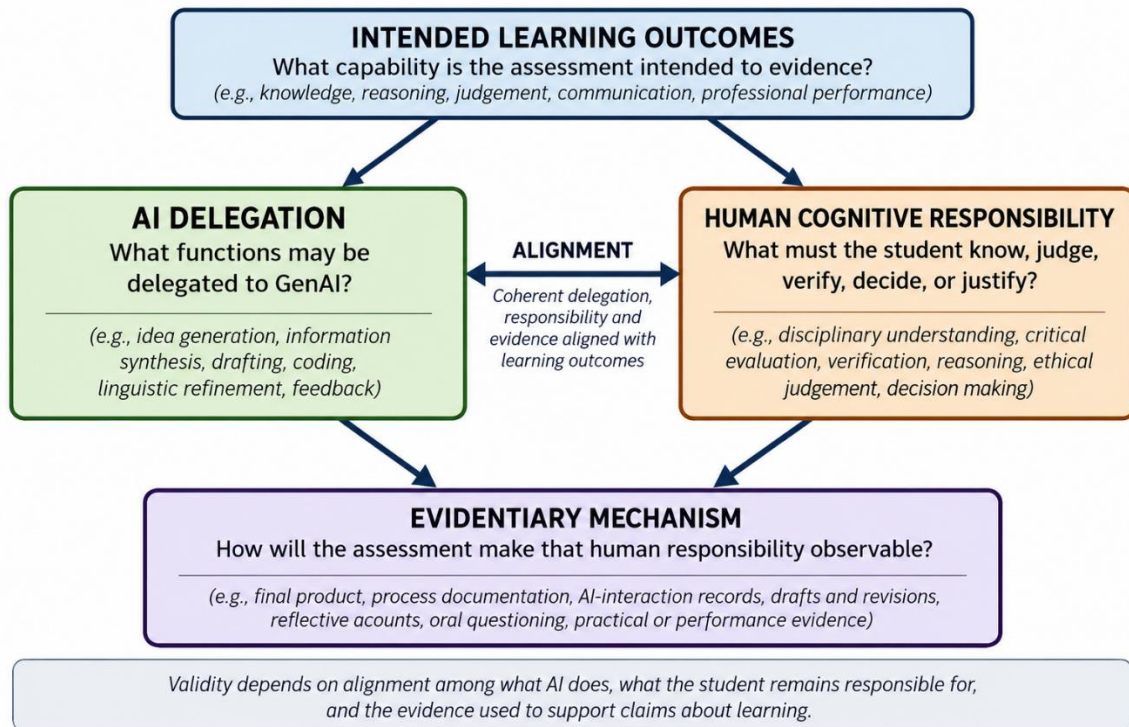


Figure 1. AI-Human Assessment Responsibility Model

4.5 Critical Evaluation May Be More Educationally Important Than Prompt Production Alone

Another implication concerns the competencies higher education chooses to develop around GenAI. Considerable attention has been given to prompt engineering and students' ability to obtain useful outputs from AI systems. Although effective prompting may be valuable, the reviewed interventions suggest that the more enduring educational capability may lie in students' ability to evaluate what AI produces.

GenAI systems can generate plausible but inaccurate, incomplete, biased, poorly reasoned, or contextually inappropriate responses.

Consequently, students who can obtain sophisticated outputs without possessing the knowledge required to evaluate them may become more dependent on AI while appearing increasingly competent through the quality of their products.

Assessment that rewards output generation without examining evaluative judgement may therefore inadvertently reinforce superficial AI dependence.

Interventions requiring students to identify errors, verify claims, compare AI-generated material against disciplinary knowledge, improve inadequate responses, or justify acceptance and rejection decisions represent a different pedagogical approach. In these designs, GenAI becomes a source of material upon which disciplinary judgement is exercised.

This distinction may be particularly important for higher education because expertise is not defined merely by the capacity to produce answers. It also involves the ability to recognize when an answer is inadequate and to explain

why. GenAI-responsive assessment may therefore provide an opportunity to place greater emphasis on evaluative judgement, verification, epistemic responsibility, and critical AI literacy.

4.6 Implementation and Scalability Matter

A pedagogically sophisticated assessment intervention has limited institutional value if it cannot be implemented sustainably. The reviewed evidence therefore indicates that implementation outcomes deserve attention alongside learning outcomes.

Oral verification provides a useful example. Oral assessment can potentially provide direct evidence of student understanding and reduce uncertainty concerning authorship. However, large-scale implementation may raise concerns about staff workload, scheduling, consistency of questioning, reliability of marking, student anxiety, accessibility, and cost.

Importantly, emerging evidence indicates that these consequences cannot simply be assumed. Large-cohort implementations suggest that carefully designed oral approaches may be more scalable than commonly expected, while smaller pilots also demonstrate that student experiences can be mixed.

Similarly, requiring students to submit complete AI interaction histories may improve process transparency but create substantial volumes of additional material for assessors. Reflective components may make reasoning visible but may also become formulaic if students learn to produce strategically desirable accounts of their AI use. AI-integrated assessment may increase professional authenticity while simultaneously creating new technological requirements for institutions and students.

These findings emphasize the need to evaluate GenAI-responsive assessment as an educational system rather than solely as a task design. Effectiveness should therefore encompass not only learning but also reliability, workload, scalability, accessibility, student experience, and institutional feasibility.

4.7 Equity and Access

The increasing integration of GenAI into assessment also raises questions of equity. Students do not necessarily have equivalent access to AI technologies, particularly where more capable models, larger context windows, advanced reasoning features, or specialist functions require paid subscriptions. Evidence from redesigned assessment contexts indicates that students themselves recognize differences between free and premium access as a potential source of inequality.

This creates an assessment-design problem. If effective completion of an assessment increasingly depends on the quality of AI assistance available to individual students, differences in technological access may become differences in assessment opportunity. Institutions that explicitly integrate GenAI into assessment therefore need to consider whether equivalent tools should be institutionally provided, whether assessment requirements can be completed adequately using universally accessible systems, and whether the competencies being assessed depend excessively on particular commercial technologies.

Equity also extends beyond financial access. Students differ in prior AI experience, digital competence, disciplinary knowledge, language background, disability, and confidence in experimenting with emerging technologies. GenAI-responsive assessment should therefore avoid assuming that all students enter AI-rich learning environments with equivalent capabilities.

4.8 Limitations of the Evidence Base

Despite rapid growth in empirical research, the evidence base remains methodologically immature. A substantial proportion of emerging studies rely on student perceptions, reflections, self-reported confidence, or evaluations of acceptability. Such evidence is valuable for understanding implementation and student experience, but positive perceptions should not be interpreted as equivalent to demonstrated improvements in learning.

Relatively fewer studies provide comparative evidence capable of establishing whether redesigned assessment improves learning, validity, evaluative judgement, or other educational outcomes relative to alternative assessment conditions. Short intervention periods, small samples, discipline-specific implementations, absence of comparison groups, and reliance on researcher-developed measures further limit the generalizability of some findings.

The rapidly changing capabilities of GenAI introduce an additional challenge. An assessment design evaluated with one generation of AI may operate differently when students gain access to substantially more capable

systems. Consequently, assessment strategies based primarily on what AI *cannot currently do* may have limited durability.

Future research should therefore place greater emphasis on the educational capabilities that students should retain irrespective of changes in AI performance. Longitudinal studies, cross-disciplinary comparisons, multi-institutional research, objective measures of learning, and evaluations of workload and cost are particularly important.

Research should also examine whether interventions that increase confidence in authorship actually improve assessment validity and whether process documentation accurately represents students' cognitive contributions rather than merely their ability to describe those contributions retrospectively.

4.9 Future Research

The emerging evidence base suggests several priorities for future research. First, studies should move beyond whether students *like* GenAI-responsive assessment and investigate whether specific interventions improve learning, reasoning, evaluative judgement, and transfer of knowledge.

Second, comparative research is needed to determine when process evidence, oral verification, critical AI evaluation, or structured AI collaboration provides meaningful advantages over conventional assessment.

Third, researchers should investigate combinations of strategies rather than treating individual assessment formats as isolated solutions. An AI-integrated project combined with process documentation and selective oral verification, for example, may provide stronger evidence than any of these mechanisms alone.

Fourth, implementation research should examine scalability, staff workload, accessibility, equity, reliability, and cost across large and diverse cohorts. Fifth, longitudinal research should investigate whether students exposed to GenAI-responsive assessment develop durable capabilities for responsible AI collaboration rather than task-specific strategies for satisfying assessment requirements.

Finally, future studies should investigate the concept of human cognitive responsibility directly. Research could examine which intellectual functions can be delegated to GenAI without undermining particular learning outcomes, which forms of evidence most effectively demonstrate students' retained capabilities, and how these relationships differ across disciplines and levels of study.

4.10 Concluding Interpretation

The emergence of GenAI does not signal the end of meaningful assessment, but it does challenge higher education to reconsider what assessment evidence represents. When AI can contribute substantially to the production of academic work, the quality of the final artefact alone may provide an incomplete account of student capability. The empirical literature examined in this review indicates that educators are beginning to respond by structuring AI use, requiring critical evaluation, making learning processes more visible, and introducing additional mechanisms for demonstrating human understanding.

The key challenge is therefore not to remove AI from assessment but to ensure that the presence of AI does not make human learning invisible. GenAI-responsive assessment is strongest when it makes explicit what AI may contribute, what intellectual responsibility remains with the learner, and how that responsibility will be demonstrated.

From this perspective, the future of assessment is unlikely to be defined by a simple choice between human and artificial intelligence. It will instead depend on the capacity of higher education to design credible evidence of human learning within increasingly AI-mediated forms of academic and professional work.

5. Implications for Practice

The findings of this review have several implications for educators, assessment designers, programme leaders, and higher education institutions responding to the increasing presence of generative artificial intelligence (GenAI). A central implication is that assessment redesign should move beyond the binary question of whether GenAI should be permitted or prohibited. Instead, assessment decisions should begin with the intended learning outcomes and explicitly consider what functions may appropriately be delegated to AI, what cognitive responsibilities should remain with students, and what evidence is necessary to demonstrate that students have exercised those responsibilities.

5.1 Design from Learning Outcomes, Not from the Technology

Assessment redesign should begin with the capability that educators intend to assess rather than with the capabilities or limitations of a particular GenAI system. Designing assessment around what current AI tools cannot accomplish may provide only temporary protection because the capabilities of these systems continue to evolve. By contrast, identifying the knowledge, reasoning, judgement, communication, ethical decision making, or professional performance that students are expected to demonstrate provides a more durable basis for assessment design.

Educators should therefore distinguish among capabilities that students need to demonstrate independently, capabilities that may legitimately be augmented by AI, and capabilities involving responsible human–AI collaboration. The appropriate balance will differ across disciplines, educational levels, and learning outcomes. There is consequently unlikely to be a single assessment format that constitutes an optimal response to GenAI across higher education.

5.2 Specify the Role of GenAI Explicitly

Where GenAI is permitted, assessment instructions should specify its intended role rather than relying solely on broad statements that AI use is “allowed.” Students may need guidance concerning whether GenAI can be used for brainstorming, searching for alternatives, drafting, linguistic refinement, coding, feedback, data interpretation, or other functions.

Equally important is identifying activities for which students retain responsibility. These may include verifying factual claims, evaluating evidence, constructing arguments, applying disciplinary standards, identifying limitations, making decisions, or justifying conclusions.

Clear specifications of these boundaries can serve both pedagogical and integrity purposes. Students are given a clearer understanding of responsible AI use, while educators can align assessment criteria with the capabilities that students are actually expected to demonstrate.

5.3 Structure AI Use When It Supports the Learning Outcomes

Permitting GenAI without pedagogical structure should not be assumed to produce meaningful AI literacy or higher-order learning (Fischer et al., 2024). Where human–AI collaboration is relevant to the learning outcomes, educators may need to design explicit activities that require students to engage critically with AI-generated material.

Such activities might require students to compare alternative AI responses, identify factual or conceptual errors, verify claims against appropriate sources, revise inadequate outputs, explain why particular suggestions were accepted or rejected, or evaluate the assumptions underlying AI-generated recommendations.

In this way, GenAI becomes more than a productivity tool. It becomes an object through which students demonstrate disciplinary knowledge and evaluative judgement.

5.4 Consider Evidence Beyond the Final Product

Where GenAI can substantially contribute to the production of an assessed artefact, educators should consider whether the final product provides sufficient evidence of the intended learning outcomes. If not, complementary evidence may be necessary.

Depending on the discipline and assessment purpose, this evidence may include drafts, annotated revisions, selected AI-interaction records, reflective commentary, decision logs, critical evaluations, oral questioning, presentations, demonstrations, or practical performance. These mechanisms can help make students’ reasoning and decision making more visible.

However, increasing evidence requirements should not become an end in itself. Requiring students to submit extensive prompt histories or lengthy reflective accounts may increase workload without necessarily improving assessment validity. Additional evidence should therefore be collected selectively and only when it contributes meaningfully to judgements about student learning.

5.5 Use Oral and Performance Verification Strategically

Oral, dialogic, and performance-based assessment can provide valuable opportunities for students to demonstrate understanding independently of a polished AI-mediated product (Hutson et al., 2026; Ogle & Jarrett, 2026). Nevertheless, the evidence reviewed does not justify treating oral assessment as a universal solution to GenAI.

Implementation should consider cohort size, staff workload, consistency of questioning, marking reliability, student anxiety, accessibility, scheduling, and cost. Selective oral verification may in some contexts be more practical than converting an entire assessment regime to oral examination. For example, a brief defense could be combined with an AI-supported project when direct evidence of student reasoning is particularly important.

The principle is therefore not that every student should be examined orally, but that assessment designers should consider when direct or dialogic evidence is necessary to support credible judgements about competence.

5.6 Assess Critical AI Judgement, Not Merely AI Productivity

Higher education should be cautious about equating effective GenAI use with the ability to generate sophisticated outputs.

Students also require the capacity to recognize when AI output is inaccurate, unsupported, biased, incomplete, inappropriate, or inconsistent with disciplinary standards.

Assessment can contribute directly to this capability by requiring students to verify, critique, correct, and justify AI-generated material. Such activities position students as accountable decision makers rather than passive recipients of machine-generated answers.

This is particularly important in professional disciplines where inappropriate reliance on apparently plausible AI output may have significant consequences. Critical evaluation and verification should therefore be considered central components of AI literacy where they align with programme learning outcomes.

5.7 Address Equity Before Requiring GenAI

Institutions should also consider equity when GenAI becomes an explicit component of assessment. Students may have unequal access to paid AI systems, advanced models, specialist functions, reliable digital infrastructure, or previous experience with AI technologies (Foung et al., 2024; Stratton-Maher & Kelly, 2026).

Where the use of GenAI is required for assessment, institutions should seek to ensure that students have access to sufficiently comparable tools and appropriate guidance. Assessment performance should not inadvertently become a proxy for students' ability to purchase more capable AI services.

Accessibility, language background, digital competence, disability, and previous exposure to AI should similarly be considered when designing and evaluating GenAI-responsive assessment.

5.8 Evaluate Assessment Redesign as an Implementation Problem

Assessment innovation should be evaluated not only according to its pedagogical attractiveness but also according to its feasibility. Institutions introducing GenAI-responsive assessment should therefore monitor student learning, academic integrity, student experience, educator workload, marking reliability, accessibility, scalability, technological requirements, and cost.

Pilot implementation may be particularly valuable before large-scale adoption. Evidence collected during implementation can identify unintended consequences and enable assessment designs to be refined before they become embedded across programmes.

Ultimately, sustainable GenAI-responsive assessment requires alignment among learning outcomes, AI delegation, human cognitive responsibility, assessment evidence, and implementation conditions. The aim should not be to design assessment that is permanently resistant to technological change, but to develop assessment capable of producing credible evidence of student learning as the technological environment continues to evolve.

6. Limitations of the Present Review

The findings of this systematic review should be interpreted in light of several limitations.

First, GenAI in higher education is a rapidly developing field. The period between the widespread public availability of ChatGPT in late 2022 and the completion of this review is relatively short, while both technological capabilities and institutional responses have changed considerably during that period. Consequently, the evidence base represents an evolving rather than mature field of research. New assessment interventions and evaluations are likely to appear rapidly, and some conclusions of the present review may require reconsideration as stronger empirical evidence becomes available.

Second, terminology within the field remains inconsistent. Studies may describe similar practices using terms such as AI-integrated assessment, AI-enabled assessment, AI-supported assessment, assessment redesign, authentic assessment, process-oriented assessment, AI literacy assessment, or human–AI collaboration. Conversely, the same terminology may refer to substantively different interventions. Although the search strategy incorporated multiple terms associated with GenAI and assessment, relevant studies using unexpected terminology may have been missed.

Third, the review deliberately adopted a relatively focused definition of a GenAI-responsive assessment intervention. Studies were included in the principal synthesis when an assessment practice, procedure, AI-use condition, verification mechanism, or evaluative activity was deliberately configured in response to GenAI and implemented with higher education students. This decision strengthened the conceptual coherence of the review but excluded adjacent evidence concerning student perceptions, institutional policy, AI detection, automated grading, naturally occurring GenAI use, and the ability of AI systems to complete conventional assessments. Such literature remains relevant to the broader transformation of assessment but addresses a different research question.

Fourth, heterogeneity across the included studies limits direct comparison. Assessment interventions vary by discipline, educational level, cohort size, assessment purpose, role of GenAI, technological platform, research design, and outcome measurement. The studies also differ substantially in whether they investigate perceptions, behaviours, learning processes, academic performance, assessment validity, integrity, workload, or implementation feasibility. This heterogeneity makes statistical aggregation inappropriate for many outcomes and places greater emphasis on narrative and thematic synthesis.

Fifth, the strength of conclusions is constrained by the methodological characteristics of the available primary research. Emerging studies frequently rely on self-reported perceptions, reflections, convenience samples, single-course implementations, and relatively short intervention periods. Positive perceptions of an intervention cannot be assumed to represent improved learning, and associations between GenAI use and assessment performance do not necessarily demonstrate causal effects. The review therefore distinguishes different forms of evidence and interprets findings in relation to methodological quality rather than treating all reported outcomes as equivalent.

Sixth, the speed of technological development creates a particular problem for evidence synthesis. Studies conducted with earlier GenAI systems may not fully represent assessment conditions involving newer and more capable models. Findings concerning the limitations of specific AI systems may therefore become outdated more rapidly than findings concerning broader pedagogical principles. For this reason, the review places greater emphasis on assessment design, cognitive responsibility, and evidence of learning than on the performance characteristics of individual GenAI platforms.

Seventh, restricting the review to English-language publications may have reduced representation of assessment practices reported in other languages and educational systems. The geographical distribution of the available literature may also limit the transferability of findings across higher education contexts with different technological infrastructures, assessment cultures, regulatory environments, and institutional resources.

Finally, the analytical categories and the proposed AI–Human Assessment Responsibility Model are interpretive products of the synthesis. Although they are grounded in recurring characteristics of the empirical literature, they should not yet be regarded as a validated assessment theory. The model requires further empirical examination across disciplines, assessment formats, institutional contexts, and levels of study. Its value at this stage lies in providing a structured way to examine the alignment among AI delegation, human cognitive responsibility, and evidence of student learning.

These limitations do not diminish the importance of the emerging evidence but indicate the level of caution required when translating early findings into assessment policy and practice. The review should therefore be understood as a synthesis of a rapidly developing empirical field and as a foundation for further testing rather than as a definitive account of GenAI-responsive assessment.

7. Conclusion

Generative artificial intelligence is changing the conditions under which higher education assessment operates. As GenAI becomes increasingly capable of contributing to writing, reasoning, problem solving, coding, feedback, synthesis, and other activities traditionally associated with student work, assessment can no longer rely uncritically

on the assumption that the quality of a submitted product provides transparent evidence of the learner's capabilities.

This systematic review examined the emerging empirical literature on GenAI-responsive assessment interventions that have been implemented with higher education students. Rather than focusing on conceptual recommendations concerning how assessment *should* respond to AI, the review concentrated on the transition from principles to practice: how educators have actually redesigned or configured assessment in response to GenAI and what evidence has emerged from those implementations.

The synthesis indicates that GenAI-responsive assessment extends beyond a simple choice between prohibiting and permitting AI. Emerging interventions regulate the conditions of AI use, structure human–AI collaboration, require students to critically evaluate AI-generated material, make learning processes more visible, and introduce oral, dialogic, or performance-based mechanisms for verifying student competence. These approaches reflect different educational purposes and should not be treated as interchangeable solutions.

A central implication of the review is that the amount of AI used within an assessment may be less important than the distribution of cognitive responsibility between the student and the technology. Allowing GenAI does not necessarily result in meaningful engagement, while extensive AI involvement does not necessarily undermine assessment when students remain responsible for disciplinary judgement, verification, critical evaluation, decision making, and justification.

To capture this relationship, the review proposes the AI–Human Assessment Responsibility Model, organized around three interconnected dimensions: AI delegation, human cognitive responsibility, and evidentiary mechanism. The model suggests that GenAI-responsive assessment should explicitly determine what functions may be delegated to AI, what intellectual responsibilities must remain with students, and what evidence will demonstrate that students have exercised those responsibilities.

This perspective shifts attention away from the pursuit of universally “AI-proof” assessment. Assessment strategies built primarily around the current limitations of GenAI may become increasingly fragile as technological capabilities advance. More sustainable assessment design begins instead with intended learning outcomes and asks which capabilities students must demonstrate independently, which may legitimately be augmented by AI, and which involve responsible human–AI collaboration.

The emerging evidence also demonstrates that pedagogical promise alone is insufficient. GenAI-responsive assessment must be evaluated in relation to learning, validity, integrity, student experience, educator workload, scalability, accessibility, equity, and cost. An intervention that successfully makes student thinking visible but cannot be implemented reliably or equitably at scale may have limited practical value. Similarly, an assessment that students perceive positively should not be assumed to improve learning without appropriate outcome evidence.

The current evidence base remains young and methodologically heterogeneous. Stronger comparative, longitudinal, cross-disciplinary, and multi-institutional research is needed, particularly research employing objective measures of learning and examining the long-term consequences of different distributions of responsibility between humans and AI. As GenAI capabilities continue to change, research should prioritize durable educational constructs such as disciplinary understanding, evaluative judgement, verification, ethical responsibility, and the capacity to justify decisions.

Ultimately, the challenge posed by GenAI is not simply that artificial intelligence can produce academic work. The deeper challenge is determining what an assessment allows educators to conclude about the person who submitted that work. The future of assessment therefore depends less on separating human activity from artificial intelligence than on ensuring that human learning remains identifiable, demonstrable, and educationally meaningful within AI-mediated academic and professional practice.

GenAI-responsive assessment should consequently be designed around a simple but demanding principle: when AI contributes to assessed work, assessment must remain capable of showing what the student knows, understands, judges, and can do.

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From Technical Literacy to AI-Integrated Pedagogy: A Scoping Review of Digital Competence Frameworks for Higher Education (2000–2026)

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ABSTRACT

Digital competence frameworks have multiplied over the past quarter century, and researchers in higher education must select among them with little comparative guidance. This scoping review, reported with the PRISMA-ScR checklist, charts a purposive corpus of 43 frameworks, standards, certification schemes and self-reflection tools in use between 2000 and 2026. Each entry was verified against its primary source in October 2026, and a search of ERIC, OpenAlex, Scopus, Web of Science and Google Scholar (6,598 records) then tested the coverage of the corpus. Explicit decision rules assign every entry to one of five clusters, which are general digital literacy, pedagogical integration, teacher-specific competence, national and regional policy, and the European Commission ecosystem with its derivatives. Five overlapping waves describe the movement from operational skills through pedagogical integration, structured progression and expanded professional dimensions towards AI competence. Only two entries were designed for higher education, 10 are accompanied by an assessment instrument, and peer-reviewed psychometric evidence was located for two, both from the DigCompEdu family. AI became the organising subject of corpus entries from 2023, although no issuing body has released an AI self-assessment instrument. The taxonomy gives researchers a transparent basis for selecting and justifying frameworks.

Keywords: digital competence, competence frameworks, scoping review, higher education, DigCompEdu, AI literacy

INTRODUCTION

Digital competence has become central to the quality of teaching in higher education. Universities expect their teachers to integrate technology into teaching, assessment and student engagement, and yet defining what digital competence means, and selecting appropriate tools to measure it, remains a difficult task. Governments, international organisations, research institutions and individual scholars have each produced frameworks, and each framework reflects its own assumptions about what digital competence includes and how it develops.

The result is a crowded landscape in which some frameworks define competence as technical skill, others emphasise pedagogical integration, and others again concentrate on measurement, policy implementation or, most recently, artificial intelligence (AI). For researchers who study the digital competence of teachers, this proliferation creates a practical problem, because the choice of a framework determines which constructs are measured and how the findings can be compared with other studies. The choice is rarely neutral, since every framework carries particular assumptions about the nature of competence.

Existing reviews have examined parts of this landscape. Zhang et al. (2026) reviewed 38 studies of the digital competence of pre-service teachers and found rising publication numbers, TPACK as the most widely adopted framework, and a growing tendency to integrate several frameworks in one study. Domínguez-González et al. (2025) reviewed 19 studies and identified DigCompEdu, the ISTE standards, the UNESCO ICT Competency Framework for Teachers and the Spanish national framework as the most recognised references. Saltos-Rivas et al. (2022) mapped 88 studies that evaluated digital competence in higher education and reported that more than half provided no joint evidence of reliability and validity, while most relied on ad hoc instruments. Flam et al.

(2025) compared 16 global, regional and national frameworks for a single national client, and earlier compilations listed frameworks for citizens (Law et al., 2018) and for teachers (Falloon, 2020). None of these sources, however, places frameworks from different traditions on a single map with explicit rules of classification.

Higher education presents a further difficulty of its own. Few frameworks have been written for university teaching, so researchers in the sector tend to borrow frameworks developed for citizens, for schools or for the workforce. A review confined to higher education frameworks would therefore miss most of the instruments that higher education research uses in practice. For this reason the present review maps the wider landscape, and it records for every entry whether higher education lies at the centre of its scope, within a wider scope, or outside it.

The review charts 43 frameworks and related instruments, assigns them to five clusters through explicit decision rules, and traces five waves of conceptual change, including the AI wave that has become visible since 2023. Three research questions guided the analysis.

RQ1. How have digital competence frameworks evolved conceptually between 2000 and 2026?

RQ2. What patterns emerge when frameworks are grouped according to their approach to defining and measuring competence?

RQ3. What gaps persist across the landscape that bear on future framework development and on the selection of instruments in higher education research?

METHOD

Design

The study followed the scoping review approach proposed by Arksey and O'Malley (2005), which is suited to questions about the extent and nature of a field where the purpose is to map concepts rather than to evaluate the effectiveness of interventions. Reporting follows the PRISMA extension for scoping reviews (Tricco et al., 2018). The unit of analysis is the framework rather than the study. The corpus was built in three stages, which are summarised in Figure 1. The first two stages were purposive, and the third stage, carried out in October 2026, verified every entry and tested the coverage of the corpus through a structured search.

Corpus Construction

Stage 1 formed part of the doctoral literature review conducted by the first author. Between April and May 2023, the researcher compiled a comparative inventory of 31 digital competence frameworks from the documents and web pages of the bodies that issued them, and charted each entry on its title, scope, dimensions, levels, indicators, target population and source. The inventory was built by reading the frameworks themselves rather than through a protocol-driven database search, and it had grown to 37 entries by February 2025. Its content overlaps with two published compilations, since seven of its entries also appear in Appendix 1 of Law et al. (2018) and eight appear in the appendix of Falloon (2020). Stage 2 followed in April 2026, when six frameworks addressing AI competence were added, which brought the corpus to 43 entries. The corpus is therefore a purposive selection of prominent and contrasting frameworks rather than a census of all frameworks in existence.

Source Verification and Structured Search

Stage 3 was carried out on October 2026 and consisted of two parts. In the first part, every corpus entry was checked against the document or web page of its issuing body, and its title, authorship, year, target population, structure, levels and assessment provision were charted from that source. All 43 entries were confirmed to exist, although the check corrected the recorded year, authorship or title of a majority of them. Successive versions of one framework were counted as a single entry, so that DigComp 1.0 to 3.0 form one entry, and the attributes describe the latest version consulted.

In the second part, a structured search was conducted to establish how far the purposive corpus covers the literature that proposes frameworks. ERIC and OpenAlex were queried through their public interfaces, Scopus and the Web of Science Core Collection through their advanced search pages, and Google Scholar through title-only searches, in each case with strings that combined competence terms with the terms framework, model and standard, in English and in Spanish (Appendix B). Scholars supply result snippets rather than abstracts, so its records were screened on less information than those from the other sources. So, it is treated here as a supplementary source rather than a principal one (Gusenbauer & Haddaway, 2020).

The searches returned 6,598 records, and after the removal of 2,392 duplicates, 4,206 records were screened on title and abstract against a written rubric. The researcher conducted this screening with the support of a generative

AI tool, and the records first marked as unclear were examined a second time, and final screening is done by the researcher. The search was not used to enlarge the corpus. Its purposes were to estimate the coverage of the corpus, to count how often other studies take up the corpus frameworks, and to date the AI wave.

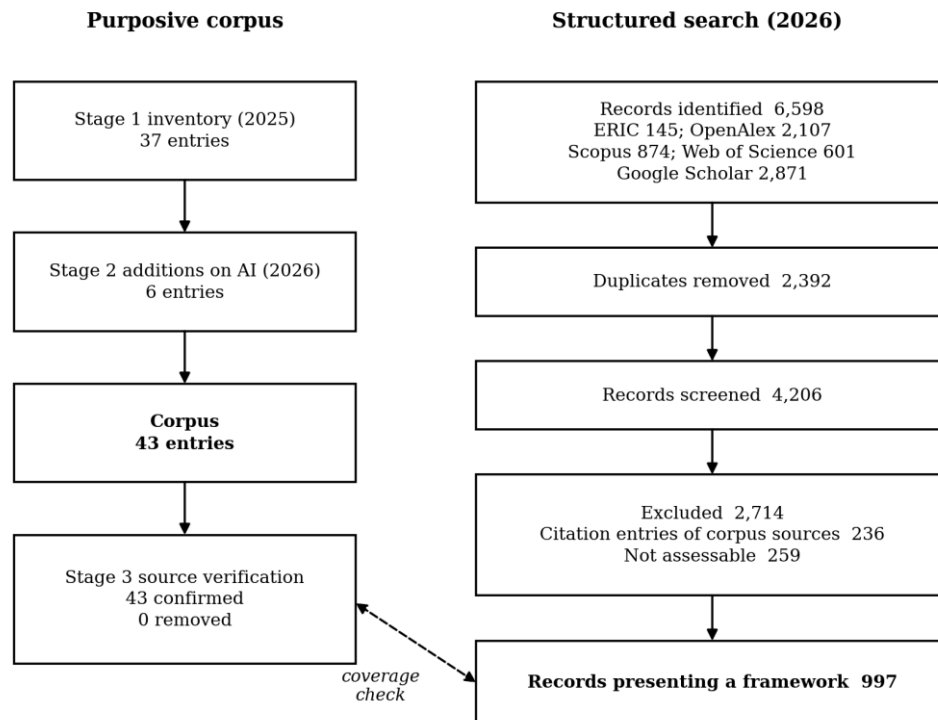


Figure 1: Construction of the corpus and the structured search

Note. Stages 1 and 2 were purposive. The search tested coverage and did not add entries to the corpus. Excluded records are broken down by reason in Table B2.

Eligibility

An entry was eligible when it satisfied four conditions. It had to set out components of digital, ICT or AI competence or literacy, or to model the use of technology in teaching; it had to address citizens, workers, learners or educators; its primary source had to be retrievable and readable; and it had to be in use at some point between 2000 and 2026. Studies that merely applied an existing framework were not eligible. Sources were read in English or Spanish, with the single exception of the Indonesian national roadmap, for which no official English edition could be found.

The corpus deliberately includes instruments that are not frameworks in the strict sense. Certification schemes, course curricula, national programmes and self-reflection tools were retained because they put competence into operation for large populations, and Table A1 labels each entry according to its type. Two entries, Kenya's Digital Literacy Programme and India's National Digital Literacy Mission, define no competence areas at all; they entered the inventory as national initiatives and are retained as contrasting cases.

Charting and Cluster Assignment

Each entry was charted on its source, year, developer, origin, type, target population, competence dimensions, levels and assessment provision (Tables A1 and A2). This template preserves the fields of the 2023 inventory and adds type, origin and evidence of validation. During the doctoral review the clusters had been formed inductively by grouping frameworks with a similar purpose, in the manner of thematic analysis (Braun & Clarke, 2006). For the present review the cluster boundaries were converted into five ordered decision rules so that any reader can reproduce the assignment. The first rule that applies determines the cluster.

Rule 1. The entry was issued by the European Commission, or its source states that it adapts or extends DigComp or DigCompEdu. It joins Cluster 5.

Rule 2. The entry was issued by or for a national or sub-national public authority as an instrument for its own population, workforce or education system. It joins Cluster 4.

Rule 3. The entry models how technology enters teaching and learning without listing competences. It joins Cluster 2.

Rule 4. The entry specifies what teachers or other educators should know or be able to do. It joins Cluster 3.

Rule 5. Any remaining entry addresses citizens, learners or workers in general. It joins Cluster 1.

The order of the rules matters because many frameworks carry the features of several clusters. The UNESCO AI Competency Framework for Teachers illustrates the point, since it is at the same time an international policy instrument, a teacher competence framework and an AI framework. Rules 1 and 2 do not apply to it, because UNESCO is neither the European Commission nor a national authority, and Rule 3 does not apply because the framework lists competences. Rule 4 applies, so the framework joins Cluster 3, and Table A1 records its policy character as a secondary affinity. Lineage was placed first because derivation from DigComp or DigCompEdu is stated in the source document itself and can therefore be checked. The researcher applied the rules to all 43 entries.

Dating the Waves

The waves were dated by their onset rather than by closed periods, because each wave continues after the next one begins. A wave is dated from the year by which its defining feature had appeared in at least two corpus entries, and Table 1 states the feature and the marker entries for each wave. Two of the boundaries rest on additional counts. For the fourth wave, the educator-specific frameworks issued by organisations were counted by period (Table 2), and for the fifth wave, the entries with AI as their organising subject were counted both in the corpus and, separately, among the records returned by the structured search.

FINDINGS

The Corpus

The corpus consists of 43 entries, which are charted in Tables A1 and A2. Thirty-three of them are documents or web resources of organisations, nine are peer-reviewed journal articles and one is a conference presentation. Twenty-two entries are educator-specific, 19 define proficiency or progression levels, and 10 are accompanied by an assessment or self-reflection instrument from the issuing body, although peer-reviewed psychometric evidence was located for only two of these. Higher education lies at the centre of only two entries, CheckIn Higher Education and the Digital Education Council framework, while 11 further entries name higher or tertiary education within a wider scope. The remaining 30 entries address citizens, schools or the workforce.

Five Waves of Conceptual Evolution

The concept of digital competence developed through successive waves of thinking, each of which widened the understanding of what it means to engage effectively with digital technologies. Table 1 summarises the five waves identified in the corpus.

Table 1: Five waves in the conceptualisation of digital competence

Wave	Onset	Defining feature	Marker entries	Open limitation
1. Operational skills	By 2000	Technical and operational skills defined apart from teaching	ICDL (1996); SFIA (2000); IC3 (2002)	No pedagogical purpose
2. Pedagogical integration	2006	Models of how technology enters teaching	TPACK and SAMR (2006); Krumsvik's model (2007); DECK (2012)	No levels and no instrument in the source models
3. Structured progression	2013	Competence areas combined with progression levels	DigComp 1.0 and ICTE-MM (2013); precursor UNESCO ICT framework (2008)	Citizen or institutional focus; few educator-specific models
4. Expanded professional dimensions	2017	Educator frameworks from organisations that add professional engagement, ethics and learner empowerment	DigCompEdu, ISTE Standards for Educators, Norway and Spain (2017); CheckIn Higher Education (2021)	Uneven validation evidence; little specificity for higher education
5. AI competence	2023	AI as the organising subject	Ng et al. and AI Pioneers (2023); UNESCO AI framework (2024); Digital Education Council (2025)	No instrument from an issuing body

Note. Onset is the year by which the defining feature had appeared in at least two corpus entries. Waves overlap, and each continues after the next begins.

The earliest wave treated digital competence as operational skill. The European Computer Driving Licence, launched in 1996 and now known as ICDL, certifies module-based skills such as word processing and the use of spreadsheets (ICDL Foundation, n.d.). The Skills Framework for the Information Age, launched in 2000, describes the skills of ICT professionals at seven levels of responsibility (SFIA Foundation, 2024), and IC3 followed in 2002 as a certification of digital literacy (Certiport, n.d.). None of these three entries addresses teaching.

A second wave turned attention towards pedagogy. Mishra and Koehler (2006) argued that effective teaching with technology draws on the intersection of technological, pedagogical and content knowledge, and Puentedura (2006) described four levels of technology use ranging from substitution to redefinition. Krumsvik (2008, 2011) added a model for teachers with four components that run from basic ICT skills to digital Bildung. These models gave priority to pedagogy, but their source texts define neither proficiency levels nor instruments, although later researchers developed and validated TPACK surveys (Schmidt et al., 2009; Willermark, 2018).

A third wave combined competence areas with levels of progression. UNESCO had taken this step for teachers in 2008, and the current version of its framework crosses six aspects with three levels (UNESCO, 2018). The pattern spread in 2013, when DigComp set out five areas and 21 competences for citizens at three levels, later extended to eight and now reduced to four (Carretero et al., 2017; Cosgrove & Cachia, 2025; Ferrari, 2013; Vuorikari et al., 2022), and when the ICTE-MM maturity model applied five capability levels to schools (Solar et al., 2013). From this point competence came to be understood as a continuum that could be described step by step.

The fourth wave arrived in 2017, when four organisations issued educator-specific frameworks within a single year. DigCompEdu defined 22 competences in six areas for educators at every level of education, with six stages running from Newcomer (A1) to Pioneer (C2) (Redecker, 2017). The ISTE Standards for Educators set out seven standards (International Society for Technology in Education, 2017), Norway published seven competence areas for teachers (Kelentrić et al., 2017), and Spain issued its common framework for teachers (Instituto Nacional de Tecnologías Educativas y de Formación del Profesorado [INTEF], 2017). These frameworks reach beyond the use of tools and address professional engagement, ethics and the empowerment of learners.

Table 2 shows the scale of this shift. Organisations had issued one educator-specific corpus entry before 2017, compared with 10 between 2017 and 2022. CheckIn Higher Education extended the pattern in 2021 by adding open education as a seventh area for academics (European Commission, Joint Research Centre, 2021).

Table 2: Corpus entries by period of first issue and defining feature

Period of first issue	Entries	Educator models by scholars	Educator frameworks by organisations	AI as organising subject
1996–2005	3	0	0	0
2006–2012	6	4	1	0
2013–2016	7	1	0	0
2017–2022	21	2	10	0
2023–2026	6	2	2	6
All periods	43	9	13	6

Note. Scholars' models are educator-specific entries published as journal articles or presentations. Organisations' frameworks are educator-specific documents or tools of organisations.

A fifth wave is now emerging. Within the corpus, AI is the organising subject of no entry issued before 2023 and of all six entries issued from 2023 onwards. Ng et al. (2023) re-described the six DigCompEdu areas for the age of AI, and the AI Pioneers project supplemented the same six areas for vocational and adult educators (Bekiaridis, 2023). UNESCO subsequently published 15 competency blocks for teachers, formed by crossing five aspects with three levels (Miao & Cukurova, 2024). The Digital Education Council (2025) addressed students and faculty in higher education, the OECD and European Union (2026) addressed school learners, and Yoon et al. (2026) derived 17 competencies for Korean teachers through a Delphi study and aligned them with four career stages.

Established frameworks have also absorbed AI. DigComp 2.2 added examples of citizens interacting with AI systems, and DigComp 3.0 integrates AI across all 21 of its competences (Cosgrove & Cachia, 2025; Vuorikari et al., 2022). The structured search supports the dating of this wave independently. Among the retrieved records that present a framework, only 13 had AI as their organising subject up to 2022, whereas the figure rose to 29 in 2023, 54 in 2024 and 65 in 2025. These indications mark 2023 as the onset of the wave, but they do not yet show a settled reconceptualisation of digital competence, and the fifth wave is best understood as an emerging trajectory.

No wave has replaced its predecessor. Operational skill remains necessary, pedagogical integration remains central and structured progression remains useful, so that later frameworks add new concerns to earlier ones, with the AI wave as the most recent addition.

Cluster 1: General Digital Literacy

Cluster 1 gathers eight entries that address citizens, learners or workers without any teaching role in view. ICDL and IC3 are certification schemes with proctored tests, and ICDL reports availability in more than 100 countries. Microsoft offers six free courses without an assessment (Microsoft, n.d.). SFIA and the DELTAs describe workforce skills, and only 11 of the 56 DELTAs are digital (Dondi et al., 2021). The DQ framework aggregates 25 earlier frameworks into eight areas at three levels (Park, 2019), MediaSmarts (2022) organises digital media literacy for Canadian school students in nine topics, and the Digital Education Council (2025) brings AI literacy for students and faculty into the same tradition.

These entries define what any competent user should be able to manage, but they leave pedagogy aside. A teacher may hold a certificate in digital skills and still be uncertain how to design learning with technology.

Cluster 2: Pedagogical Integration

Cluster 2 holds four models of how technology enters teaching. TPACK remains the most studied of them, and reviews have catalogued both its literature and its many self-report instruments (Voogt et al., 2013; Willermark, 2018). SAMR describes levels of technology use and has framed professional development and classroom studies in varied settings (Aldosemani, 2019; Kihoza et al., 2016). DECK groups purposeful learning activity with technology into four categories, which are distributed thinking and knowing, engagement, community and communication, and knowledge building (Fisher et al., 2012), while PICRAT crosses the relationship of the student to technology with its effect on teaching practice (Kimmons et al., 2020). Teachers who evaluated models of this kind did not always find the most widely used ones the most useful (Kimmons & Hall, 2018).

The four models share one property. Their sources describe integration but do not specify competences, levels or instruments, and where measurement exists it was added by later researchers.

Cluster 3: Teacher-Specific Competence

Cluster 3 contains 10 entries that state what teachers should know or be able to do. Several of them were written by scholars. The model of Krumsvik (2008, 2011) emerged in Norwegian teacher education, Falloon (2020) joined curriculum competencies aligned with TPACK to personal-ethical and personal-professional competencies, Klebansky and Fraser (2013) built an information literacy framework for teacher education students at one university, and Yoon et al. (2026) addressed Korean school teachers. The others were issued by organisations. The ISTE standards come from a professional association (International Society for Technology in Education, 2017), the ProFuturo framework from a foundation (Trujillo Sáez et al., 2020) and the READY model from a European Union agency (European Training Foundation, 2022; Kampylis et al., 2024); these three define standards, identities or practices without levels. The two UNESCO frameworks, by contrast, cross their aspects with three levels (Miao & Cukurova, 2024; UNESCO, 2018).

One entry sits at the edge of the cluster. ICTE-MM assesses schools rather than teachers, who form one of its five domains (Solar et al., 2013), and it is also the only entry in the cluster that is accompanied by an assessment tool, which was tested in a small pilot. Researchers have since built instruments on some of these models; Tang et al. (2022), for example, drew on the broader conception of Falloon to validate a 35-item scale for online teaching.

Cluster 4: National and Regional Policy

Cluster 4 comprises 10 instruments issued by or for public authorities, and they differ widely in kind. Kenya's Digital Literacy Programme has supplied devices, content, connectivity and teacher training to public primary schools since 2016 (ICT Authority, n.d.), and India's National Digital Literacy Mission trained 5.37 million people between 2014 and 2016 through two certified courses (Ministry of Electronics and Information Technology, 2022). British Columbia defined six characteristics of digital literacy for school students (British Columbia Ministry of Education, 2013), and Quebec set out 12 dimensions for learners and staff from preschool to higher education, with a 2026 edition that integrates AI (Ministère de l'Éducation, 2026; Ministère de l'Éducation et de l'Enseignement supérieur, 2019).

Australia produced a draft framework for adult foundation skills and a proposed framework for the workforce outside the ICT sector (Department of Education, Skills and Employment, 2020; Gekara et al., 2019), Singapore mapped skills to 128 job roles in its ICT sector (SkillsFuture Singapore et al., 2022), and Indonesia organised a national roadmap and a national index around four pillars (Kementerian Komunikasi dan Informatika & Katadata

Insight Center, 2022). Two entries address teachers directly. Norway defined seven competence areas without levels (Kelentrić et al., 2017), and South Africa defined 13 educator competencies and supplied a diagnostic self-assessment tool (Department of Basic Education, 2018).

The cluster shows that public authorities translate digital competence into very different instruments according to their infrastructure, their population and their policy aims, although McGarr et al. (2021) observed that national policies for teacher education nonetheless converge on supranational frameworks.

Cluster 5: The European Commission Ecosystem and Its Derivatives

Cluster 5 groups 11 entries by lineage. Five of them were issued by the European Commission, alone or together with the OECD, and six adapt or extend DigComp or DigCompEdu. The core of the cluster consists of DigComp for citizens and DigCompEdu for educators, and four derivatives carry the family into other systems. Spain followed DigComp in 2017 and DigCompEdu in 2022 (INTEF, 2017; Ministerio de Educación y Formación Profesional & Administraciones educativas de las comunidades autónomas, 2022), and the 2022 framework was accompanied by official accreditation routes for non-university teachers. In England, the Digital Teaching Professional Framework adapts DigCompEdu statements for further education (Education and Training Foundation, 2018). The framework proposed for SDG indicator 4.4.2 extends DigComp 2.0 to seven areas (Law et al., 2018), and CFRIDiL integrates DigComp 2.0 with language and intercultural frameworks (Sindoni et al., 2019).

Two self-reflection tools put DigCompEdu into operation. SELFIEforTEACHERS serves primary and secondary teachers with 32 items (Economou, 2023), and CheckIn Higher Education serves academics with 25 items in seven areas (European Commission, Joint Research Centre, 2021). The evidence behind these tools is uneven. The original 22-item Check-In was evaluated by its developers and validated with 2,262 university teachers in Andalusia (Cabero-Almenara et al., 2020; Ghomi & Redecker, 2019), and it was subsequently used with 30,407 academics in seven countries (Inamorato dos Santos et al., 2023). Chifla-Villón et al. (2025) reported a six-factor structure for a 22-item version among 166 university teachers in Ecuador, and SELFIEforTEACHERS was validated with 3,218 teachers in four countries (Economou et al., 2026). No peer-reviewed validation of the 25-item version for higher education was located.

Three recent entries bring AI into the lineage, which are the framework of Ng et al. (2023), the AI Pioneers supplement and the AILit Framework, and an update of DigCompEdu itself has been announced (OECD & European Union, 2026). Derivation also continues beyond the corpus; Santos et al. (2025), for example, validated e-DigCompEdu for online higher education through a Delphi panel.

Cross-Cluster Synthesis

Table 3: Comparison of the five clusters

Attribute (number of entries)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	All
Entries	8	4	10	10	11	43
Documents or web resources of organisations	8	0	5	10	10	33
Educator-specific	0	4	9	2	7	22
Proficiency or progression levels defined	4	0	3	3	9	19
Instrument from the issuing body	2	0	1	3	4	10
Peer-reviewed psychometric evidence located	0	0	0	0	2	2
AI as organising subject	1	0	2	0	3	6
Higher education central or included	2	1	4	2	4	13

Note. Cluster 1 = general digital literacy; 2 = pedagogical integration; 3 = teacher-specific competence; 4 = national and regional policy; 5 = European Commission ecosystem and derivatives. Entries are charted individually in Tables A1 and A2.

Four patterns follow from Table 3. First, the corpus moves from operational skill towards pedagogical, professional and AI-related concerns, and the later waves add to the earlier ones rather than replacing them.

Second, assessment provision is limited and unevenly evidenced. Ten of the 43 entries are accompanied by an instrument from the issuing body. In order to test a claim that is often made for the European Commission ecosystem, four criteria were applied to every entry, which are that it is educator-specific, that it defines

proficiency levels, that it comes with an instrument from its issuing body, and that peer-reviewed psychometric evidence exists for that instrument. Two entries met all four criteria, DigCompEdu with its Check-In tool and SELFIEforTEACHERS, and both belong to Cluster 5.

This result is bounded in three ways. It describes what issuing bodies provide, whereas researchers have built validated instruments for other traditions, notably TPACK. It rests on the evidence located in this review, which did not search the psychometric literature systematically. And it does not extend to CheckIn Higher Education, whose 25-item version lacks published validation.

Third, no single framework has achieved universal adoption, although a few are taken up far more often than the others. Among the 4,206 screened records, 790 named a corpus framework. DigComp was named in 315 records, DigCompEdu in 199, TPACK in 70, the UNESCO AI framework in 56 and the UNESCO ICT framework in 50. Since the search strings favour competence vocabulary, these counts understate TPACK. Zhang et al. (2026) likewise found that researchers increasingly combine frameworks.

Fourth, context matters. Competence in Singapore's ICT sector differs from competence in Kenya's primary schools, and any framework applied across contexts should be examined for its assumptions about infrastructure, institutional support and culture.

Results of the Structured Search

Of the 4,206 records screened, 997 presented a framework, model or standard of their own, and a further 555 applied, adapted or validated an existing framework. The remaining exclusions were statistical or acceptance models (536), courses or programmes without a competence framework (851), reviews and commentaries (518), records on other topics (208) and non-documents (46). A further 236 Google Scholar records were citation entries for the source documents of corpus frameworks, and 259 records could not be assessed from the available title and abstract (Table B2).

The records that presented a framework addressed educators in 294 cases, learners in 285, sector or general workforces in 164 and citizens in 94, with the remainder addressing mixed or unstated populations. The source documents of 14 corpus entries were among the retrieved records, which reflects the fact that most corpus entries are organisational documents that bibliographic databases do not index. The purposive corpus of 43 entries therefore covers a small share of the frameworks proposed in the literature, most of which are single studies, and this breadth strengthens the case for a classification that later work can extend.

DISCUSSION

Selecting Frameworks for Higher Education Research

For researchers in higher education the taxonomy functions as a sequence of questions about the purpose of a study. Where the study concerns the baseline skills of staff or students, Cluster 1 offers certification schemes and general literacy frameworks, of which only one was written for higher education. Where it concerns how technology changes teaching practice, Cluster 2 offers conceptual lenses, and TPACK brings a large instrument literature of its own. Where it concerns what academics should be able to do, Clusters 3 and 5 supply competence statements, and where it concerns a national system, Cluster 4 shows how far instruments depend on their policy setting.

The scarcity of frameworks designed for higher education is itself a finding. Researchers in the sector mostly work with borrowed frameworks, so the question of fit deserves explicit attention. The tool with the largest validation study in the corpus, SELFIEforTEACHERS, was built for schools, whereas CheckIn Higher Education fits the sector by design but has not yet been validated in its current form, so researchers who adopt it should examine its measurement properties in their own samples. Frameworks for higher education also exist outside this corpus, such as the Jisc framework of six elements of digital capability for staff and students (Jisc, 2024).

The Prominence of the DigComp Family

Researchers who require an educator-specific model, proficiency levels and an instrument from the issuing body will find that combination, on the criteria used here, in the DigCompEdu family. This is a statement about what is provided rather than about conceptual merit, since TPACK and SAMR pursue different aims and third parties have measured TPACK extensively.

The prominence of one family raises a question of intellectual diversity. When a single lineage supplies both a common vocabulary and the most widely used instruments, research may converge on a single perspective. DigCompEdu was developed within European institutions, and its descriptors may assume resources and

institutional support that some education systems cannot guarantee. This does not invalidate instruments based on DigCompEdu in other settings, but it means that researchers who apply them across contexts should examine what the instrument captures and what it misses. Mixed-methods designs that pair self-reflection scores with qualitative inquiry offer one productive response.

The Emerging AI Wave

AI-focused frameworks have multiplied since 2023, and established frameworks now integrate AI. Whether AI will reshape the concept of digital competence or be absorbed as one further dimension cannot yet be determined, because the evidence points in both directions. UNESCO placed a human-centred mindset and ethics alongside AI foundations and pedagogy, which suggests a reframing (Miao & Cukurova, 2024), whereas DigComp 3.0 distributed AI across its existing competences, which suggests absorption (Cosgrove & Cachia, 2025).

Measurement is developing rapidly, but outside the issuing bodies. None of the organisations behind the AI frameworks in the corpus has released an assessment or self-reflection instrument, whereas researchers have published scales with psychometric evidence, among them TAICS for school teachers, AICO_edu for vocational teachers and GAICS-TR for academics (Chiu et al., 2025; Delcker et al., 2025; Xia et al., 2026). These scales rest on their own models, and instruments derived directly from DigCompEdu-based tools remain at the pilot stage (Tenberga & Daniela, 2024). Lintner (2024) has reviewed AI literacy scales systematically. For research design, the practical question is whether to adopt one of the new scales or to wait for the updated DigCompEdu.

Limitations

Several limitations qualify these findings. The corpus is purposive, since Stages 1 and 2 followed no protocol for identifying frameworks, so that the selection may favour well-known frameworks, organisational documents and sources in English. The structured search covered five sources and titles only, and it under-retrieves traditions that do not use competence vocabulary. Google Scholar returned only part of its estimated results and provided snippets rather than abstracts, so its records were screened on less information than the others. The screening was supported by a generative AI tool, although it was reviewed by author but still relied on few partial records, so the resulting counts are approximate. Records are also not unique frameworks, and the counts therefore describe the literature rather than the number of frameworks.

Cluster assignment involves judgement. The decision rules make each assignment reproducible, but the order of the rules is itself a choice and one researcher applied them, so a second coder may place boundary cases differently, and no agreement statistic is reported. The restriction to English and Spanish sources probably under-represents national frameworks from Asia, Africa and the Middle East, and the Indonesian entry was charted from Indonesian-language official sources because its roadmap document could not be retrieved.

Evidence of validation means the evidence located in this review, and other studies may exist. The attributes describe the latest version consulted, and several entries changed during the period of the review, since the AILit Framework moved from draft to final in 2026, Quebec issued a new edition, and an update of DigCompEdu is pending. The account of the AI wave is therefore a snapshot taken in October 2026.

A Research Agenda

Four priorities follow from the analysis. First, the field needs validation studies from outside Europe, because the evidence cited here for DigCompEdu-based instruments comes from Europe and Latin America, and studies in South Asian and African higher education would test whether the instruments travel. Second, frameworks should treat infrastructure as a structural condition rather than as a background assumption, because where infrastructure is unreliable, competence takes forms that current instruments may not capture.

Third, AI competence needs instruments that issuing bodies stand behind, together with independent validation of the scales that researchers have already built, especially for academics. Fourth, the classification offered here should be tested and extended, since independent coders can apply the decision rules to this corpus and the frameworks identified by the structured search provide new cases.

CONCLUSIONS

This scoping review charted 43 digital competence frameworks and related instruments, verified each of them against its primary source, and tested the coverage of the corpus with a structured search. Five clusters organise the landscape. General literacy frameworks set baselines without pedagogy, pedagogical integration models describe teaching with technology without specifying competences, teacher-specific frameworks state what educators should know or do but mostly without instruments, and policy instruments vary with their national

settings. The European Commission ecosystem and its derivatives combine educator-specific models with levels and instruments, and two of its entries carry peer-reviewed validation evidence.

Five overlapping waves describe how the concept has widened, from operational skill to pedagogical integration, structured progression, expanded professional dimensions and, since 2023, AI competence. The fifth wave is an emerging trajectory whose frameworks are multiplying while its instruments come from researchers rather than from the issuing bodies.

For higher education the main gap is specificity. Few frameworks were designed for academic teaching, and the instrument built for the sector still lacks published validation of its current version. The decision rules, the full corpus tables and the search protocol are provided so that other researchers can check, contest and extend the classification.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AUTHOR CONTRIBUTIONS

Muhammad Tayyab Ilyas was responsible for the conceptualisation, methodology, investigation, data curation and writing. Cristina Mercader contributed supervision, review and editing. Alejandra Bosco supervised the doctoral research from which the corpus derives, and all her contributions were made before her death in 2025.

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APPENDIX A. THE CORPUS

Tables A1 and A2 chart the corpus. Entries are numbered in order of first issue.

Table A1: Identification, origin, type, population and cluster of the corpus entries

No.	Framework and source	First issued	Developer and origin	Type	Target population	Cluster	Higher education
1	ICDL (formerly ECDL). ICDL Foundation (n.d.)	1996	ICDL Foundation, Ireland; international	Certification scheme	General public, students and workforce	1	Adjacent
2	Skills Framework for the Information Age (SFIA). SFIA Foundation (2024)	2000 (SFIA 9, 2024)	SFIA Foundation, United Kingdom; international	Occupational skills framework	ICT and digital professionals	1	Adjacent
3	IC3 Digital Literacy Certification. Certiport (n.d.)	2002 (Global Standard 6)	Certiport, United States; international	Certification scheme	Students and job seekers	1	Included
4	SAMR. Puentedura (2006)	2006	Puentedura, United States	Conceptual model	Educators and school districts	2	Adjacent
5	TPACK. Mishra and Koehler (2006)	2006	Mishra and Koehler, United States	Conceptual model	Teachers	2 (3)	Adjacent
6	Krumsvik's digital competence model. Krumsvik (2008, 2011)	2007 (English sources 2008, 2011)	Krumsvik, Norway	Conceptual model	Teachers and teacher educators	3 (2)	Included
7	Microsoft Digital Literacy. Microsoft (n.d.)	Online by 2007 (current courses)	Microsoft, United States; international	Course curriculum	Anyone with basic reading skills	1	Adjacent
8	UNESCO ICT Competency Framework for Teachers. UNESCO (2018)	2008 (Version 3, 2018)	UNESCO; international	Framework	Pre-service and in-service teachers, school to tertiary level	3 (4)	Included
9	DECK. Fisher et al. (2012)	2012	Fisher, Denning, Higgins and Loveless, United Kingdom	Conceptual framework	School teachers	2	Adjacent

No.	Framework and source	First issued	Developer and origin	Type	Target population	Cluster	Higher education
10	BC's Digital Literacy Framework. British Columbia Ministry of Education (2013)	2013 (draft)	British Columbia Ministry of Education, Canada (provincial)	Framework	School students, kindergarten to grade 12	4 (1)	Adjacent
11	DigComp (versions 1.0 to 3.0). Ferrari (2013); Carretero et al. (2017); Vuorikari et al. (2022); Cosgrove and Cachia (2025)	2013 (3.0, 2025)	European Commission, Joint Research Centre; European Union	Framework	Citizens	5 (1)	Adjacent
12	ICTE-MM. Solar et al. (2013)	2013	Solar, Sabattin and Parada, Chile	Maturity model	Schools; teachers are one of five domains	3	Adjacent
13	Teacher Education Information Literacy (TEIL). Klebansky and Fraser (2013)	2013	Klebansky and Fraser, University of Tasmania, Australia	Conceptual framework (single institution)	Teacher education students	3	Included
14	National Digital Literacy Mission (NDLM and DISHA). Ministry of Electronics and Information Technology (2022)	2014 (closed 2016)	Government of India	Training and certification scheme	One person without IT literacy in each eligible household	4 (1)	Adjacent
15	USE, UNDERSTAND & ENGAGE. MediaSmarts (2022)	2015 (renamed 2022)	MediaSmarts, Canada (charity)	Framework	School students, kindergarten to grade 12	1	Adjacent
16	Digital Literacy Programme (DigiSchool). ICT Authority (n.d.)	2016	Government of Kenya, ICT Authority	National programme	Pupils and teachers in public primary schools	4	Adjacent
17	Common Digital Competence Framework for Teachers (Spain). INTEF (2017); Ministerio de Educación y Formación Profesional and Administraciones educativas de las comunidades autónomas (2022)	2017 (replaced 2022)	INTEF, Ministry of Education, Spain	Framework	Teachers; the 2022 framework covers non-university teaching	5 (4)	Adjacent
18	DigCompEdu. Redecker (2017)	2017	European Commission, Joint Research Centre; European Union	Framework	Educators at all levels, early childhood to higher and adult education	5 (3)	Included
19	ISTE Standards for Educators. International Society for Technology in Education (2017)	2017	ISTE, United States; international	Standards	Educators	3	Adjacent
20	Professional Digital Competence Framework for Teachers (Norway). Kelentrić et al. (2017)	2017	Norwegian Centre for ICT in Education, Norway	Framework	Teachers, student teachers and teacher educators	4 (3)	Included

No.	Framework and source	First issued	Developer and origin	Type	Target population	Cluster	Higher education
21	Skills Framework for Infocomm Technology. SkillsFuture Singapore et al. (2022)	2017 (refreshed 2022)	SkillsFuture Singapore, Workforce Singapore and Infocomm Media Development Authority, Singapore	Sector skills framework	ICT-sector workforce, employers and training providers	4 (1)	Adjacent
22	Digital Literacy Global Framework. Law et al. (2018)	2018	UNESCO Institute for Statistics; authors at the University of Hong Kong; international	Proposed framework	Youth and adults (SDG indicator 4.4.2)	5 (1)	Adjacent
23	Digital Teaching Professional Framework. Education and Training Foundation (2018)	2018	Education and Training Foundation with Jisc, England	Framework	Teachers and trainers in further education and training	5 (3)	Adjacent
24	Professional Development Framework for Digital Learning. Department of Basic Education (2018)	2018	Department of Basic Education, South Africa	Framework	Teachers, school leaders and teacher trainers	4 (3)	Adjacent
25	Australian Workforce Digital Skills Framework. Gekara et al. (2019)	2019	National Centre for Vocational Education Research, Australia	Proposed framework (research report)	General non-ICT workforce	4 (1)	Adjacent
26	Common Framework of Reference for Intercultural Digital Literacies (CFRIDiL). Sindoni et al. (2019)	2019	EU-MADE4LL Erasmus+ project, led by the University of Messina, Italy	Framework	Students, teachers and researchers; built with university students	5 (1)	Included
27	DQ (Digital Intelligence) Global Standards. Park (2019)	2019	DQ Institute; international	Framework (IEEE standard 3527.1-2020)	All individuals, children to workforce	1	Adjacent
28	Digital Competency Framework (Quebec). Ministère de l'Éducation et de l'Enseignement supérieur (2019); Ministère de l'Éducation (2026)	2019 (updated 2026)	Gouvernement du Québec, Canada (provincial)	Framework	Learners, teachers and other professionals at all education levels	4 (1)	Included
29	Digital Literacy Skills Framework. Department of Education, Skills and Employment (2020)	2020 (draft)	Australian Government	Framework	Adults in foundation-skills programmes	4 (1)	Adjacent
30	Global Framework of Competence for Education in the Digital Age. Trujillo Sáez et al. (2020)	2020	Fundación ProFuturo, Spain; international	Framework	Educators, especially in Latin America, Africa and Asia	3	Adjacent

No.	Framework and source	First issued	Developer and origin	Type	Target population	Cluster	Higher education
31	PICRAT. Kimmons et al. (2020)	2020	Kimmons, Graham and West, United States	Conceptual model	Teacher candidates and teacher educators	2	Included
32	Teacher Digital Competency (TDC) framework. Falloon (2020)	2020	Falloon, Australia	Conceptual framework	Teacher education students and teacher educators	3	Included
33	CheckIn Higher Education. European Commission, Joint Research Centre (2021)	2021	European Commission, Joint Research Centre; European Union	Self-reflection tool	Academics teaching in higher and further education	5 (3)	Central
34	DELTA's (skills for the future world of work). Dondi et al. (2021)	2021	McKinsey & Company; international	Skills taxonomy	All citizens in the labour market	1	Adjacent
35	Digital literacy roadmap (Indonesia). Kementerian Komunikasi dan Informatika and Katadata Insight Center (2022)	2021	Ministry of Communication and Informatics with Siberkreasi, Indonesia	National roadmap and curriculum framework	General public	4 (1)	Adjacent
36	SELFIEforTEACHERS. Economou (2023)	2021 (launch)	European Commission, Joint Research Centre; European Union	Self-reflection tool	Primary and secondary teachers	5 (3)	Adjacent
37	READY model. European Training Foundation (2022); Kampylis et al. (2024)	2022	European Training Foundation (European Union agency), Italy	Reference model	All educators, with emphasis on vocational and adult education	3	Adjacent
38	AI Pioneers supplement to DigCompEdu. Bekiaridis (2023)	2023	AI Pioneers Erasmus+ project, University of Bremen, Germany	Framework supplement	Vocational and adult educators	5 (3)	Adjacent
39	Teachers' AI digital competencies. Ng et al. (2023)	2023	Ng, Leung, Su, Ng and Chu, Hong Kong	Conceptual framework	Teachers	5 (3)	Included
40	UNESCO AI Competency Framework for Teachers. Miao and Cukurova (2024)	2024	UNESCO; international	Framework	Teachers who apply AI in core subject areas	3 (4)	Adjacent
41	AILit Framework. OECD and European Union (2026)	2025 (draft); 2026	OECD and European Commission; international	Framework	Learners in primary and secondary education	5 (1)	Adjacent
42	Digital Education Council AI Literacy Framework. Digital Education Council (2025)	2025	Digital Education Council; international membership body	Framework	Higher education students and faculty	1 (3)	Central
43	AI-Digital Competency Framework. Yoon et al. (2026)	2026	Yoon, Ryu, Kim and Kim, Republic of Korea	Framework (Delphi study)	In-service primary and secondary teachers	3	Adjacent

Note. Cluster shows the primary cluster and, in parentheses, a secondary affinity. Higher education is central when the entry was designed for the sector, included when the source names higher or tertiary education within a wider scope, and adjacent otherwise.

Table A2: Competence dimensions, levels and assessment provision of the corpus entries

No.	Framework	Major competence dimensions	Levels	Assessment availability and evidence located
1	ICDL (formerly ECDL)	Modular syllabus from basic computer use to advanced digital skills; no fixed set of dimensions	None within modules; module groups	Certification tests at accredited centres; no psychometric evidence located
2	Skills Framework for the Information Age (SFIA)	Professional skills described through autonomy, influence, complexity, business skills and knowledge	7 levels of responsibility	None in the framework; third-party credentials can be aligned to it
3	IC3 Digital Literacy Certification	7 domains: technology basics; digital citizenship; information management; content creation; communication; collaboration; safety and security	3 levels	Proctored certification examinations; no psychometric evidence located
4	SAMR	4 levels of technology use: substitution, augmentation, modification, redefinition	None for teachers; the levels describe technology use	None
5	TPACK	Technological, pedagogical and content knowledge and their intersections	None	None in the source; third-party surveys with validation evidence (Schmidt et al., 2009)
6	Krumsvik's digital competence model	4 components: basic ICT skills; didactic ICT competence; learning strategies; digital Bildung	None formal; 4 developmental phases (adoption, adaptation, appropriation, innovation)	None
7	Microsoft Digital Literacy	6 courses: work with computers; access information online; communicate online; participate safely and responsibly online; create digital content; collaborate and manage content digitally	None	None at present; earlier versions carried a certificate test
8	UNESCO ICT Competency Framework for Teachers	6 aspects crossed with 3 levels, giving 18 competencies	3: knowledge acquisition, knowledge deepening, knowledge creation	None official
9	DECK	4 categories: distributed thinking and knowing; engagement; community and communication; knowledge building	None	None; qualitative testing with 12 teachers
10	BC's Digital Literacy Framework	6 characteristics: research and information literacy; critical thinking, problem solving and decision making; creativity and innovation; digital citizenship; communication and collaboration; technology operations and concepts	None; grade bands	None

No.	Framework	Major competence dimensions	Levels	Assessment availability and evidence located
11	DigComp (versions 1.0 to 3.0)	5 competence areas and 21 competences; version 3.0 integrates AI across all competences	3 (2013); 8 (2017, 2022); 4 (2025)	Self-assessment grid in the 2013 report; no instrument in later reports
12	ICTE-MM	5 leverage domains (educational management; infrastructure; administrators; teachers; students) and 25 key domain areas	5 capability levels	Web-supported assessment tool for schools; small pilot only
13	Teacher Education Information Literacy (TEIL)	7 information literacy elements drawn from the ANZIIL standards	Developmental, from novice to advanced	None
14	National Digital Literacy Mission (NDLM and DISHA)	No competence areas defined; two courses (appreciation of digital literacy; basics of digital literacy)	2 course levels	External certification examination; no psychometric evidence located
15	USE, UNDERSTAND & ENGAGE	9 topics: reading media; media representation; ethics and empathy; privacy and security; community engagement; media health; consumer awareness; finding and verifying; making and remixing	None; grade bands	None
16	Digital Literacy Programme (DigiSchool)	No competence areas; components are devices, digital content, connectivity and teacher training	None	None
17	Common Digital Competence Framework for Teachers (Spain)	2017: the 5 DigComp areas and 21 competences; 2022: 6 areas adapted from DigCompEdu and 23 competences	6: A1 to C2	Self-assessment in a teacher portfolio (2017); official accreditation routes since 2022; no psychometric evidence located
18	DigCompEdu	6 areas (professional engagement; digital resources; teaching and learning; assessment; empowering learners; facilitating learners' digital competence) and 22 competences	6: A1 Newcomer to C2 Pioneer	Check-In self-reflection tool, 22 items (Ghomi & Redecker, 2019); validation with 2,262 university teachers (Cabero-Almenara et al., 2020)
19	ISTE Standards for Educators	7 standards: learner, leader, citizen, collaborator, designer, facilitator, analyst	None	None in the standards
20	Professional Digital Competence Framework for Teachers (Norway)	7 competence areas: subjects and basic skills; school in society; ethics; pedagogy and subject didactics; leadership of learning processes; interaction and communication; change and development	None	None
21	Skills Framework for Infocomm Technology	8 tracks and 128 job roles; technical skills and competencies with critical core skills	6 proficiency levels for technical skills and competencies	None
22	Digital Literacy Global Framework	7 competence areas and 26 competences, extending DigComp 2.0	None	None; expert consultation only
23	Digital Teaching Professional Framework	Elements and components with competency statements adapted from DigCompEdu	3 stages: exploring, adopting, leading	Training modules with badges; no psychometric evidence located

No.	Framework	Major competence dimensions	Levels	Assessment availability and evidence located
24	Professional Development Framework for Digital Learning	13 educator competencies in 3 areas: professional growth and knowledge; curriculum focus; leadership	None for the competencies	Diagnostic self-assessment tool for teachers and a school rubric; no psychometric evidence located
25	Australian Workforce Digital Skills Framework	4 skill categories (digital tools for working; digital ways of working; digital ways of thinking; living in the digital age), 8 sub-categories and 17 indicators	5: literacy, competency, proficiency, fluency, savvy	None; the authors call for further validation
26	Common Framework of Reference for Intercultural Digital Literacies (CFRIDiL)	3 dimensions (multimodal orchestration; digital technologies; intercultural communication) plus transversal skills; integrates the CEFR and DigComp 2.0	3: waystage, intermediate, proficient	No standalone test; peer and teacher assessment forms in appendices
27	DQ (Digital Intelligence) Global Standards	8 areas crossed with 3 levels, giving 24 competencies	3: digital citizenship, creativity, competitiveness	A DQ assessment is referenced outside the report; not verified
28	Digital Competency Framework (Quebec)	12 dimensions of a single digital competency; the 2026 edition integrates AI	None in the 2019 framework	None
29	Digital Literacy Skills Framework	2 indicators in 4 focus areas: connect, communicate and collaborate; digital identity and safety; digital technologies and systems; create, organise, present and problem solve	4 performance levels, pre-level 1 to level 3	None
30	Global Framework of Competence for Education in the Digital Age	3 identities (citizen, teacher, connector) and 9 roles	None, by design	None built on the framework; content validation by a two-round Delphi panel
31	PICRAT	Student relationship to technology (passive, interactive, creative) crossed with effect on practice (replacement, amplification, transformation)	None	None
32	Teacher Digital Competency (TDC) framework	Curriculum competencies aligned with TPACK; personal-ethical competencies; personal-professional competencies	None	None in the source
33	CheckIn Higher Education	25 items in 7 areas: the 6 DigCompEdu areas and open education	Progression levels revised on an adapted Bloom's digital taxonomy	Self-reflection tool; evidence concerns the 22-item predecessor; no peer-reviewed validation of the 25-item version located
34	DELTA's (skills for the future world of work)	4 categories (cognitive, interpersonal, self-leadership, digital), 13 skill groups and 56 elements, of which 11 are digital	None published	Research survey of 18,000 people in 15 countries; instrument not published
35	Digital literacy roadmap (Indonesia)	4 pillars: digital skill; digital ethics; digital safety; digital culture	None; national index scored from 1 to 5	National index survey of 10,000 respondents; no psychometric evidence located

No.	Framework	Major competence dimensions	Levels	Assessment availability and evidence located
36	SELFIEforTEACHERS	32 items across the 6 DigCompEdu areas	6 per item, A1 to C2	Self-reflection tool; validation with 3,218 teachers in four countries (Economou et al., 2026)
37	READY model	6 domains of professional activity plus a context-specific domain, 22 professional practices and 73 descriptors; digital technologies is one domain	None	None
38	AI Pioneers supplement to DigCompEdu	The 6 DigCompEdu areas, each extended with AI-related activities	6: Newcomer to Pioneer	None
39	Teachers' AI digital competencies	The 6 DigCompEdu areas re-described for AI, with a revised P21 framework	None	None
40	UNESCO AI Competency Framework for Teachers	5 aspects (human-centred mindset; ethics of AI; AI foundations and applications; AI pedagogy; AI for professional learning) crossed with 3 levels, giving 15 competency blocks	3: acquire, deepen, create	None official; derived third-party tools are preliminary
41	AILit Framework	4 domains: engage with AI; create with AI; manage AI; shape AI	3: basic, intermediate, advanced	None; informs a planned PISA 2029 assessment
42	Digital Education Council AI Literacy Framework	5 dimensions: understanding AI and data; critical thinking and judgement; ethical and responsible AI use; human-centricity, emotional intelligence and creativity; domain expertise	3 levels	None
43	AI-Digital Competency Framework	3 dimensions, 8 categories, 17 competencies and 51 behavioural indicators	None; competencies aligned with 4 career stages	None; content validity through a two-round Delphi

Note. Evidence located means peer-reviewed psychometric evidence found during this review. Absence of located evidence does not show that none exists.

APPENDIX B. SEARCH PROTOCOL

The Scopus, Web of Science, Google, ERIC and OpenAlex searches were updated on 6 of October 2026. The Scopus and Web of Science Core Collection search through the advanced search pages of each database with institutional access, and the records were exported with citation information, bibliographical information, abstracts and keywords. The Spanish title-field search returned no records in Web of Science, which indexes Spanish-language articles under English titles, so the same terms were run once more in the topic field (S7b). Google Scholar shows 5529 estimated results where 2871 relevant records were retrieved, and they carry result snippets rather than abstracts. Google Scholar is treated here as a supplementary source. Table B1 gives each string exactly as submitted, the time of execution and the number of records returned. No limits were applied beyond those shown in the strings.

Table B1: Search strings, execution times and records returned

Search	String	Records
S1. ERIC, title field	title:("digital competence" OR "digital competency" OR "digital competencies" OR "digital competences" OR "digital literacy" OR "digital literacies" OR "digital skills" OR "digital capability" OR "digital capabilities" OR "ICT competence" OR "ICT competency" OR "ICT competencies" OR "ICT competences" OR "AI literacy" OR "AI competence" OR "AI competency" OR "AI competencies" OR "artificial intelligence literacy") AND title:(framework OR frameworks OR model OR standard OR standards) AND publicationdateyear:[2000 TO 2026]	145
S2. OpenAlex, title field, English terms	title.search:("digital competence" OR "digital competency" OR "digital competencies" OR "digital competences" OR "digital literacy" OR "digital literacies" OR "digital skills" OR "digital capability" OR "digital capabilities" OR "ICT competence" OR "ICT competency" OR "ICT competencies" OR "ICT competences" OR "AI literacy" OR "AI competence" OR "AI competency" OR "AI competencies" OR "artificial intelligence literacy") AND (framework OR frameworks OR model OR standard OR standards),publication_year:2000-2026,language:en es	1,820
S3. OpenAlex, title field, Spanish terms	title.search:("competencia digital" OR "competencias digitales" OR "alfabetización digital" OR "competencia digital docente" OR "alfabetización en inteligencia artificial") AND (marco OR modelo OR estándar OR estándares),publication_year:2000-2026	287
S4. Scopus, title field, English terms	TITLE("digital competence" OR "digital competency" OR "digital competencies" OR "digital competences" OR "digital literacy" OR "digital literacies" OR "digital skills" OR "digital capability" OR "digital capabilities" OR "ICT competence" OR "ICT competency" OR "ICT competencies" OR "ICT competences" OR "AI literacy" OR "AI competence" OR "AI competency" OR "AI competencies" OR "artificial intelligence literacy") AND TITLE(framework OR frameworks OR model OR standard OR standards) AND PUBYEAR > 1999 AND PUBYEAR < 2027 AND (LANGUAGE(english) OR LANGUAGE(spanish))	844
S5. Scopus, title field, Spanish terms	TITLE("competencia digital" OR "competencias digitales" OR "alfabetización digital" OR "competencia digital docente" OR "alfabetización en inteligencia artificial") AND TITLE(marco OR modelo OR estándar OR estándares) AND PUBYEAR > 1999 AND PUBYEAR < 2027	30
S6. Web of Science, title field, English terms	TI=("digital competence" OR "digital competency" OR "digital competencies" OR "digital competences" OR "digital literacy" OR "digital literacies" OR "digital skills" OR "digital capability" OR "digital capabilities" OR "ICT competence" OR "ICT competency" OR "ICT competencies" OR "ICT competences" OR "AI literacy" OR "AI competence" OR "AI competency" OR "AI competencies" OR "artificial intelligence literacy") AND TI=(framework OR frameworks OR model OR standard OR standards) AND PY=(2000-2026) AND LA=(English OR Spanish)	593
S7a. Web of Science, title field, Spanish terms	TI=("competencia digital" OR "competencias digitales" OR "alfabetización digital" OR "competencia digital docente" OR "alfabetización en inteligencia artificial") AND TI=(marco OR modelo OR estándar OR estándares) AND PY=(2000-2026)	0

Search	String	Records
S7b. Web of Science, topic field, Spanish terms	TS=("competencia digital" OR "competencias digitales" OR "alfabetización digital" OR "competencia digital docente" OR "alfabetización en inteligencia artificial") AND TS=(marco OR modelo OR estándar OR estándares) AND PY=(2000-2026)	8
S8a. Google Scholar, title only, digital competence terms	allintitle: ("digital competence" OR "digital competency" OR "digital competencias" OR "digital competences") (framework OR frameworks OR model OR standard OR standards)	831 of about 1,780
S8b. Google Scholar, title only, digital literacy and skills terms	allintitle: ("digital literacy" OR "digital literacies" OR "digital skills" OR "digital capability" OR "digital capabilities") (framework OR frameworks OR model OR standard OR standards)	1,123 of about 1,960
S8c. Google Scholar, title only, ICT competence terms	allintitle: ("ICT competence" OR "ICT competency" OR "ICT competencias" OR "ICT competences") (framework OR frameworks OR model OR standard OR standards)	129 of about 205
S8d. Google Scholar, title only, AI terms	allintitle: ("AI literacy" OR "AI competence" OR "AI competency" OR "AI competencias" OR "AI competences" OR "artificial intelligence literacy") (framework OR frameworks OR model OR standard OR standards)	441 of about 892
S8e. Google Scholar, title only, Spanish terms	allintitle: ("competencia digital" OR "competencias digitales" OR "alfabetización digital" OR "competencia digital docente") (marco OR modelo OR estándar OR estándares)	347 of about 692
All searches		6,598

Note. For Google Scholar the first number is the records retrieved and the second the estimate that Scholar displayed for the same query.

Records were merged and duplicates removed by DOI and then by normalised title and year. This step removed 2,392 records and left 4,206 for screening. Of the 874 Scopus records, 701 duplicated records already retrieved from ERIC or OpenAlex, and of the 601 Web of Science records, 548 duplicated records already retrieved from the other sources; of the 2,871 Google Scholar records, 979 did. Each record was screened on title and abstract against one question. Does the record itself present, propose, develop, revise or extend a framework, model, standard or competence profile that specify components of digital, ICT or AI competence or literacy for citizens, workers, learners or educators? The researcher applied the rubric in Table B2. The record-level screening log is available from the corresponding author.

Table B2: Screening codes and outcome

Code	Decision	Records
I	Presents or revises a framework, model, standard or competence profile	997
E1	Applies, adapts, translates or validates an existing framework or instrument	555
E2	Statistical, causal, predictive or acceptance model	536
E3	Course, curriculum, training model or programme without a competence framework	851
E4	Review, comparison, critique or commentary without a new framework	518
E5	Not about the digital, ICT or AI competence or literacy of people	208
E7	Not a document, or not in English or Spanish	46
S	Citation entry for the source document of a corpus framework (Google Scholar only)	236
N	Not assessable from the available title and abstract	259
	All screened records	4,206

Japanese University Students' Pre-Course Perceptions of American Society, Group Formation, and Discrimination: Implications for Needs Analysis in Intercultural Teaching

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ABSTRACT

This study was conducted as a pre-course survey in a university class on American society and culture to identify students' perceptions before formal instruction. It aimed to explore how these initial perceptions could inform intercultural teaching and learning, particularly regarding classroom design. Students' pre-course responses were treated as a form of needs analysis, examining what they suggested about designing a course on American society. Text mining and co-occurrence network analysis were used to examine the responses of 127 Japanese university students to open-ended questions. The analysis focused on how students described American society, group formation, and differences between discrimination and distinction. The results suggested that students often described positive values and social issues. They emphasized psychological factors in group formation and evaluated discrimination by considering fairness in specific situations. These patterns suggest that students do not enter the classroom with fixed views. Students' initial ideas can provide starting points for classroom discussions, reflections, and activities, encouraging them to reconsider their interpretation of cultural differences. The findings also suggest how text-mining tools can turn students' words into concrete input for course design, indicating a practical, low-cost model for technology-enhanced needs analysis that could be used in other language and intercultural classrooms.

Keywords: Intercultural education, text mining, American society, needs analysis, undergraduate students

1. INTRODUCTION

Contemporary society faces the critical challenge of addressing how people engage with others whose cultures and values differ from their own and develop a mutual understanding (Bennett, 1993). In educational settings that aim to foster intercultural understanding, the preconceptions, interpretive habits, and value judgments that students bring when encountering other societies must be considered. Before learners can engage critically with social complexity, educators must understand the initial assumptions through which students conceptualize other cultures because learners interpret new information through culturally shaped frameworks of meaning (Bruner, 1996). In this context, American society is often associated with "freedom," "individualism," and "diversity," while simultaneously discussed in relation to racial discrimination, gun violence, political division, and economic inequality.

Understanding what students already know is helpful before designing any course. In curriculum planning, this step is often called a needs analysis. It typically asks what learners already know, what gaps remain, and what type of instruction would be useful. However, this step is often skipped in intercultural education. Courses on topics such as American society are often designed with general aims, such as raising awareness or reducing stereotypes, without first identifying students' beliefs. This study treats students' pre-course written responses as a form of needs analysis. Rather than assuming what students think, this study examines what students wrote and considers what this means for designing a course on American society.

This type of needs analysis has traditionally relied on a teacher's own reading of learner responses, which becomes more difficult to manage as class size increases and can be shaped by the individual reader's interpretive habits. Computational text-mining tools offer an alternative. They enable a large set of learner-generated texts to be processed systematically to identify recurring lexical patterns and co-occurrence structures that would be difficult to notice through manual reading alone. Therefore, applying such tools to pre-course responses represents a technology-enhanced method for conducting needs analysis that a teacher could realistically repeat every time a course is offered rather than treat as a one-time research exercise. This study explores that possibility by using KH Coder to analyze learner-generated data and considers what computational approach can contribute to instructional design in intercultural education.

Clarifying how Japanese university students conceptualize American society is relevant not only for

understanding their social perceptions but also for designing educational practices that help them move beyond one-sided or moralistic interpretations of cultural differences. Examining students' perspectives on society and how they give it meaning facilitates the identification of the frameworks and assumptions that contemporary young people use to understand other cultures and groups. This analytical approach can provide a basis for fostering perspectives of other cultures as complex rather than one-sided. This perspective aligns with the emphasis on critical cultural awareness and multiple perspectives in intercultural education (Byram, 1997).

The concept of "discrimination" is an essential perspective when considering relationships with others and groups and has attracted substantial social attention in relation to certain individuals or groups receiving unfair treatment, as research on intergroup relations and social bias has highlighted (Dovidio et al., 2009). However, this concept is often used ambiguously and not clearly distinguished from "distinction." Therefore, the criteria by which people understand and differentiate between "discrimination" and "distinction" must be clarified when examining how differences and fairness are understood in modern society. This understanding is also valuable for intercultural education because it highlights how one's judgments of and actions toward others may be perceived.

Based on these concerns, this study analyzed students' responses to open-ended questions collected at the beginning of a university course to examine how they described society, others, and social differences before receiving formal instruction. This study focused on Japanese students' perceptions of American society to illustrate how they perceive, evaluate, and understand other cultures. Furthermore, it examined how students wrote about social issues, group relations, and cultural differences to identify patterns in their current interpretations that may be significant for planning intercultural discussions, reflections, and instruction.

2. LITERATURE REVIEW

In this section, previous research is reviewed from three perspectives to situate this study: the characteristics of American society, factors related to group formation, and an understanding of discrimination and distinction. Furthermore, this section clarifies why these topics are important in intercultural education. Students do not start from a neutral standpoint when asked to interpret another society. They bring pre-course images, assumptions, and value judgments into the classroom. Thus, the reviewed research describes these three topics and clarifies how students' pre-course written responses can be used as a starting point for teaching. This study also draws on social identity theory as a broad interpretive framework. Previous research has suggested that people often understand society through group categories, belonging, differences, and fairness (Tajfel & Turner, 1979). From this perspective, students' descriptions of American society, explanations of why similar people form groups, and judgments regarding discrimination can be understood as related types of social perceptions rather than separate topics. The literature reviewed below helps position this study as a pedagogically relevant analysis of how students make sense of cultural differences before they receive formal classroom instruction.

2.1 PERCEPTIONS OF AMERICAN SOCIETY

Studies have characterized American society as strongly emphasizing values such as freedom, individualism, and diversity. Hofstede et al. (2010) noted that individualism is a central cultural value in the United States, emphasizing personal autonomy and self-expression. Although these values can promote freedom and diverse ways of life, research has noted that they may contribute to social tension, competition, and conflict. Furthermore, the United States is a highly diverse, multiethnic society shaped by immigration, with cultural and racial diversity as defining features. According to Putnam (2007), social trust and connections may weaken in the short term in highly diverse societies, suggesting that diversity does not automatically lead to social integration or mutual understanding.

Research has indicated that Japanese students may have selective or stereotypical perceptions of American society. Figoni (2011) found that Japanese university students tend to hold simplified or biased views of Americans that overlook the diverse backgrounds, positions, and social contexts in American society. These studies suggest that American society is understood through admired ideals and visible social problems. Being aware of this dichotomy is important for intercultural education because students may enter the classroom with mixed yet incomplete images of the United States, which may influence how they interpret classroom materials, discussions, and comparisons with Japan. Therefore, examining students' pre-course written responses can help identify the ideas with which students are already familiar, and what areas may require further context in the classroom. This concern is consistent with more recent research on intercultural competence in higher education, emphasizing that students often begin coursework with a partial, story-based understanding of other cultures (Figoni, 2011). This issue calls for deliberate pedagogical attention, achieved through structured curricular interventions such as targeted coursework and study abroad, rather than being left to develop on their own (Sierra-Huedo & Nevado-Llopi, 2022).

2.2 COMMONALITY AND GROUP FORMATION

Previous studies have examined why people who share similar backgrounds or values tend to form relationships with each other. Research has shown that such relationships facilitate mutual understanding and provide a sense of psychological safety because shared values and experiences reduce uncertainty and the likelihood of misunderstandings. Brewer (2007) argued that group belonging is important for maintaining self-esteem and a sense of security, suggesting that gathering with similar individuals reflects a natural adaptive response meant to reduce anxiety rather than an intention to exclude others. More recent research incorporating social identity theory has examined how social identity concerns shape group belonging in new educational contexts. Among students in higher distance education, Bick et al. (2024) found that greater social identity threat was associated with a lower sense of belonging and reduced motivation for social interaction with peers. This association was particularly relevant for non-traditional students, such as those with disabilities or a migration background, who reported particularly high levels of social identity threat. These findings suggest that a stable, threat-free sense of social identity remains important for group belonging, even in evolving educational settings such as online and distance learning (Bick et al., 2024). From this perspective, group formation can be understood as a basic strategy for achieving psychological stability in society.

This tendency is particularly evident in intercultural contexts. Ward et al. (2001) demonstrated that forming relationships with people who share their cultural background can reduce anxiety and stress and support cultural adjustment among individuals living in unfamiliar environments. Differences in language, customs, and values can increase uncertainty. Therefore, connections with people from similar cultural backgrounds are often an important source of psychological support. Overall, studies have suggested that group formation in intercultural settings should not be understood only in terms of exclusion or prejudice. Furthermore, it should be examined in relation to safety, belonging, and adaptation. This point is useful in intercultural education because students may initially use everyday terms, such as comfort, ease, or shared understanding, to explain group formation. Identifying these pre-course explanations can enable teachers to design activities that help students transition from personal and psychological explanations to broader discussions regarding how people form groups, distinguish themselves from others, and sometimes exclude those who are perceived as different. Thus, students' responses to open-ended questions reveal what they think and where teaching can begin.

2.3 UNDERSTANDING “DISCRIMINATION” AND “DISTINCTION”

Research has increasingly emphasized the perspective that discrimination is not only a result of individual prejudices or emotions but also produced and maintained within social structures and everyday practices. Dovidio et al. (2009) argued that discrimination is not always overtly hostile or aggressive but can be embedded in judgments, institutional arrangements, and routine behaviors that appear rational or neutral. Feagin (2006) conceptualized racial discrimination as a structural phenomenon shaped by historical and social systems, suggesting that discrimination should not be understood as an exceptional event but as an ongoing societal feature beyond individual intentions or moral judgments.

Studies that distinguish between discrimination and distinction have highlighted the need to consider people's intentions and how others experience their actions. Dovidio et al. (2010) demonstrated that although people may perceive their judgments as rational or justified, others may experience them as exclusionary or causing disadvantages or psychological harm. From this perspective, discrimination is not a one-sided action but a relational process shaped by social context and positional differences. This point is particularly salient in educational settings, in which students often try to determine whether an act is reasonable and necessary or unfair. Teaching discrimination only as an obvious moral wrong may prevent students from developing the language necessary to examine ambiguous cases. Building on these insights, this study examined how Japanese university students understand discrimination and distinction before classroom instruction. Attention is paid to the criteria they use, meanings they assign, and limits of their current methods of reasoning. The educational importance of this focus lies in the potential for pre-course responses to help teachers design tasks that encourage discussion, reflection, and comparison, thereby moving students from simple oppositional viewpoints, such as morally right or wrong or fair or unfair.

2.4 NEEDS ANALYSIS AND PRE-COURSE PERCEPTIONS IN INTERCULTURAL TEACHING

Needs analysis in language and intercultural education generally asks what learners already know, what gaps exist between their current understanding and course goals, and what type of instruction would be most useful given that starting point. According to Brown (2016), needs analysis is the systematic process of gathering and analyzing subjective and objective information about learners. This information is used to define curriculum goals that meet students' language-learning needs within a specific institutional setting. Long (2005) recommended collecting information from multiple sources to obtain reliable and valid results, but cautioned that learners' opinions should be carefully incorporated. The quality of the information obtained can vary depending on how much language-

learning or field-specific experience learners have. However, this step is rarely applied to intercultural teaching about a specific target culture in practice. Course materials on topics such as American society and discrimination are typically built around broad aims, such as raising awareness or correcting stereotypes, without first identifying what students already believe. This creates a risk that lessons repeat ideas students already hold or miss the specific assumptions that actually shape their thinking. Reviewing students' own written descriptions, rather than pre-set survey categories, makes it possible to see this more clearly. This study takes this approach, asking not only what students think but also what their existing views suggest for how a course on American society could be structured.

The concept of a need in this study must be clarified because it differs from how the term is typically used in language needs analysis. Hutchinson and Waters (1987) distinguished among three components of learner need: necessities, which are what a learner must know or do to function in a target situation; lacks, which reflect the gap between current ability and those necessities; and wants, which identify learners' own subjective sense of what they need. This framework was developed primarily to identify linguistic needs, such as the vocabulary or genre conventions required for a specific purpose. Applying this framework to a different type of object, this study applies needs analysis to address not language forms but interpretive frameworks, that is, the categories and assumptions students already use to make sense of another society, group behavior, and fairness. In this reworked framework, necessities correspond to the more contextualized understanding that intercultural instruction aims to build, and wants correspond to students' own sense of what they need to understand about other groups or societies. However, this study focuses on lacks. Here, a lack is conceptualized as the gap between students' current interpretive resources and the more contextualized understanding that intercultural instruction aims to build. For example, explaining discrimination only through individual intent, without considering structural factors, counts as a lack, not because information is missing, but because a way of reasoning is not yet available. Thus, the instruction that follows will be less about supplying missing facts and more about expanding students' interpretive repertoire, as reflected in the pedagogical suggestions in Section 7.

2.5 TECHNOLOGY-ENHANCED APPROACHES TO NEEDS ANALYSIS

A growing body of language and educational research uses computational tools to analyze learner-generated text, situating itself within the broader shift toward learning analytics (Siemens, 2013). In this approach, data produced by learners are used to inform teaching decisions. Text-mining software, such as KH Coder, makes it possible to identify frequent terms and co-occurrence patterns across such open-ended responses, offering a systematic and repeatable alternative to manual thematic coding. KH Coder has recently been used to analyze semi-structured interview data from learners in other educational contexts, such as identifying patterns in how children describe their school adaptation (Li & Araki, 2026). This may suggest that this type of computational approach has some potential to travel across learner populations and topics, although this inference is drawn from a single small-scale case study. Within needs analysis specifically, this type of computational processing can help teachers move from an impressionistic reading of a handful of responses to a more complete, corpus-based picture of what an entire class already believes at a scale that would be difficult to reach manually. Despite this potential, computational text analysis has rarely been applied to needs analysis in intercultural teaching, in which students' pre-course understanding is more often informally inferred or not assessed at all. This study addresses this gap by applying text mining and co-occurrence network analysis to learner-generated responses, demonstrating how a technology-enhanced method can support needs analysis and broader instruction design.

Previous research helps clarify why American society, group formation, and discrimination are meaningful topics in intercultural education. However, a gap remains in the literature regarding how these three themes are studied together and how computational, technology-enhanced methods are used to study them. Earlier studies have discussed these themes separately; however, few have examined how students connect them in pre-course written responses using computational text analysis or how such responses can inform intercultural teaching. This study addresses this gap by analyzing how Japanese university students describe other societies, explain why similar people gather together, and judge the line between distinction and discrimination before receiving formal classroom instruction.

3. RESEARCH QUESTIONS

This study examined how Japanese university students understand society, others, and differences, focusing on their perceptions of American society. Accordingly, the following research questions (RQs) were addressed:

RQ1: What aspects do university students focus on when viewing American society, and how do they discuss these aspects in relation to each other?

RQ2: How do Japanese university students explain the tendency to form groups with others who share similar cultural backgrounds or experiences?

RQ3: How do Japanese university students understand “discrimination” and “distinction,” and how do

they perceive the criteria and social meanings underlying this differentiation?

Across these three RQs, this study also addressed a broader issue: How can students' existing perceptions of a target culture serve as a type of needs analysis for course design in intercultural teaching?

4. THEORETICAL PERSPECTIVE

This study used social identity theory as a framework for reading students' responses to open-ended questions. This theory was not used to measure identity processes directly, but to provide a method for interpreting recurring references to in-groups, out-groups, belonging, threat, fairness, and exclusion in students' written responses. Social identity theory posits how people understand society and others as both individuals and members of social groups (Tajfel & Turner, 1979). From this viewpoint, social perception often involves categorization, comparison, and evaluation across group boundaries. For example, people often feel a sense of familiarity and safety toward others who share their nationality or culture or have similar experiences, whereas they may feel distant from groups that are different from their own. Such differences can sometimes lead to misunderstandings or conflicts.

Regarding RQ1, social identity theory helps explain why students' descriptions of American society repeatedly shifted between valued ideals and perceived divisions, and why social groups emerge as a central unit through which society is conceptualized. For RQ2, this theory provides a foundation for interpreting students' emphasis on safety, ease, belonging, and mutual understanding as aspects of perceived in-group formation rather than simply personal preferences. Regarding RQ3, this theory offers a framework for understanding how students describe discrimination in the context of broader questions related to boundary-making, exclusion, and unequal treatment across group categories.

5. METHOD

5.1 PARTICIPANTS AND DATA COLLECTION

This study surveyed 127 undergraduate students enrolled at two Japanese universities (59 students at University A and 68 at University B). The participants were second- to fourth-year students interested in American society and culture. All participants were enrolled in social science or humanities programs. One of the two universities does not offer science or engineering programs, while at the other university, which does, no students from those programs were enrolled in this particular elective course. Participants had already chosen to enroll in a course on this topic; therefore, their pre-course perceptions may not represent those of students without a prior interest in American society. Data were collected in the first class before students were exposed to course content related to American society and culture when they had limited prior knowledge of the topic. The responses were collected before formal instruction and were thus treated as baseline written data that could elucidate learners' existing perceptions.

The survey comprised open-ended questions inviting students to describe their thoughts and perceptions in their own words. This format was selected to capture how students understand and connect different concepts, which is difficult to identify through predefined response options. The purpose of this study was to identify recurring themes and patterns in students' descriptions of society, group relations, and discrimination, rather than reconstruct complete belief systems from short texts.

Although the survey collected information on gender and academic year, these characteristics were not considered in the analysis, and their distributions are not reported here. This decision reflected two considerations. First, this study aimed to identify social perceptions and narrative patterns shared across the group as a whole rather than to compare individual respondents or subgroups. With 127 respondents spread across two institutions, several subgroup cells would likely have been too small to support stable or meaningful comparisons. Second, reporting a detailed cross-tabulation of gender, academic year, and institution for a sample of this size would risk making individual respondents identifiable. Therefore, this information was withheld to protect participants' privacy. Instead, this study aimed to clarify how widely shared social perceptions and narratives are structured among Japanese university students. The text-mining analysis focused on meaning structures emerging from word frequency and co-occurrence patterns rather than individual attributes. Age and academic major were not collected through the survey. The information on participants' fields of study reported above came from the institutional and course context rather than individual self-reports.

5.2 OPEN-ENDED SURVEY USED TO ADDRESS THE RESEARCH QUESTIONS

Students were asked to respond to three open-ended questions. These were used as prompts to elicit written responses relevant to each of the three research questions (RQ1–RQ3) rather than directly restating them. The survey questions were designed to capture students' social perceptions, understanding of group formation, and views on discrimination from various perspectives.

Open-ended survey questions:

- (1) What types of images or impressions do you have about the United States today? What characteristics do you think American society has?
- (2) Why do people naturally gather with others who share similar cultural backgrounds or experiences?
- (3) When you hear the word “discrimination,” what images or events come to mind? How do you think “discrimination” and “distinction” differ?

5.3 DATA ANALYSIS

All student responses were originally written in Japanese. The text mining analysis was conducted using the original Japanese responses, and English translations are provided only for illustrative quotations. The open-ended response data collected in this study were analyzed using KH Coder, a text-mining software program (Higuchi, 2016, 2017), to identify frequently occurring terms and relationships between words that frequently appeared together. KH Coder was selected because it can process a large set of open-ended responses systematically and consistently, thereby reducing the risk that the resulting patterns simply reflect one reader’s subjective impressions. Furthermore, this program is feasible for a teacher to run before a course begins without specialized programming skills. Morphological analysis (word segmentation and part-of-speech tagging) was performed using KH Coder’s default analyzer and dictionary settings without modification. This analysis focused on recurring lexical patterns in the corpus rather than individual-level differences. The Japanese text was cleaned before the analysis to remove symbols, non-substantive expressions, and words with little analytical value. Only words tagged as nouns, adjectival nouns (na-adjectives), proper nouns, organization names, personal names, place names, adjectives, adverbs, and interjections were retained for analysis. Other parts of speech, such as particles and auxiliary verbs, were excluded. Words that appeared fewer than 15 times in the corpus were excluded from the co-occurrence network, enabling the analysis to focus on sufficiently frequent, and therefore more stable, lexical patterns. No synonym grouping or forced-extraction procedures were applied to merge notational variants or compound expressions. Words were analyzed as segmented using the default morphological analyzer.

Subsequently, co-occurrence network analysis was used as an exploratory tool to visualize the words that tended to appear together within the dataset. The co-occurrence unit was the sentence (KH Coder’s default setting) and the strength of the association between words was measured using the Jaccard coefficient. Only the 60 strongest co-occurrence relationships (edges) were displayed for each set of responses to keep the networks readable. Clusters were identified using KH Coder’s default community-detection procedure, which groups words into subgraphs based on modularity. The number of clusters obtained for each set of responses (five for American society, three for group formation, and five for discrimination and distinction) was generated automatically by this procedure and was not fixed in advance or adjusted manually. After the algorithm produced these subgraphs, the researcher interpretively assigned cluster labels. The characteristic words in each subgraph were read alongside the original student responses from which they were drawn, and a label summarizing the shared theme was assigned on this basis, as illustrated in Section 6. Recurring themes in the data were interpreted based on these clusters. The resulting clusters were cautiously interpreted by comparing the network patterns with the original student responses from which the patterns emerged. Thus, the networks were not treated as self-sufficient evidence, but were examined alongside representative excerpts to prevent overinterpreting simple frequency effects. Accordingly, the analytic procedure illustrates how technology-supported text analysis can be built into routine pre-course needs analysis rather than used only as a research method.

Representative quotations were selected from responses containing each cluster’s characteristic words. When more than one response met this criterion, one was selected at random for illustration. This study was conducted by a single researcher; therefore, cluster interpretation did not involve independent coding by a second researcher. Two additional checks were conducted to support the credibility of the interpretation. First, cluster labels were revisited and re-read after a period of time had passed to check whether the same interpretation held on a second reading. Second, each algorithmically generated word cluster was checked individually against the original responses from which the words were drawn to confirm that the assigned label was consistent with what the students had actually written, rather than relying on the co-occurring words alone.

5.4 ETHICAL CONSIDERATIONS

This study used data collected through a questionnaire administered during a regular class session as part of an ordinary classroom activity rather than through a separate research recruitment procedure. The study was exempt from formal ethics committee review because responses were collected anonymously and used in a manner that did not allow individual students to be identified. The questionnaire included a written explanation at the beginning stating that the responses might be used for research purposes. Students were informed in writing that participation was voluntary, choosing not to respond would have no effect on their course grade, and their

responses would remain anonymous. No identifying information was collected, and the labels used to present illustrative quotations in this article (e.g., Student 1A) were assigned only to distinguish between different students' responses. They do not correspond to any information that could identify a participant. The collected data have been stored as password-protected files and will be discarded in accordance with the author's institutional data-retention policy.

6. RESULTS

Before presenting the clusters, it is worth reiterating that co-occurrence network analysis is an exploratory technique. It shows which words tended to appear together in students' responses, not a direct measurement of students' underlying beliefs or psychological structures. The interpretations offered below describe patterns in how students wrote about each topic and should be read in that light, rather than as evidence of a fully formed or stable conceptual understanding.

6.1 CHARACTERISTICS OF STUDENTS' VIEWS ON AMERICAN SOCIETY

Co-occurrence network analysis using KH Coder revealed that students' open-ended responses could be classified into five distinct clusters, a number generated automatically by KH Coder's modularity-based community-detection procedure rather than set in advance (see Section 5.3) (Figure 1).

The first cluster suggested that students often described American society in terms of liberal values, such as freedom, self-expression, and acceptance of different lifestyles. The co-occurrence network analysis showed that words such as "freedom," "culture," "individual," "opinion," "respect," "coexistence," "ideology," and "strong" frequently appeared together and were strongly interconnected. Students' responses suggested that clearly expressing their ideas and acting based on personal values are key characteristics of American society. Students also referenced the coexistence of people from diverse cultures and backgrounds, indicating that respect for individual freedom is recognized as a foundation that supports a multicultural environment. The following excerpts were translated into English from the original Japanese by the author.

I have the impression that the United States is a multiethnic nation and that it is difficult to live there without a strong sense of self. Within a culture that emphasizes individualism, I feel that there is a contradiction between diversity and individualism. (Student 1A)

The second cluster showed that students often associated multiculturalism with racial discrimination. The co-occurrence network analysis showed that words such as "diversity," "race," "discrimination," and "many" frequently co-occurred and were strongly interconnected. Students' responses indicated that they understood immigration and racial diversity as key positive features of American society. However, they were also aware that such diversity does not necessarily lead to equality or coexistence.

I have an impression of American society as a mix of diverse racial groups and, as a result, I associate it with high levels of crime and discrimination. (Student 1B)

The third cluster suggested that students tended to view gun control and gun-related crime as major social issues that symbolize American society. In the co-occurrence network analysis, the words "guns" and "problems" frequently co-occurred and were strongly interconnected. Students' open-ended responses frequently referenced the legality of gun ownership and media reports on gun-related incidents, suggesting that gun culture is closely linked to feelings of anxiety and danger in everyday American life.

While I associate the United States with freedom, frequent news about gun-related incidents gives me a somewhat frightening impression. Compared to Japan, I also see it as a society where people express their opinions more openly. (Student 1C)

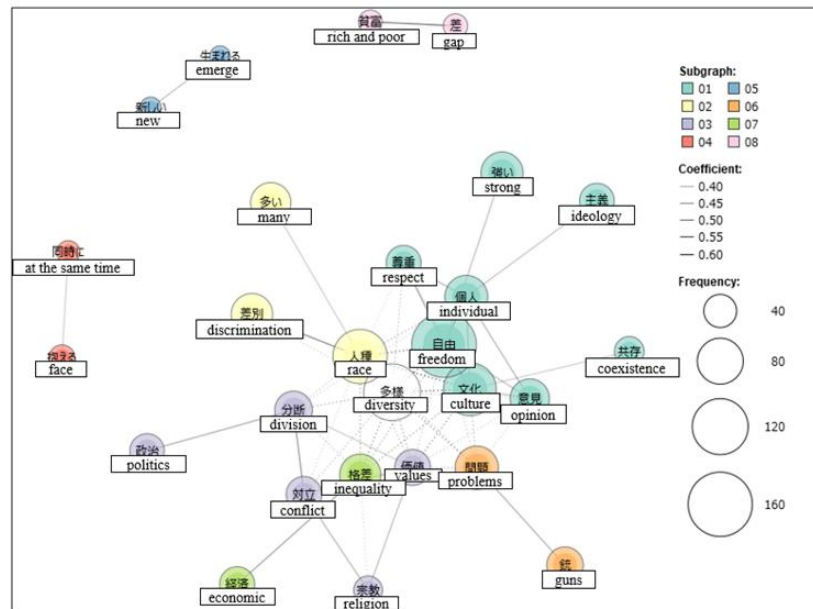


Figure 1: Co-occurrence Network of Students' Views on American Society

The fourth cluster suggested that students described differences in values and interests that lead to political and religious conflicts in American society. The co-occurrence network analysis showed that words such as “division,” “conflict,” “religion,” and “politics” frequently co-occurred and were strongly interconnected. Their responses indicated an awareness that different political positions and religious beliefs can create social division. Although American society guarantees freedom of opinion, students expressed concerns regarding a social structure in which conflict is likely to intensify.

I view the United States as a diverse society, but also one shaped by invisible barriers, such as racial discrimination, poverty, immigration issues, and political division. The coexistence of freedom and equality, as well as diversity and division, characterizes contemporary American society. (Student 1D)

The fifth cluster suggested that students perceived America as an economically wealthy country and a society facing serious inequality. The co-occurrence network analysis showed that words such as “inequality” and “economic” frequently co-occurred and were strongly interconnected. Students’ responses included several references to gaps between the rich and poor and imbalances between social classes, indicating a strong awareness of the coexistence of economic opportunity and structural inequality.

I feel that the United States is a diverse society that strongly values individual freedom, but I also associate it with large gaps between the rich and the poor and a visible homeless population in urban centers. (Student 1E)

This analysis suggested that students’ responses reflected multidimensional views of American society. Although freedom, individualism, and diversity emerged as core values, other clusters highlighted social issues, such as racial discrimination, gun violence, political and religious division, and economic inequality.

6.2. COMMON UNDERSTANDINGS AND FACTORS IN GROUP FORMATION AMONG STUDENTS

This section presents the results of analyzing students’ responses to the following open-ended question: Why do people naturally tend to gather with others who share similar cultural backgrounds or experiences? Co-occurrence network analysis using the same algorithmic procedure described in Section 5.3, revealed three distinct word clusters (Figure 2). The first cluster indicated that forming groups with people who share similar cultural backgrounds or experiences is intended to achieve psychological comfort and mutual understanding. The co-occurrence network analysis showed that words such as “safety,” “values,” “self,” “understand,” and “seeking” frequently co-occurred and were strongly interconnected. Students’ responses suggested that shared values and experiences facilitate communication and relationship-building and provide a foundation for stable social ties. In unfamiliar cultural settings or high-anxiety situations, individuals tend to connect with others who are similar to them, suggesting that groups based on shared characteristics are a source of psychological support.

I think people feel a sense of safety when they share even small things in common with others, which

naturally draws them together. In stressful environments, such connections can provide psychological support. (Student 2A)

The second cluster indicated that students viewed forming groups with people who share similar cultural backgrounds or experiences as a way to simplify everyday interactions and reduce psychological burdens. The co-occurrence network analysis showed that words such as “comfort,” “positive,” “conversation,” and “thinking styles” frequently co-occurred and were strongly interconnected. Students’ responses indicated that interacting with people who think similarly and share the same values allows conversations to flow naturally and reduces the need for constant consideration of others. Such relationships were described as “comfortable.” Furthermore, having several things in common was viewed as making it easier to empathize and receive positive responses, thus helping maintain or increase self-esteem.

When I am with people who have ways of thinking or feeling similar to mine, I feel that we can understand each other even without many words, and it feels comfortable ... I feel that conversations are easier to continue with people who share similar ideas or topics, and that these relationships are more likely to deepen. (Student 2B)

The third cluster indicated that students understood forming a group with people who share similar cultural backgrounds or social positions as a process of gaining companions with whom one can share experiences and emotions beyond simple feelings of safety or comfort. The co-occurrence network analysis showed that words such as “others,” “sharing,” “companions,” and “gaining” frequently co-occurred and were strongly interconnected, suggesting that students recognized group formation as a process of acquiring companions with whom one can share experiences and emotions. Students’ responses suggested that connecting with others in similar situations provides psychological stability when facing difficulties or feelings of exclusion and facilitates mutually supportive relationships. The responses also described how discovering shared traits can trigger a sense of belonging and trust. Furthermore, the responses described how students choose individuals who are highly similar to themselves to avoid discrimination, stereotypes, and potential risks.

At the moment when people find something in common, a sense of safety emerges and a feeling of belonging based on shared circumstances becomes stronger ... as an extension of this, I feel that friendships and relationships of trust are often formed. (Student 2C)

Overall, the analysis suggested that students tended to describe group formation with similar others as a layered and gradual process associated with functions such as psychological safety, mutual understanding, and social support, particularly in the context of anxiety or exclusion.

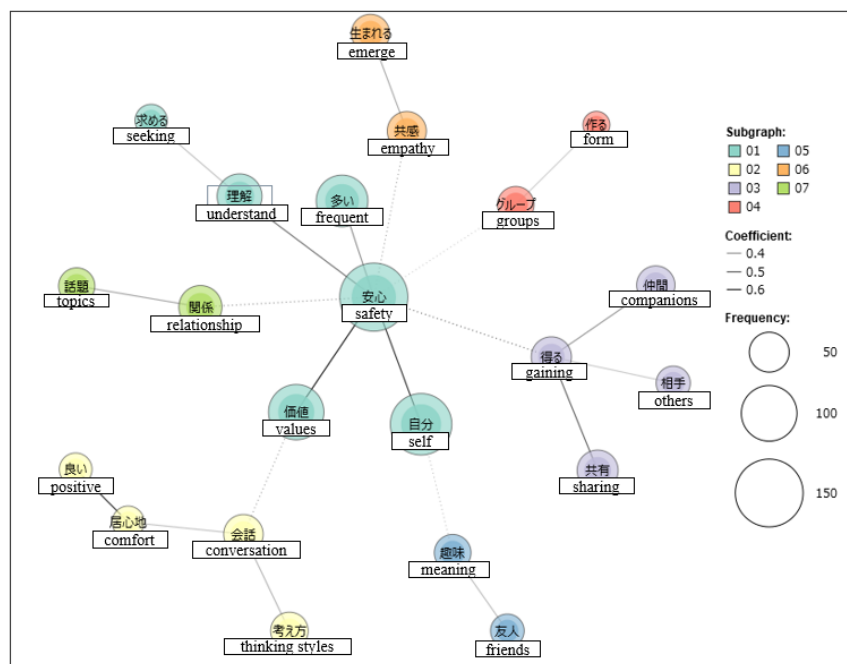


Figure 2: Co-occurrence Network of Students' Views on Group Formation

6.3 STUDENTS' VIEWS ON “DISCRIMINATION” AND “DISTINCTION”

Using the automatic community-detection procedure described in Section 5.3, co-occurrence network analysis identified five distinct word clusters (Figure 3).

The first cluster included words such as prejudice, judgment, values, harm, and dignity, which frequently co-occurred and were strongly interconnected. The co-occurrence network analysis showed that words such as “prejudice,” “judgment,” “values,” “harm,” and “dignity” frequently co-occurred and were strongly interconnected. The students’ open-ended responses clearly distinguished between distinction and discrimination. They described distinction as a neutral and sometimes necessary judgment based on the recognition of differences. In contrast, they held negative views of discrimination, conceptualizing it as unfair treatment based on differences. Students viewed the key criterion separating them as whether a judgment or value assessment is based on valid reasons. Furthermore, they commonly perceived discrimination as an act of exclusion based on prejudice or ill intent, in which others are judged unfairly and their dignity is damaged. Students also indicated that assigning superiority or inferiority based on attributes that cannot be changed through personal effort, such as race or place of origin, constitutes discrimination.

Distinction means recognizing differences between things ... In contrast, I think discrimination means treating people unfairly because of those differences ... I feel that distinction is necessary, but discrimination is something that should be eliminated. (Student 3A)

Discrimination feels like excluding people based on ill will or prejudice ... boundaries made for safety or consideration are distinction, but limiting opportunities based on skin color or place of origin is discrimination. (Student 3B)

The second cluster showed that students understood discrimination not only as a matter of personal feelings or prejudice but also as actions that socially exclude and disadvantage others. The co-occurrence network analysis results demonstrated that words such as “action,” “understand,” “exclusion,” “others,” and “society” frequently co-occurred and were strongly interconnected. Students’ responses suggested that they viewed discrimination as unfair behavior that fails to respect others and prioritizes one’s own position or interests at the expense of someone else. They understood discrimination not only as a problem related to values but also as a set of practices that manifest through concrete actions in society. Furthermore, they described discrimination as an act that denies others’ identity and causes psychological harm, often involving ill intent or contempt. Students also viewed discrimination as a social problem that takes several forms, including discrimination based on race, socioeconomic status, and family background.

I think discrimination is an act that looks down on another person’s identity and causes discomfort or emotional harm ... When contempt or a lack of respect is added, distinction can turn into discrimination. (Student 3C)

The third cluster showed that students prioritized unfairness over rationality and necessity when distinguishing between discrimination and distinction. The co-occurrence network analysis results demonstrated that words such as “unfair,” “race,” “gender,” “necessity,” “rationality,” “separating,” and “receiving” frequently co-occurred and were strongly interconnected. Students’ responses suggested that they conceptualized discrimination as unfair treatment based on attributes that cannot be changed through personal effort, such as race, gender, or place of origin. In contrast, they viewed distinction positively as a rational and necessary form of classification based on factors such as safety or physical characteristics.

They further noted that distinctions related to gender or disability may be perceived as discriminatory, depending on the situation and perspectives of those affected.

I think that discrimination involves unfair treatment of people in weaker positions without reasonable justification, whereas distinction is based on rational and objective reasons. However, in cases such as gender or disability, distinction can risk turning into discrimination, depending on how it is applied or perceived. (Student 3D)

When I hear the word “discrimination,” I think of racial discrimination ... I believe discrimination means restricting or excluding people without a justified reason or basis ... even distinction can feel unpleasant to the person involved, so I think it needs to be considered carefully. (Student 3E)

The fourth cluster demonstrated that students understood discrimination as treating people as a single entity simply because they belong to a particular group. The co-occurrence network analysis showed that words such as

“specific,” “groups,” and “individuals” frequently co-occurred and were strongly interconnected. These responses suggested that discrimination is often associated with historical cases involving groups such as Black and Asian people, and they viewed it as a structural problem reproduced at the group level. When differentiating between discrimination and distinction, students considered a situation discriminatory when one side is clearly prioritized over the other. Furthermore, students understood that the concept of discrimination is unclear and judgments can be difficult to make in modern society. Actions can be viewed as discriminatory, even if that is not the intention. Students' responses also suggested that although discrimination targets groups, its effects were often described as falling on individuals in psychological and physical terms.

I think that “discrimination” is an abstract and difficult concept. While hostile attacks on specific groups are clearly discriminatory, even non-hostile statements can be perceived as discrimination, making the boundary between discrimination and distinction unclear. (Student 3F)

The fifth cluster suggested that students emphasized the appropriateness of ability evaluation and maintenance of fairness when differentiating between discrimination and distinction. The co-occurrence network analysis showed that words such as “age,” “unfairness,” and “ability” frequently co-occurred and were strongly interconnected. Students commonly described discrimination as actions that result in disadvantages or exclusion based on attributes that people cannot choose to change. In contrast, classifications based on age or ability were viewed positively as rational judgments made to ensure fairness. Students also recognized that discrimination is rooted in structural inequalities based on factors such as gender.

I think discrimination means excluding or disadvantaging people based on unchangeable factors, such as race or place of origin, whereas distinction depends on reasonable and justified criteria. For example, separating people by gender or weight in competitions may ensure fairness, but refusing employment based on race is discrimination. (Student 3G)

Overall, this analysis suggested that students' responses described discrimination in terms of a broad and context-dependent phenomenon, extending beyond personal prejudice to include unfair judgments and social exclusion. Although several students distinguished between discrimination and distinction based on rationality and fairness, they also recognized that rational judgments may be experienced as discriminatory depending on social context and positionality.

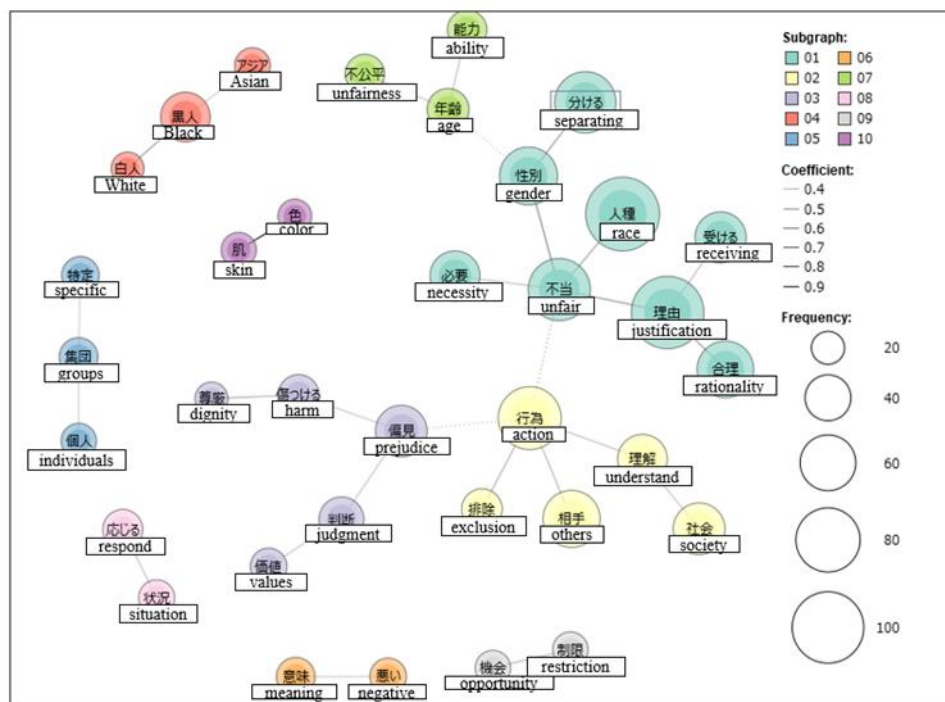


Figure 3: Co-occurrence Network of Students' Views on Discrimination and Distinction

7. DISCUSSION

This study showed that rather than being based on a single fixed image, Japanese university students' views on other cultures are layered and reflect an awareness of group differences and social relationships. These features

of students' perceptions have important implications for intercultural education, particularly when considering how people understand multicultural societies and engage with others and differences.

7.1 STUDENTS' VIEWS OF AMERICAN SOCIETY (RQ1)

The analysis of RQ1 suggested that Japanese university students tended to describe American society positively in terms of values such as freedom, individualism, and diversity. However, they also recognized that these ideals do not always lead to equality, safety, or social stability. This suggests that the students did not idealize American society but understood it as having multiple and sometimes conflicting aspects. These findings align with previous research describing the United States as a society that emphasizes individualism. Although it can support personal freedom, this emphasis also contributes to social division and makes it difficult to achieve a consensus (Hofstede et al., 2010). Students also referenced issues such as racial discrimination, political and religious conflict, economic inequality, and gun-related violence, which is consistent with a view of the United States as a multicultural and structurally complex society in which valued ideals and social challenges coexist.

These findings suggest that several students entered the course with layered and occasionally internally conflicting descriptions of American society that were neither entirely idealized nor negative. From an educational perspective, this indicates that teachers should not assume ignorance or fixed stereotyping to be the starting point. Instead, classroom work should begin by addressing the mixed and uneven ways in which students already perceive other societies. This can help students examine how ideals such as freedom and diversity become linked to danger, division, or inequality in their thinking. In practical terms, these pre-course perceptions can inform the design of discussion prompts, comparative tasks, and reflective writing activities aimed at moving students from impression-based descriptions toward more contextualized social analysis.

Given that students had already connected “freedom” and “individualism” with social division and inequality (Clusters 1 and 2), one possible instructional strategy would be for the first class to treat this tension as a starting point rather than new information. Specifically, the class could begin with an example such as the debate over gun policy or racial disparities in housing and ask students why a society based on individual freedom produces these issues.

7.2 UNDERSTANDING GROUP FORMATION (RQ2)

The analysis of RQ2 suggests that Japanese university students view group formation with individuals who share similar cultural backgrounds or experiences as a gradual social process rather than simply a matter of personal preference. Their responses suggest that they consider group formation a means of gaining psychological safety and mutual understanding that can develop into stable relationships characterized by comfort and shared experiences and emotions. This concept aligns with social identity theory, which posits that belonging to an in-group fosters a sense of safety and self-esteem (Tajfel & Turner, 1979). In this study, students emphasized feeling understood and secure when interacting with similar others, reflecting the psychological stability associated with in-group belonging.

These findings suggest that students perceive group formation as an important social practice that encompasses psychological and social dimensions. In terms of intercultural education, these responses suggest that students may initially interpret group formation through the language of comfort and safety rather than through that of prejudice. This is pedagogically important because classroom discussions regarding in-groups and out-groups can easily become moralized. If educators begin only with the claim that gathering with similar others is exclusionary, students may respond defensively. A more productive approach may be to start from students' own recognition of safety, belonging, and anxiety, and then examine when such tendencies remain adaptive or begin to turn into exclusion.

Given that the students already understand group formation as a search for psychological safety and comfort rather than an act of exclusion, one possible instructional strategy would be for the first class to begin with an exercise in which students write in their own words why people feel more comfortable with others from similar backgrounds. The terms “in-group” and “exclusion” could then be introduced once students have expressed the idea in their own words.

7.3 STUDENTS' UNDERSTANDING OF DISCRIMINATION AND DISTINCTION (RQ3)

The analysis of RQ3 indicated that Japanese university students view discrimination as social actions that harm dignity and create disadvantages through unfair judgments rather than as personal prejudice or negative feelings. Several students distinguished discrimination from distinction by emphasizing rationality, legitimacy, and fairness. These views align with the argument that discrimination becomes problematic when disadvantages are imposed without reasonable grounds (Pager & Shepherd, 2008). Furthermore, students' responses suggested that they

recognized that judgments perceived as rational may be experienced as discrimination depending on the position of those affected and surrounding social context. This understanding reflects the perspective of discrimination as a relational and context-dependent process rather than a one-sided act based solely on intent.

These findings suggest that students perceived discrimination as a complex and multifaceted phenomenon shaped by intergroup relations, social structures, and lived experiences. From an intercultural educational perspective, these findings indicate the importance of moving beyond teaching discrimination as a simple moral issue of right versus wrong. From an educational standpoint, this highlights the need for teachers to help students distinguish between intention, justification, and impact. Several responses showed that despite attempting to differentiate between “reasonable distinction” and “unfair discrimination,” students lacked the language to examine how context, power, and the standpoint of the affected person complicate that distinction. This underscores the importance of learning activities that encourage students to consider how a judgment appears to the actor and may be experienced by those subject to it.

Students were found to already use fairness and reasonableness as their criteria for distinguishing discrimination from distinction (Clusters 3 and 5); therefore, the first class could begin with a borderline case from the survey, such as categorizing competitors by gender or age. Students could then be invited to argue both sides before academic definitions of discrimination are introduced.

7.4 IMPLICATIONS FOR TECHNOLOGY-ENHANCED NEEDS ANALYSIS AND INSTRUCTIONAL DESIGN

Beyond the specific findings for RQ1–RQ3, this study has broader implications for how technology can support instructional design in intercultural education. Collecting open-ended responses through a simple digital survey and processing them with KH Coder made it possible to identify recurring patterns across 127 responses within a short period without extensive manual coding. This type of procedure could be repeated at the start of every course offering, producing a cluster-based picture of what a specific group of students already thinks that a teacher could use directly when planning the first few lessons, as illustrated in Sections 7.1–7.3. Viewed this way, the text-mining approach used here works less as a one-time research technique and more as a model for a low-cost, technology-enhanced needs-analysis tool that teachers without a background in computational methods could realistically adopt, given that KH Coder is freely available and does not require programming skills. This positions computational analysis of learner-generated data as a practical resource for learning analytics in language and intercultural classrooms, rather than only an academic research method.

8. LIMITATIONS

This study had several limitations. First, the participants were enrolled in a course related to American society and culture at two Japanese universities. Therefore, the findings should not be generalized to all Japanese university students. Second, the data comprised relatively short written responses to open-ended questions collected before instruction at one point in time. Thus, the analysis only identified recurring descriptive patterns in students’ writing without capturing the full depth, stability, or development of individual views. Consistent with Long’s (2005) recommendation to draw on multiple sources of information, this study relied on a single method of data collection at one point in time. Future needs analyses could combine this approach with other sources, such as interviews or classroom observation, to obtain a more complete picture of students’ perceptions. Third, although gender and academic year were collected, subgroup differences were not examined, and their detailed distributions were not reported to protect participants’ privacy given the sample size. Information on age and academic major was not collected. Consequently, this study cannot address whether the identified patterns vary across these characteristics. Fourth, this study was conducted by a single researcher; therefore, the interpretation of clusters and selection of illustrative quotations did not involve an independent second coder, and no formal inter-rater reliability statistic could be calculated. The two checks described in Section 5.3, namely, revisiting cluster labels after a time interval and comparing each word cluster individually against the original responses, were used to support the credibility of the interpretation. However, they cannot fully substitute for independent coding by more than one researcher. Future studies could strengthen this process by involving multiple coders or incorporating member-checking with participants. Finally, co-occurrence network analysis was used as an exploratory method to identify patterned associations in the data. Thus, these findings should not be taken as direct evidence of fully formed psychological structures.

9. CONCLUSION

This study suggests that students’ existing perceptions before a course begins provide a useful starting point for intercultural education. Analyzing students’ narratives reveals that their understanding of other cultures and societies does not stem from fixed images or simple moral judgments, but from the interaction of multiple factors, including anxiety, safety needs, social positioning, and broader social contexts. Instead of assuming that

intercultural education is mainly about transmitting desirable values, the findings of this study suggest the importance of first identifying the ambiguities, tensions, and partial understandings that students bring to the classroom.

Students' views on group formation and discrimination suggest that behaviors often interpreted as exclusionary or prejudiced may also serve as adaptive responses to psychological and situational demands. From an educational perspective, this highlights the importance of approaches that encourage learners to consider social distance and intercultural friction relationally and contextually, rather than in simple terms of right or wrong. When these perceptions are brought to light, they can provide materials for teaching comparison, dialogue, reflection, and reinterpretation. This study contributes to the literature by bringing together students' descriptions of American society, group formation, and discrimination, and examining how these themes appear in the same set of responses. These descriptions reveal how students shift between describing cultural features, explaining behavior in psychological terms, and evaluating fairness. Thus, this study's contributions lie less in offering a definitive account of students' beliefs than in demonstrating how their pre-instruction descriptions can inform the design of more reflective and context-sensitive intercultural learning.

Accordingly, this study provides an example of a technology-enhanced needs analysis in intercultural education. Rather than assuming what students need to learn, this study starts from what students already know and shows how computational text analysis can transform their own words into materials that directly inform instructional design. This approach, which uses open-ended pre-course questions analyzed through text mining to assess students' existing knowledge, could be applied to other intercultural courses at low cost. Although this study was conducted in a Japanese university setting, the approach can be adapted to other contexts in which students have preconceived notions about a target culture before instruction begins.

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Measuring Cognitive Engagement in AI-Supported Writing: Introducing the Revision Responsiveness Index (RRI) as a Process-Based Assessment Model

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Abstract

This study examines students' revision behaviors in AI-feedback-supported environments by analyzing domain- and subskill-level changes in writing, patterns of gains and losses, effort allocation across revisions, and the effectiveness of a process-based metric, the Revision Responsiveness Index. Grounded in cognitive load theory, the study evaluates how reductions in cognitive effort during writing, enabled by artificial intelligence tools, may diminish deeper engagement and learning. A quantitative, within-subjects pretest-posttest design was employed to examine revision outcomes as a writing process. The sample included 1,348 high school students who produced more than 3,800 writing samples across persuasive, informative, and narrative genres. Data were collected in a classroom-based setting using a baseline writing task completed without assistance, followed by a timed revision task supported by structured AI feedback. Revision outcomes were analyzed using the Revision Responsiveness Index (RRI), defined as the change in analytic writing scores between initial and revised drafts, supplemented by domain-level scoring and linguistic analyses. Revision outcomes demonstrated high variability with 48 percent of students improving, 34 percent declining, and 18 percent showed no meaningful change. Students who improved exhibited expected gains across multiple writing domains, while those who declined showed larger and uneven losses. These findings suggest that revision is not inherently beneficial and that ineffective integration of feedback can result in a reduction in overall writing quality.

Keywords: Revision Impact Modeling, Analytic Rubric Scoring, Feedback-Driven Revision, Writing Metrics, Cognitive Load, AI-Mediated Feedback

Introduction

The rapid integration of artificial intelligence into educational settings has transformed how students engage with writing tasks. AI tools now offer the ability to generate text, summarize information, and provide immediate feedback, fundamentally altering the cognitive demands of writing (Deep & Chen, 2025, Xue & Song, 2025). While these tools hold promise for improving efficiency and access, they also raise important questions about the relationship between effort and learning. Research suggests that reducing the cognitive demands of writing may come at a cost (Stadler et al., 2024). Emerging research suggests that when students rely on AI to generate or refine text, they may engage less deeply with the underlying ideas and processes required for learning reducing critical thinking, creativity, and authentic writing skills (Budiyono et al., 2025). Writing is a cognitively intensive activity that requires the organization, evaluation, and synthesis of ideas. As a result, the extent to which students actively engage in these processes is critical to their development as writers and critical thinkers. How AI influences this process is yet to be determined.

Background

Revision represents an important stage in the writing process (Bamberg & Clark, 2019). Unlike initial drafting, which reflects a student's current level of understanding, revision requires students to evaluate their own work, interpret feedback, and make deliberate changes to improve clarity, coherence, and effectiveness (Olive, 2022). This process places significant demands on working memory and requires the coordination of multiple dimensions of writing simultaneously (Fidalgo et al., 2009). Further, since writing demands coordinating multiple interdependent domains, including idea development, organization, language use, and adherence to conventions, effective revision requires students to balance these domains under conditions of limited cognitive capacity (Ahmed et al., 2022).

Despite revision's importance, it does not always lead to overall writing improvement due to multiple factors. Primary obstacles to improving writing through revisions include a combination of superficial focus (Aben et al., 2026); ineffective feedback (Stuulen et al., 2024), emotional and cognitive barriers (Surat et al., 2014), lack of training (Arias-Gundin & Garcia-Sanchez, 2008), and individual differences. Understanding why this occurs requires a closer examination of how students engage with feedback and how they allocate cognitive effort during the revision process.

Cognitive Demands of Writing and Revision

Revision places substantial demands on working memory as students evaluate existing text while attempting to generate improvements across multiple dimensions of writing. Writing is inherently cognitively demanding and requires simultaneously managing multiple processes, including generating ideas, organizing information, selecting appropriate language, and maintaining grammatical accuracy (Fitzgerald, 1987). These demands place significant strain on working memory, particularly for developing writers (Vanderberg & Lee, 2007). Revision further increases cognitive stresses by requiring students to evaluate existing text while simultaneously generating improvements. This dual demand can lead to cognitive overload, particularly when students must address multiple aspects of writing at once (Olive, 2022). Under such conditions, learners may simplify the task by focusing on one dimension of writing while neglecting others.

Writing as a Recursive and Multi-Dimensional Process

Models of writing emphasize its recursive and multi-dimensional nature (Fitzgerald, 1987; Flower & Hayes, 1981). Rather than progressing linearly from planning to drafting to revision, writers continually move between these processes, revising and refining their work as new ideas emerge. Further, effective writing depends on the integration of multiple domains, including content development, organization, language use, and conventions (Ahmed et al., 2022). These domains are interdependent. Adding new ideas may require reorganization, while revising sentence structure may affect clarity and coherence. Revision, therefore, is not simply a matter of correcting errors or adding detail. It requires metacognition, critical thinking, and restructuring ideas in a way that maintains balance across multiple dimensions of writing. This makes revision cognitively complex and can significantly increase cognitive load.

AI and Cognitive Engagement in Writing

The emergence of AI tools in writing instruction has introduced new dynamics into the writing process. While AI can reduce the effort required to generate and refine text, recent research suggests that this reduction in effort may also reduce cognitive engagement. Fan et al. (2025) reported that students who used AI for revision achieved higher scores but demonstrated lower levels of metacognitive engagement, often relying on direct incorporation of AI-generated text. Dhawan et al. (2025) confirmed these dependencies and added that reliance on AI was associated with reduced neural activity and lower retention of content. Stadler et al. (2024) reported that students using AI tools to support writing tasks produced less accurate and less nuanced responses, despite perceiving the task as easier. These findings suggest that AI can shift the cognitive demands of writing in ways that may undermine learning.

Much of this research focuses on environments in which AI contributes directly to content generation or revision. Less is known about how students engage with feedback in environments where AI provides guidance but does not perform the writing itself (Moni, 2025; Wahyuni et al., 2026; Zhan & Yan, 2025). In such contexts, the cognitive demands of revision remain with the learner, creating an opportunity to examine how students interpret and apply feedback.

Revision as a Process of Cognitive Coordination

While cognitive load theory (CLT) and writing models provide insight into the complexity of writing, limited research has examined how these dynamics operate specifically during revision. Revision requires students to interpret feedback, prioritize changes, and apply those changes across multiple domains of writing within a limited time frame (Aben et al., 2026; Fitzgerald, 1987). This process can be understood as a form of cognitive coordination, in which students must allocate attention and effort across competing demands (Ahmed et al., 2022). When this coordination is successful, students achieve balanced improvements across domains. When it is not, revision may result in uneven outcomes, including gains in some areas and declines in others. Understanding revision as a process of cognitive coordination provides a foundation for examining not only whether students improve, but how they improve and where breakdowns occur.

Purpose of Study

Although prior research has examined the effects of AI-supported feedback on writing performance and cognitive engagement, comparatively little attention has been given to how students independently process and apply feedback during revision. The purpose of this study is to examine students' revision behaviors in AI-feedback-supported environments by analyzing domain- and subskill-level changes in writing, patterns of gains and losses, effort allocation across revisions, and the effectiveness of a process-based metric, the Revision Responsiveness Index.

Context is central to this investigation, as most existing studies examine feedback use within instructional or guided learning environments. In contrast, this study focuses on revision behavior when feedback is processed

independently, outside of the teaching environment. Further, this study compares these independent behaviors to feedback engagement within instructional settings. Through this focus, the study seeks to advance understanding of revision as a cognitively demanding process and to inform assessment approaches that more accurately capture how students engage with feedback in AI-supported learning contexts. Theoretically, distinguishing between in-class and independent revision addresses a gap in cognitive and writing research by positioning revision as a context-sensitive process of cognitive coordination, rather than a uniform response to feedback, with implications for how revision outcomes are interpreted and assessed.

Research Questions

- RQ1: How does student writing change between initial and revised drafts after receiving structured, rubric-aligned AI-supported feedback?
- RQ2: What patterns of gains and losses occur across writing domains and subskills during revision?
- RQ3: How do students allocate cognitive effort during revision, and how does this allocation relate to successful versus unsuccessful revision outcomes?
- RQ4: To what extent does the Revision Responsiveness Index (RRI) function as an effective process-based measure of revision impact and cognitive engagement?

Theoretical Framework

To move from descriptive accounts of revision difficulty to explanatory theory, this section applies cognitive load theory (CLT) to clarify how working memory constraints shape students' coordination of multiple writing demands during revision. CLT is applied here as a complementary explanatory framework rather than a causal account of observed revision patterns. CLT provides a foundational framework for understanding how learners process complex tasks (Sweller, 1988; Sweller et al., 2011). CLT asserts that working memory has limited capacity, and learning depends on how effectively cognitive resources are allocated among different types of load: intrinsic, extraneous, and germane. Revision intensifies cognitive load by requiring writers to manage multiple, overlapping cognitive processes simultaneously, including critical evaluation, error detection, and idea refinement (Roussey & Piolat, 2005).

Revision as Cognitive Coordination

Revision plays a central role in writing development, yet it remains undertheorized as a cognitive process through which learners translate feedback into change (Graham & Harris, 2018). Much of the writing literature emphasizes drafting processes or final product quality, offering limited explanation for how writers evaluate feedback, prioritize revisions, and coordinate changes across multiple dimensions of text (Flower & Hayes, 1981). Unlike drafting, which reflects a writer's current understanding, revision reveals how that understanding is actively restructured, making it one of the most cognitively demanding phases of writing (Fidalgo et al., 2009; Olive, 2022).

From a cognitive perspective, revision requires the simultaneous activation of multiple processes, including monitoring existing text, interpreting feedback, generating alternative formulations, and maintaining coherence across the composition (Fidalgo et al., 2009). Writers must hold both the original and intended versions of a text in working memory while making targeted changes, a dual representation that places substantial demands on attentional resources and introduces the potential for instability in performance (Ahmed et al., 2022).

Building on cognitive load theory and models of writing, revision is conceptualized in this study as a process of cognitive coordination, in which writers must allocate limited cognitive resources across multiple, interdependent domains, including idea development, organization, language use, and conventions. Because these domains are interconnected, changes in one area can produce unintended effects in others. For example, expanding an argument may improve idea development while introducing organizational inconsistencies or grammatical errors, and revising sentence structure for clarity may disrupt tone or stylistic coherence.

Effective revision therefore depends on the writer's ability to negotiate competing demands under cognitive constraint. When this coordination is successful, revision results in balanced improvement across domains. When coordination falters, revision may produce uneven outcomes, including gains in some areas alongside declines in others. These challenges are amplified when writers must address both lower-level revisions, such as grammar and spelling, and higher-level revisions, such as coherence and argumentation, within limited time and cognitive capacity (Roussey & Piolat, 2005). Less skilled writers tend to revise more frequently but at smaller scopes, a pattern that can further increase cognitive load and undermine text quality. Emotional factors, including frustration or reduced motivation during revision, may further compound these demands.

Feedback, Decision-Making, and Revision Behavior

Feedback plays a critical role in guiding revision, but its effectiveness depends on how the writer interprets and applies it (Hattie & Timperley, 2007). In many instructional contexts, feedback is assumed to lead directly to improvement. However, this assumption overlooks the cognitive work required to translate feedback into meaningful changes (Stadler et al. 2022). Students must first understand the feedback, then decide which elements to prioritize, and finally determine how to implement those changes within the structure of their existing text. Each of these steps introduces potential points of breakdown. Feedback may be immediate and detailed in AI-supported environments, but it does not reduce the need for student decision-making. Instead, it may increase cognitive demands by presenting multiple areas for improvement simultaneously (Roodsari et al., 2024). Without the ability to prioritize and coordinate changes, students may focus narrowly on specific aspects of feedback, leading to fragmented revision. Feedback alone is insufficient to support learning. The critical factor is how students engage with feedback during revision.

Toward a Process-Based Measure of Revision

Traditional approaches to writing assessment have predominantly emphasized final product quality, offering limited insight into the cognitive and strategic processes through which revisions are generated (Flower & Hayes, 1981). While such measures provide useful information about performance, they offer limited insight into the processes that produce that performance (Graham & Harris, 2018). A process-based approach to assessment shifts attention from outcomes to writing growth. Evaluating how writing evolves between drafts makes it possible to capture nuances of learning that are not visible in a single snapshot of performance. Recognizing these nuances transforms the writing process into a measurable indicator of cognitive engagement. Iterations in writing reflect how students interpret feedback, allocate attention, and manage competing demands.

Methodology & Design

This study employed a within-subjects design to examine changes in student writing following structured feedback and revision. Each student completed an initial writing task, received targeted feedback aligned to a standardized rubric, and then revised their writing within a constrained time frame. The design allowed for direct comparison between initial and revised drafts, enabling analysis of revision impact at the overall, domain, and subskill levels. The study was conducted in authentic classroom settings, reflecting typical instructional conditions while maintaining consistency in task structure and scoring procedures.

Participants and Data Set

The sample included 1,348 high school students from one Mid-Atlantic United States public school district across multiple course levels, including advanced, academic, and lower-track classes. Students produced more than 3,800 writing samples across three genres: persuasive, informative, and narrative. This large and diverse sample provides a robust basis for examining patterns of revision behavior across varying levels of student proficiency and instructional contexts.

Writing Tasks and Conditions

Students completed a baseline writing task (writing on demand) in response to a standardized prompt aligned to one of three genres: persuasive, informative, or narrative. All writing was completed independently without access to external resources or generative AI tools. Following the initial draft, students received structured feedback aligned to the analytic rubric used for scoring. Feedback was provided at the domain and subskill levels, offering specific guidance on areas for improvement.

Students then engaged in a timed revision period of approximately 15 minutes. During this time, they were required to interpret and apply feedback independently. No generative AI tools or external assistance were permitted during revision. This condition ensured that any changes in writing reflected student cognitive engagement rather than automated text generation.

Scoring Framework

Each writing sample was evaluated using a structured analytic rubric consisting of five domains. Four domains were consistent across all genres: Ideas and Purpose; Organization; Language and Style; and Conventions and Knowledge. The fifth domain was genre-specific: Narrative Technique for narrative writing and Evidence and Development for persuasive and informative writing. Each domain consisted of five subskills, with each subskill scored on a scale from 0 to 10. This resulted in a maximum of 50 points per domain and a total possible score of 250 points per writing sample. Scoring was conducted consistently across both initial and revised drafts using the same rubric and criteria. This ensured that differences in scores reflected changes in student writing rather than variations in evaluation standards. The use of subskill-level scoring enabled detailed analysis of writing performance, allowing for examination of changes within and across domains.

Conceptualizing the Revision Responsiveness Index (RRI)

The Revision Responsiveness Index (RRI) is introduced as a process-based construct designed to capture how students engage with feedback during revision. Unlike traditional assessment models that focus solely on final product quality, RRI emphasizes the process of change between drafts. In its broader conceptual model, RRI is defined as a multi-dimensional construct encompassing three key components: Responsiveness to Feedback (the degree to which students address targeted feedback; Revision Efficiency (the effectiveness of changes made within a constrained time frame); and Impact on Writing Quality (the measurable change in writing performance across domains). These dimensions define the broader conceptual scope of RRI as an index of students' cognitive engagement during revision. In the present study, RRI is operationalized specifically as a measure of revision impact, defined as the change in analytic writing scores between initial and revised drafts. While responsiveness and efficiency are central to the broader conceptual model, they are not directly measured in this analysis and are treated as areas for future research.

RRI as a Measure of Revision Impact

Within the context of this study, RRI captures the extent to which student writing improves or declines following feedback. This approach shifts the focus of assessment from static performance to dynamic change. By examining differences between initial and revised drafts, RRI provides insight into how students process and apply feedback. Positive RRI values indicate improvement, while negative values indicate decline. Importantly, this formulation allows for the identification of factors that lead to the variability in revision outcomes, including cases where revision does not lead to improvement. This perspective aligns with a process-based view of learning, in which growth is reflected not only in final outcomes but in the ability to respond effectively to feedback.

Operational Definition of the Revision Responsiveness Index (RRI)

The Revision Responsiveness Index (RRI) is operationalized in this study as the difference between a student's total writing score on a revised draft and their total writing score on an initial draft, based on a structured analytic rubric. RRI as operationalized is a study-specific indicator of revision impact, not a validated comprehensive assessment instrument. Each writing sample is evaluated across five domains. Four domains are consistent across genres: Ideas and Purpose, Organization, Language and Style, and Conventions and Knowledge. The fifth domain is genre-specific, with Narrative Technique used for narrative writing and Evidence and Development used for informative and persuasive writing. Each domain consists of five subskills, each scored on a scale from 0 to 10. Subskill scores are aggregated to produce a maximum of 50 points per domain and a total possible score of 250 points per writing sample. RRI is calculated as: $RRI = \text{Final Total Score} - \text{Initial Total Score}$.

The Final Total Score represents the sum of all domain and subskill scores in the revised draft, and Initial Total Score represents the sum of all domain and subskill scores in the initial draft. Expanded, this calculation can be expressed as: $RRI = \sum (D_{post} - D_{pre})$ where D_{pre} represents the score for each subskill within each domain in the initial draft, and D_{post} represents the corresponding score in the revised draft. Domain-level revision is calculated as: $\text{Domain Delta}_i = \text{Domain Post}_i - \text{Domain Pre}_i$. Positive RRI and Domain Delta values indicate net gains across drafts, while negative values indicate net losses. This formulation enables analysis at multiple levels, including overall writing change, domain-specific gains and losses, and subskill-level variation. In this study, RRI reflects the impact dimension of revision. Future iterations of the model may incorporate additional measures of responsiveness to feedback and revision efficiency to support a more comprehensive process-based index.

Data Analysis

Revision was measured as the change in writing performance between the initial and revised drafts. Differences were calculated at three levels: Overall score change (total score out of 250); Domain-level change (score out of 50 per domain); and Subskill-level change (score out of 10 per subskill). These differences form the basis for calculating the Revision Responsiveness Index (RRI), as defined in Section 4, and for analyzing patterns of revision behavior across the sample. Descriptive analyses were conducted to examine overall trends in revision outcomes, including the proportion of students who improved, declined, or remained unchanged. Domain-level and subskill-level changes were analyzed to identify patterns of growth and decline across different aspects of writing. In addition, quantitative writing metrics, including word count, lexical diversity, and sentence-level measures, were analyzed to examine changes in writing characteristics associated with revision.

Ethical Considerations

All data were collected in accordance with standard educational research practices. Student data were anonymized prior to analysis to ensure privacy and confidentiality. The study was conducted within normal instructional activities, and no personally identifiable information was used in reporting results.

Results

Differences between initial and revised draft scores were analyzed across 1,348 students and more than 3,800 writing samples. A paired-samples t-test indicated a statistically significant difference between baseline and revised scores, $t(3875) = -21.41, p < .001$, with a moderate effect size (Cohen's $d = .34$; 95% CI $[-.376, -.311]$). Mean scores increased from 142.8 to 150.1, reflecting an average gain of 7.3 points on the 250-point scale. This indicates that, on average, revision resulted in measurable improvement in writing performance. Across the sample, approximately 48% of students demonstrated improvement in total writing score, 34% experienced a decline, and 18% showed no meaningful change (see Figure 1).

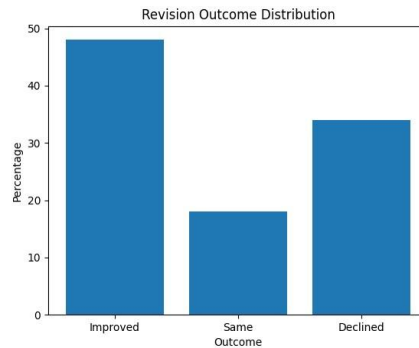


Figure 1: *Distribution of Revision Outcomes.*

Note: The percentage of students whose writing improved, declined, or showed no meaningful change following revision.

Overall Revision Responsiveness Index (RRI)

The Revision Responsiveness Index (RRI), defined as the difference between revised and initial total writing scores, provides a measure of revision impact across the analytic scoring framework. Across the full sample, the mean RRI was 7.37 on a 250-point scale, closely aligning with the observed composite gain of 7.3 points derived from paired comparisons. At the aggregate level, the observed effect size (Cohen's $d = .34$) reflects a modest but meaningful level of improvement within a single revision cycle. RRI values varied widely across students.

Domain-Level Changes Across the Full Sample

Domain-level analysis revealed statistically significant improvements across all writing dimensions when comparing initial and revised drafts ($p < .001$). Mean gains were observed in each domain, indicating that revision produced measurable changes across multiple aspects of writing performance. Average domain gains (on a 50-point scale) were as follows:

- Organization: +1.72
- Evidence & Development / Narrative Technique: +1.69
- Narrative Technique / Evidence & Development: +1.52
- Ideas & Purpose: +1.46
- Language & Style: +1.42
- Conventions & Knowledge: +1.06

These gains correspond to moderate and consistent effect sizes across higher-order domains (Cohen's $d \approx .32-.34$), with smaller but still meaningful gains observed in Conventions & Knowledge ($d = .20$).

Linguistic Characteristics of Revision

To better understand how students revise, quantitative writing metrics were analyzed, including word count, lexical diversity, and sentence-level measures. On average, students increased word count by 28.62 words and demonstrated gains in lexical diversity (+2.9). In contrast, words per sentence showed minimal change (−0.07), indicating little to no increase in syntactic complexity (see Figure 2).

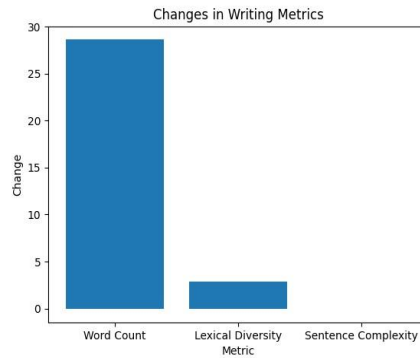


Figure 2: *Linguistic Changes Following Revision*

Note: Average changes in word count, lexical diversity, and sentence-level complexity between initial and revised drafts.

Domain-Level Decline Patterns

To better understand unsuccessful revision, domain-level changes were examined for students whose total writing scores declined following revision. Students in this group exhibited substantial and uneven losses across domains. The largest average declines were observed in:

- Conventions & Knowledge: -3.22
- Evidence & Development: -2.83
- Narrative Technique: -2.75
- Ideas & Purpose: -2.13
- Language & Style: -1.72
- Organization: -1.69

As shown in Figure 3, declines were most pronounced in foundational and evidence related domains. Notably, losses in Conventions & Knowledge were larger in magnitude than gains observed in the full sample

Domain-Level Gains for Improving Students

In contrast, students whose total writing scores increased demonstrated substantial and coordinated gains across domains. Average domain gains for this group were as follows:

- Ideas & Purpose: $+5.10$
- Evidence & Development: $+3.66$
- Conventions & Knowledge: $+3.14$
- Organization: $+2.75$
- Language & Style: $+2.47$
- Narrative Technique: $+2.31$

These gains, illustrated in Figure 3, are markedly larger than the average domain changes observed in the full sample.

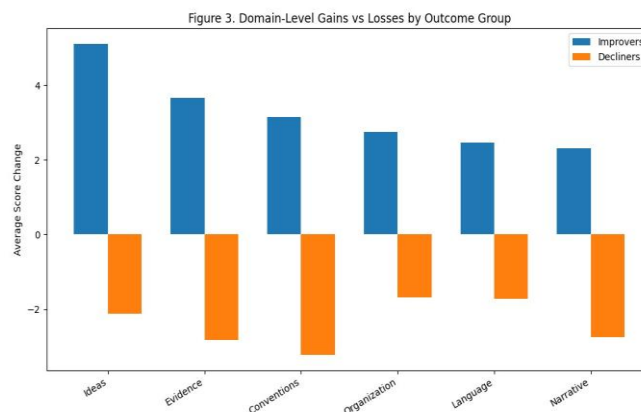


Figure 3: *Domain-Level Gains vs Losses by Outcome Group.*

Note: Average domain score changes for students who improved compared to those who declined following revision.

Cross-Domain Trade-Off Patterns

Comparison of students who improved with those who declined reveals a consistent pattern of cross-domain trade-offs in revision behavior (see Figure 4).

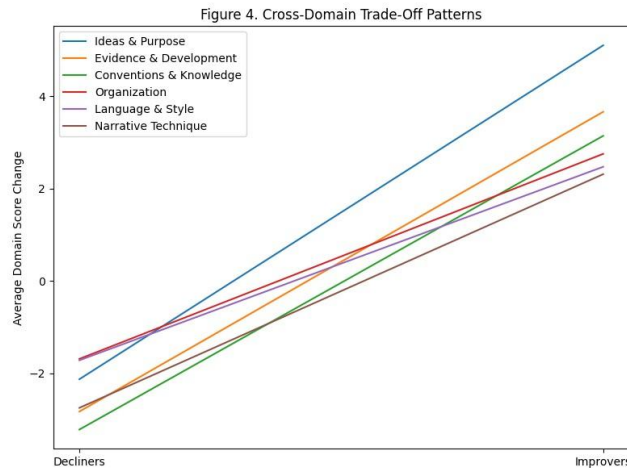


Figure 4: *Cross-Domain Trade-Off Patterns in Revision Outcomes.*

Note: Average domain-level score changes for students who declined compared to those who improved following revision. Each line represents a writing domain, illustrating asymmetry between gains and losses across outcome groups.

Students who demonstrated overall improvement exhibited coordinated gains across multiple domains, particularly in higher-order areas such as Ideas & Purpose and Evidence & Development. These gains were accompanied by stable or improving performance in lower-level domains. In contrast, declining students showed larger and more uneven domain-level losses compared to gains observed in improving students, with particularly pronounced decreases in Conventions & Knowledge and evidence-related domains. These losses were not isolated but distributed across multiple areas of writing.

Relationship Between RRI and Domain-Level Change

Analysis of RRI in relation to domain-level changes indicates that overall revision impact reflects the cumulative effect of gains and losses across domains. Students with higher RRI scores consistently demonstrated positive changes across multiple domains, while lower or negative RRI scores were associated with uneven or fragmented revision patterns.

Summary of Results

Revision produced statistically significant but modest average gains in writing scores; however, outcomes were highly variable across students. Domain-level analyses revealed divergent patterns, with coordinated multi-domain gains among improving students and larger, uneven losses among declining students. Linguistic analyses showed increased text length and lexical diversity with minimal change in syntactic structure. These findings indicate substantial heterogeneity in revision outcomes and highlight the limits of average score change in capturing revision behavior.

Discussion

Across the sample, revision outcomes were highly variable, with fewer than half of students demonstrating net improvement and a substantial proportion experiencing declines or no meaningful change. Although average gains in total writing scores were statistically significant, deeper analyses revealed that these aggregate improvements masked divergent revision trajectories. Mean score changes concealed substantial differences in how students distributed gains and losses across writing domains, underscoring the limitations of relying solely on average outcomes to characterize revision behavior.

Domain-level analyses indicated that students who improved exhibited coordinated gains across multiple dimensions of writing, particularly in higher-order domains such as Ideas and Purpose and Evidence and Development, without corresponding declines in lower-level features. In contrast, students whose writing declined showed larger and uneven losses distributed across domains, with particularly pronounced decreases in Conventions and Knowledge and evidence-related domains. In many cases, the magnitude of these losses exceeded the average domain gains observed across the full sample, suggesting that unsuccessful revision can

introduce substantial degradation rather than simply lacking improvement. Linguistic analyses further indicate that revision was typically characterized by additive strategies, such as increasing text length and lexical diversity, rather than structural transformation, potentially compounding cognitive demands when revisions were not effectively coordinated.

Taken together, these patterns suggest that revision is not a neutral or uniformly beneficial process, but one that involves the redistribution of cognitive effort across competing writing demands. Successful revision appears to depend on students' ability to integrate feedback across domains in a balanced manner, whereas unsuccessful revision is marked by fragmented or misaligned application of changes. The Revision Responsiveness Index captures this variability by reflecting the cumulative impact of domain-level gains and losses, providing a process-sensitive measure of revision outcomes that is not apparent in aggregate score changes alone.

Reframing Revision as Cognitive Coordination

To interpret these empirical patterns within existing theory, revision can be reframed as a process of cognitive coordination. The findings of this study align with the literature finding that writing is recursive, not linear (Fidalgo et al., 2009), and is a cognitively demanding act of coordination across multiple dimensions of writing (Vanderberg & Lee Swanson, 2007). Students are required to simultaneously manage ideas, evidence, organization, language, and conventions within the constraints of working memory. Under these conditions, revision becomes a process of prioritization and trade-off rather than uniform enhancement.

The observed asymmetry between gains and losses reinforces this interpretation. Students who improved demonstrated coordinated, multi-domain growth, while those who declined exhibited larger, fragmented losses across domains. This pattern indicates that successful revision depends on the ability to integrate feedback holistically, whereas unsuccessful revision reflects misaligned or isolated changes.

This conceptualization positions revision as a form of cognitive coordination, in which students must allocate limited mental resources across competing demands. When coordination is successful, writing improves across domains. When it is not, revision efforts may result in unintended degradation of writing quality.

Alignment with Cognitive Load Theory

These findings align closely with CLT, which posits that learning depends on the effective management of intrinsic, extraneous, and germane cognitive load (Sweller, 1988; Sweller et al., 2011). Writing and revision inherently involve high intrinsic load due to the complexity of coordinating multiple skills simultaneously. The domain-level trade-offs observed in this study suggest that cognitive demands may exceed some students' available processing capacity. As cognitive demands intensify, revision efforts may emphasize one domain while other dimensions receive reduced attention. For example, efforts to strengthen ideas or evidence may lead to declines in conventions or organization, reflecting a redistribution rather than an expansion of cognitive effort. These findings extend cognitive load theory into the domain of writing revision by demonstrating how overload manifests in measurable patterns of domain-level gains and losses. Rather than improving uniformly, students exhibit uneven development that reflects the constraints of working memory.

Implications for AI-Supported Writing Environments

The results of this study provide important context for understanding the role of AI in writing instruction. Recent research has shown that generative AI tools can reduce cognitive effort while also diminishing depth of understanding and metacognitive engagement (Stadler et al., 2024; Fan et al., 2025). This study's findings raise concerns about the potential for AI to bypass the very processes that support learning. In this respect, AI integration in writing instruction requires careful consideration of how cognitive effort is distributed rather than simply whether performance improves.

This study extends this line of inquiry by demonstrating that even when students are required to revise independently, without access to AI-generated text, effective revision outcomes were associated with active student engagement during feedback use. Feedback alone did not guarantee improvement across drafts. Instead, students were required to interpret, prioritize, and apply feedback in a coordinated manner. These findings indicate that cognitive engagement remains a critical determinant of revision success, even in the absence of AI-generated writing support. This distinction has important implications for how AI is implemented in writing instruction. When AI is used to generate or rewrite text, it may remove the need for students to engage in cognitive coordination altogether. Such use may obscure underlying revision challenges rather than resolve them. In contrast, when AI is used to provide feedback that must be actively processed, it preserves the cognitive demands necessary for learning. These findings suggest that the instructional value of AI depends more on how it is integrated into the learning process than on its availability.

Revision as the Site of Learning

A central implication of this study is that revision represents the primary site of learning in writing. While initial drafting reflects students' current understanding, revision reveals how they engage with feedback and whether they can transform that understanding.

The variability observed in revision outcomes indicates that learning does not occur automatically through the feedback. Instead, it depends on the quality of cognitive engagement during revision. Students who demonstrated meaningful growth were able to apply feedback across domains in a coordinated manner, while those who declined often applied feedback inconsistently. This reinforces the idea that writing instruction should focus on how they revise, not only the end product. The process of revision, rather than the final product alone, provides a more accurate window into student learning.

The Role of the Revision Responsiveness Index (RRI)

The Revision Responsiveness Index provides a framework for operationalizing revision as a measurable construct. By capturing responsiveness to feedback, efficiency of change, and impact on writing quality, RRI offers a process-based indicator of student learning. Importantly, RRI does not simply reflect improvement in final scores. Instead, it captures the degree to which students engage in effective revision behaviors. High RRI scores are associated with coordinated, multi-domain gains, while lower scores reflect fragmented or ineffective revision patterns. In this way, RRI serves as a bridge between theoretical constructs such as cognitive load and metacognition and observable classroom outcomes. It enables educators to identify not only whether students improve, but how they improve, and where breakdowns occur.

Instructional Implications

The findings of this study have several implications for instructional practice in writing and AI-supported learning environments. First, students require explicit instruction in how to revise. Feedback alone is insufficient; students must be taught how to interpret feedback, prioritize revisions, and coordinate changes across domains. Second, revision should be structured as a bounded and intentional process. Time constraints, such as a 15-minute revision window, may encourage students to engage more actively in decision-making and reduce reliance on passive or surface-level strategies. Third, instructional models should emphasize the interconnected nature of writing domains. Students need to understand that changes in one area of writing can affect others, and that effective revision requires maintaining balance across domains. Finally, AI should be used to support, rather than replace, cognitive engagement. Tools that provide feedback without generating text may be more effective in promoting learning than those that automate the writing process.

Summary

This study advances a new understanding of revision as a cognitively constrained coordination process. Rather than functioning as a straightforward mechanism for improvement, revision represents a complex interaction of competing demands that can produce either meaningful growth or unintended decline. In AI-supported environments, this distinction becomes especially important. Technologies that reduce cognitive effort may inadvertently bypass the processes that support learning, while those that preserve cognitive engagement can enhance it. By shifting the focus from product to process, and from output to cognitive engagement, this work contributes to a broader redefinition of writing instruction and assessment. The Revision Responsiveness Index offers a practical and theoretically grounded tool for capturing these processes, providing educators with new insight into how students learn through writing.

Limitations and Directions for Future Research

The study's quasi-experimental design in real classroom settings increases ecological validity but also introduces contextual variability that limits causal inference and reduces generalizability beyond secondary students or other instructional models. The Revision Responsiveness Index (RRI), while a practical for cognitive engagement, infers internal processes rather than directly measuring them, requiring further validation of its reliability, sensitivity, and alignment with established engagement and metacognitive measures, especially across longer writing trajectories. Additionally, because generative AI use was intentionally restricted, future research should experimentally compare AI-assisted, feedback-only, and independent revision; examine revision development across multiple writing cycles; and conduct domain-level analyses to determine which writing subskills are most responsive to revision and whether targeted interventions. Explicit instruction in feedback interpretation and revision planning in future studies could strengthen revision outcomes.

Conclusion

The integration of generative artificial intelligence into writing instruction represents one of the most significant shifts in modern education. While these tools offer unprecedented efficiency and access, they also challenge long-

standing assumptions about how writing supports learning. In environments where high-quality text can be produced with minimal effort, the traditional link between writing performance and cognitive engagement is no longer guaranteed. This study responds to that challenge by shifting the focus of assessment from product to process. Rather than asking what students produce, it asks how students think and how they engage with feedback and revise their work.

The findings demonstrate that revision is neither automatic nor uniformly beneficial. Even within a structured, feedback-rich environment, student outcomes varied widely. While nearly half of students improved, a substantial proportion experienced no change or decline. These results underscore a critical insight: revision is a complex cognitive activity that can either advance or undermine learning depending on how it is executed.

Patterns observed in the data further reinforce this conclusion. Students tended to increase word count and lexical diversity yet showed limited evidence of deeper structural change. Improvements in one domain were frequently accompanied by declines in another, revealing the complexity of coordinating multiple dimensions of writing. In many cases, students believed they had improved because they followed feedback, yet their performance declined due to fragmented or misaligned revision strategies. These findings challenge the assumption that access to feedback or tools is sufficient to support learning. Instead, they point to the importance of cognitive engagement as the central driver of writing development. Learning occurs when feedback is processed, interpreted, and meaningfully applied.

The Revision Responsiveness Index (RRI) addresses this gap in the revision process. By capturing responsiveness to feedback, efficiency of engagement, and impact on writing quality, RRI provides a practical and scalable way to observe the learning process. It offers educators a means of distinguishing between superficial revision and cognitively engaged improvement, bridging the gap between instructional practice and assessment.

This distinction is essential in the context of AI-supported writing. The question is no longer whether students can produce strong writing, but whether they are engaging in the thinking required to develop as writers. Tools that generate text may accelerate production and appear to develop writing skills, but they do not inherently support learning unless they are embedded within systems that require active cognitive participation.

This study suggests that writing instruction must not neglect the revision and feedback process and proficiency and advancement does not depend merely on current measurements. Educators should design learning that encourages thinking by emphasizing feedback as a tool for reflection. Teaching writing should include structured revision as an active cognitive task and should incorporate process-based metrics that make this process visible. By reframing writing assessments around cognitive engagement, educators can better align instruction with the realities of AI and ensure that writing continues to function as a vehicle for learning.

Writing remains one of the most powerful tools for developing human thought. Removing technology from writing will not solve this problem. The challenge in the age of artificial intelligence is to ensure that technology is used in ways that preserve and expand the cognitive work that writing demands. The Revision Responsiveness Index represents a step in that direction, offering a new framework for understanding, measuring, and supporting learning through writing in an increasingly AI mediated world.

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Psychological Resilience and Post-Traumatic Growth in Young Adults: A Multidimensional Analysis of Cognitive, Emotional, and Social Recovery Mechanisms

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Abstract

Psychological resilience and post-traumatic growth (PTG) have emerged as key constructs in understanding how young adults adapt to and transform following adverse life events. While trauma has traditionally been associated with negative psychological outcomes, contemporary research increasingly highlights the potential for positive psychological change and personal growth in its aftermath. This study examines the multidimensional mechanisms underlying resilience and post-traumatic growth in young adults, with particular emphasis on cognitive, emotional, and social recovery processes. Using a qualitative, theory-driven approach grounded in systematic literature analysis, the study synthesizes findings from psychological, developmental, and social research. The results indicate that resilience and PTG are not static traits but dynamic processes shaped by cognitive reappraisal, emotional regulation, meaning-making, and social support. The findings further demonstrate that young adulthood represents a critical developmental period in which adaptive coping strategies and supportive social environments significantly enhance recovery trajectories. The study concludes that integrative, multidimensional models are essential for understanding psychological recovery and for designing effective mental health interventions that promote long-term well-being and growth after trauma.

Keywords: psychological resilience; post-traumatic growth; young adults; trauma recovery; coping mechanisms

Introduction

Exposure to traumatic and highly stressful life events is a widespread phenomenon, particularly among young adults who face multiple developmental, social, and economic challenges. Traditional psychological research has long focused on the pathological consequences of trauma, emphasizing disorders such as post-traumatic stress disorder (PTSD), anxiety, and depression. However, over the past three decades, a growing body of literature has shifted attention toward adaptive processes that enable individuals not only to recover but also to experience positive psychological change following adversity (Tedeschi & Calhoun, 2004).

Two interrelated constructs have become central to this shift: **psychological resilience** and **post-traumatic growth (PTG)**. Resilience refers to the capacity to maintain or regain psychological well-being in the face of adversity, whereas PTG describes positive transformations in cognition, emotion, and identity that occur as a result of struggling with traumatic experiences (Bonanno, 2004; Tedeschi & Calhoun, 2004). In young adults, these processes are particularly salient due to ongoing identity formation, cognitive maturation, and social role transitions.

Despite increasing interest, the relationship between resilience and PTG remains theoretically complex and empirically contested. Some scholars conceptualize resilience as resistance to disruption, while PTG is viewed as transformation through disruption. Understanding how cognitive, emotional, and social mechanisms interact to support recovery and growth is therefore essential. This study aims to address this gap by providing a multidimensional analysis of resilience and post-traumatic growth in young adults.

1. Theoretical Framework

The theoretical framework of this study integrates perspectives from **positive psychology**, **cognitive stress theory**, and **developmental and social psychology** to conceptualize resilience and PTG as dynamic and interactive processes.

A foundational perspective is **Positive Psychology**, which emphasizes human strengths, adaptive capacities, and well-being in the context of adversity (Seligman, 2011). From this view, resilience is not merely the absence of pathology but a proactive process of adaptation and self-regulation.

Cognitive stress and coping theory further explains how individuals interpret and respond to traumatic events. According to Lazarus and Folkman (1984), cognitive appraisal and coping strategies determine psychological outcomes following stress. Cognitive reappraisal, meaning-making, and narrative reconstruction are especially

relevant to PTG, as they enable individuals to reinterpret trauma in ways that support personal growth (Park, 2010).

The framework also draws on **developmental theory**, recognizing young adulthood as a sensitive period for psychological transformation. Identity development, autonomy, and social integration influence how trauma is processed and integrated into one's life story (Arnett, 2000). Finally, **social support theory** underscores the role of interpersonal relationships in facilitating emotional regulation and growth after trauma (Hobfoll et al., 2007). Together, these perspectives provide a comprehensive lens for analyzing cognitive, emotional, and social recovery mechanisms.

2. Literature Review

Research on psychological resilience demonstrates that individuals exhibit diverse trajectories following trauma, ranging from chronic distress to stable functioning and growth (Bonanno, 2004). Resilience has been linked to adaptive coping strategies, optimism, self-efficacy, and emotional regulation skills (Masten, 2014).

The concept of post-traumatic growth was formalized by Tedeschi and Calhoun (2004), who identified key domains of growth, including enhanced personal strength, improved relationships, appreciation of life, and existential change. Empirical studies indicate that PTG is associated with deliberate rumination, meaning-making, and openness to emotional experiences (Calhoun & Tedeschi, 2014).

Cognitive mechanisms play a central role in both resilience and PTG. Research shows that individuals who engage in adaptive cognitive reappraisal and constructive rumination are more likely to report growth after trauma (Park, 2010). Emotional processes, such as acceptance and emotional regulation, further mediate recovery by reducing distress and enabling integration of traumatic memories (Gross, 2015).

Social mechanisms are equally significant. Strong social support networks have been shown to buffer stress, enhance resilience, and facilitate PTG by providing validation, emotional safety, and shared meaning (Hobfoll et al., 2007). Studies focusing on young adults emphasize that peer relationships and mentoring are particularly influential during this life stage.

Despite extensive research, gaps remain in integrative models that simultaneously address cognitive, emotional, and social recovery processes, particularly within the developmental context of young adulthood.

The contemporary literature on trauma adaptation increasingly emphasizes psychological resilience and post-traumatic growth (PTG) as central constructs for understanding positive adjustment following adverse life events. Rather than conceptualizing trauma responses solely in terms of psychopathology, recent research highlights diverse adaptive trajectories shaped by individual, contextual, and developmental factors.

A substantial body of work defines resilience as a dynamic process involving the maintenance or rapid recovery of psychological functioning after exposure to stress or trauma. Bonanno et al. (2011) argue that resilience represents one of the most common outcomes following potentially traumatic events, challenging deficit-oriented models that assume long-term dysfunction as the norm. Similarly, Fletcher and Sarkar (2013) conceptualize resilience as a multidimensional process encompassing cognitive flexibility, emotional regulation, and access to social resources. These perspectives underscore that resilience is not a fixed personality trait but a context-sensitive adaptive capacity that evolves over time.

Parallel to resilience research, studies on post-traumatic growth focus on qualitative positive changes that arise through the struggle with trauma. Early theoretical contributions by O'Leary and Ickovics (1995) introduced the concept of *thriving*, suggesting that adversity can catalyze psychological development beyond pre-trauma levels of functioning. Building on this foundation, Helgeson et al. (2006), through a meta-analytic review, demonstrated that benefit finding and PTG are associated with improved psychological well-being, although the strength of these associations varies depending on methodological and contextual factors. Their findings highlight that growth is neither universal nor automatic but contingent upon cognitive and emotional processing mechanisms.

The relationship between resilience and PTG has been a subject of ongoing debate. While resilience is often associated with stability and resistance to disruption, PTG implies transformation through disruption. Joseph and Linley (2005) propose an integrative framework in which positive adjustment encompasses both resilience and growth, arguing that individuals may simultaneously maintain functioning in some life domains while

experiencing profound transformation in others. This view challenges dichotomous models and supports a continuum-based understanding of trauma adaptation.

Recent scholarship has also critically re-examined the resilience construct itself. Infurna and Luthar (2018) caution against overly broad or imprecise definitions of resilience, emphasizing the need for longitudinal and domain-specific analyses. They argue that resilience should be assessed relative to clearly defined stressors and outcomes, particularly in developmental contexts such as young adulthood, where psychological functioning is inherently dynamic.

Clinical psychology literature further elaborates on the mechanisms underlying PTG. Zoellner and Maercker (2006) distinguish between *constructive* growth, which reflects genuine psychological transformation, and *illusory* growth, which may function as a short-term coping strategy. This distinction is particularly relevant for young adults, as identity development and meaning-making processes may intensify both authentic and defensive growth responses following trauma.

Collectively, these studies indicate that resilience and post-traumatic growth are interconnected yet distinct processes, shaped by cognitive appraisal, emotional regulation, and social context. The literature consistently suggests that adaptive outcomes following trauma are best understood through integrative models that move beyond linear recovery frameworks. For young adults, whose developmental stage involves ongoing identity formation and social repositioning, resilience and PTG emerge as complementary pathways of psychological adaptation, laying the groundwork for long-term well-being and personal development.

This body of literature provides a strong theoretical and empirical foundation for examining resilience and post-traumatic growth through a multidimensional lens, as adopted in the present study.

3. Methodology

This study employs a qualitative systematic literature review and interpretive synthesis design. Peer-reviewed journal articles and scholarly books published primarily between 2000 and 2024 were selected based on relevance to psychological resilience, post-traumatic growth, and young adult populations.

The analysis followed three stages:

1. thematic coding of cognitive, emotional, and social recovery mechanisms;
2. comparative analysis of resilience and PTG models;
3. integrative synthesis linking recovery processes to developmental characteristics of young adulthood.

Theoretical triangulation was used to enhance analytical rigor. As a secondary-data study, no ethical approval was required.

4. Findings and Discussion

The integrated analysis of the findings demonstrates that psychological resilience and post-traumatic growth (PTG) should be understood as interrelated and complementary dimensions of psychological adaptation, rather than as mutually exclusive or sequential outcomes of trauma. The evidence synthesized in this study indicates that resilience and PTG emerge through the dynamic interaction of cognitive, emotional, and social recovery mechanisms, which together shape how young adults respond to, process, and ultimately transform adverse experiences.

4.1 Cognitive Recovery Mechanisms

Table 1. Cognitive Mechanisms Supporting Resilience and PTG

Cognitive process	Function	Psychological outcome
Cognitive reappraisal	Reinterpretation of trauma	Reduced distress, increased meaning
Meaning-making	Integration into life narrative	Identity coherence
Deliberate rumination	Reflective processing	Post-traumatic growth

The findings highlight cognition as a primary driver of psychological recovery. Adaptive cognitive processing enables individuals to transform traumatic experiences into sources of insight and growth rather than persistent distress.

4.2 Emotional Recovery Mechanisms

Table 2. Emotional Processes in Trauma Recovery

Emotional mechanism	Role	Outcome
Emotional regulation	Managing negative affect	Psychological stability
Acceptance	Emotional integration	Reduced avoidance
Positive affect cultivation	Emotional balance	Increased resilience

Emotional flexibility emerges as essential for sustaining resilience. Individuals capable of tolerating distress while cultivating positive emotions show stronger long-term recovery trajectories.

4.3 Social Recovery Mechanisms

Table 3. Social Factors Facilitating Resilience and Growth

Social factor	Function	Effect
Social support	Emotional buffering	Reduced stress
Interpersonal disclosure	Shared meaning	PTG enhancement
Community belonging	Identity reinforcement	Sustained well-being

Social connectedness plays a crucial role in both resilience and PTG, particularly in young adulthood, where peer and community relationships are central to identity development.

The findings indicate that resilience and post-traumatic growth emerge from the **interaction of cognitive, emotional, and social mechanisms**. Rather than opposing processes, resilience and PTG represent complementary dimensions of psychological adaptation.

From a cognitive perspective, resilience and PTG are linked through processes of appraisal, meaning-making, and narrative reconstruction. Resilient individuals tend to engage in flexible cognitive appraisals that allow them to manage immediate distress and maintain functional stability. At the same time, these cognitive processes provide the foundation for post-traumatic growth by enabling deeper reflection on the significance of traumatic events and their implications for identity, values, and life goals. Deliberate rumination, in particular, appears to act as a bridge between resilience and PTG: while initially serving to reduce uncertainty and regain control, it later facilitates the reconstruction of meaning and the emergence of growth-related outcomes. Thus, cognitive adaptation supports both the preservation of psychological equilibrium and the possibility of transformative change.

At the emotional level, the findings suggest that effective emotional regulation is a prerequisite for both resilience and PTG. The ability to tolerate negative emotions—such as fear, grief, or anger—without becoming overwhelmed allows individuals to remain engaged with their internal experiences rather than resorting to avoidance or suppression. Emotional acceptance and regulation create the psychological space necessary for positive emotions, such as gratitude, hope, and compassion, to co-exist with distress. This emotional flexibility is central to resilient functioning and simultaneously fosters the emotional openness required for post-traumatic growth. In this sense, resilience does not imply emotional invulnerability but rather the capacity to experience a full range of emotions while continuing to adapt and grow.

The social dimension further integrates resilience and PTG by providing interpersonal contexts in which cognitive and emotional processes are supported and reinforced. Social support networks—comprising peers, family members, mentors, and communities—offer emotional validation, practical assistance, and shared meaning-making opportunities. For young adults, whose developmental stage is characterized by heightened reliance on peer relationships and social identity formation, these interpersonal connections are particularly influential. Supportive social environments not only buffer the immediate impact of trauma but also encourage reflective dialogue and self-disclosure, which are key facilitators of post-traumatic growth. Through social interaction, individuals are able to externalize experiences, reinterpret adversity, and integrate new perspectives into their self-concept.

Importantly, the integrated findings challenge linear models that conceptualize resilience as merely “bouncing back” and PTG as a separate, subsequent process. Instead, the evidence supports a process-oriented model in which resilience and growth unfold concurrently and reciprocally. Resilience enables individuals to maintain psychological functioning in the face of adversity, while PTG reflects deeper transformations that may arise through sustained engagement with the traumatic experience. In some cases, resilient coping strategies may

initially limit the extent of perceived growth by reducing emotional disruption; however, over time, these same strategies can facilitate reflective processing that leads to growth. Conversely, experiences of growth may reinforce resilience by strengthening self-efficacy, optimism, and relational trust.

In the context of young adulthood, this integrated model is particularly salient. Ongoing identity development, cognitive maturation, and social role exploration make young adults especially responsive to transformative experiences. Trauma encountered during this life stage can profoundly challenge existing worldviews, but it can also catalyze significant psychological development when supported by adaptive cognitive strategies, emotional regulation skills, and strong social connections. The interaction of these mechanisms underscores the importance of developmental sensitivity in both research and intervention design.

Overall, the integrated discussion underscores that resilience and post-traumatic growth are best conceptualized as complementary adaptive processes embedded within a multidimensional system of recovery. Effective psychological support and intervention strategies should therefore adopt holistic approaches that simultaneously address cognitive restructuring, emotional processing, and social connectedness. Such integrative frameworks not only promote recovery from trauma but also create conditions for enduring psychological growth and well-being in young adults.

Conclusion

This study demonstrates that psychological resilience and post-traumatic growth in young adults are best understood as **dynamic, multidimensional processes**. Cognitive reappraisal, emotional regulation, and social support interact to shape recovery trajectories following trauma. Young adulthood represents a critical developmental window in which adaptive mechanisms can foster not only recovery but meaningful psychological growth.

The findings underscore the importance of integrative mental health interventions that address cognitive, emotional, and social dimensions simultaneously. Future research should employ longitudinal and mixed-method designs to further examine how these mechanisms evolve over time and across cultural contexts.

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Role and Applications of Artificial Intelligence in Higher Education

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Abstract

The aim of this article is to explore the role and applications of artificial intelligence (AI), especially Generative AI and Large Language Models, in higher education. The study analyzes the opportunities and challenges of AI in teaching, learning, assessment, research, and institutional governance based on a literature review and real-world examples. The results show that AI provides personalized learning paths and real-time feedback for students, facilitates lesson planning and assessment for teachers, and provides data analysis and academic writing support for researchers. However, irresponsible use of AI can pose risks in terms of academic integrity, creativity, memory, and critical thinking skills. The article also emphasizes the importance of AI literacy; students should master technical and ethical skills to use AI tools responsibly and effectively. As a result, the successful integration of AI in higher education should be based on not only technological, but also pedagogical and ethical principles. The article shows that AI is important not only as a strategic tool in the future of higher education, but also as a platform that supports democratic knowledge production.

Keywords: Artificial Intelligence (AI), Higher Education, Generative AI (GenAI), AI Literacy, Personalized Learning, Academic Integrity

Introduction

Artificial intelligence (AI), particularly Generative AI (GenAI) and Large Language Models (LLMs), have revolutionized teaching, learning, assessment, research, and institutional governance in higher education in recent years (Crompton & Burke, 2023; Hazari, 2023). These technologies enable personalized learning paths and adaptive testing for students, lesson planning and automated assessment for teachers, and data analysis, academic writing, and visualization for researchers (Cheng et al., 2023; Crompton & Song, 2023). The application of AI in higher education is important not only as a technological innovation, but also in terms of ethical and pedagogical principles. Thus, risks such as algorithmic bias, data protection, digital inequality, and “cognitive debt” can arise from the irresponsible use of AI (Ganjavi et al., 2023; Kosmyrna et al., 2023).

The history of AI in higher education dates back to the 1970s. One of the first Intelligent Teaching Systems (ITS), SCHOLAR, was developed by Carbonell (1970) and provided students with personalized and adaptive learning opportunities. Later, systems such as Stanford’s BIP, MIT’s WUMPUS, SOPHIE, DEBUGGY, and AutoTutor were developed, and AI-based teaching was shown to be as effective as human teachers (Jarrah et al., 2023; Farahani & Ghasmi, 2023). In the 21st century, e-learning platforms and MOOCs have created vast databases, which paved the way for the development of machine learning and adaptive systems. For example, in 2016, an AI teaching assistant named Jill Watson, used at Georgia Tech, answered students’ forum questions and by the end of the semester, students learned that she was not human (Goel, 2016). This experience demonstrates the potential of AI to support online learning.

AI literacy refers to an individual’s ability to understand, use, and critically evaluate AI tools (Roschelle et al., 2023; Hazari, 2023). This includes not only technical skills, but also understanding algorithmic logic, “black box” systems, and the socio-ethical implications of AI (Cheng et al., 2023; Iskandarova et al., 2023). Key components of AI literacy include mastering the basic concepts of AI, actively using the tools, critically evaluating the results generated by AI, and ethically participating in public discourse (EDUCAUSE, 2023). Nowadays, AI tools provide personalized learning opportunities for students, lesson planning and assessment for teachers, and data analysis and academic writing support for researchers. However, overreliance on AI can create “cognitive debt,” impairing memory, creativity, and critical thinking skills (Kosmyrna et al., 2023). Furthermore, unequal access to technology can increase social and economic inequality (Iskandarova et al., 2023).

The aim of this study is to comprehensively examine the application of artificial intelligence in higher education, identify both opportunities and risks, and provide recommendations for the responsible use of AI. The topic is relevant in the academic field, as AI can be a strategic tool in the future of higher education, not only to improve the quality of education, but also to support democratic knowledge production. In this regard, the integration of

AI in education is not only a technological innovation, but also a process of strategic importance in ethical, pedagogical, and social contexts.

Objective

The main objective of this study is to comprehensively explore the role, applications, and impacts of artificial intelligence (AI), especially Generative AI (GenAI) and Large Language Models (LLMs), in higher education. The focus is on the opportunities and potential risks that AI creates in the areas of teaching, learning, assessment, scientific research, and institutional governance. The aim is to systematically present how AI tools can create personalized learning paths and real-time feedback for students, facilitate lesson planning and assessment for teachers, and provide data analysis and academic writing support for researchers (Crompton & Song, 2023; Cheng et al., 2023).

In addition, the study also explores the ethical and pedagogical risks that arise from the irresponsible use of AI, including issues such as academic integrity, plagiarism, creativity impairment, and “cognitive debt” (Kosmyrna et al., 2023; Ganjavi et al., 2023). The importance of AI literacy is particularly emphasized in this study; that is, it is considered important for students to develop the skills of understanding, critically evaluating, ethically using and self-directed learning of AI tools (Roschelle et al., 2023; EDUCAUSE, 2023).

The sub-objectives of the study are as follows:

To systematically identify the opportunities that AI tools create for students, teachers and researchers in higher education.

- To analyze the ethical, pedagogical and social risks associated with the use of AI.
- To explore ways to develop technical, ethical and critical skills to increase students' AI literacy.
- To formulate recommendations for ensuring the responsible and effective use of AI in higher education.

These objectives directly guide the research findings of the work and serve to systematically and comprehensively reveal both the opportunities and challenges of integrating artificial intelligence in higher education. As a result, the work illuminates the future prospects of AI in higher education, taking into account not only technological aspects, but also the pedagogical, ethical and social context.

Significance

The significance of this study lies in exploring the profound and multifaceted implications of the applications of artificial intelligence (AI), especially Generative AI (GenAI) and Large Language Models (LLMs), in higher education. First, the work fills the existing knowledge gaps for students, teachers, and researchers regarding the use of AI tools and reveals how they can optimize educational processes in the areas of personalized learning, lesson planning, assessment, and data analysis (Crompton & Song, 2023; Cheng et al., 2023). In this regard, the study provides a broad and systematic overview of the implications of AI in education to the academic literature.

Second, the work provides theoretical frameworks and practical recommendations for the responsible and effective use of AI, focusing on ethical and pedagogical aspects (Ganjavi et al., 2023; EDUCAUSE, 2023). Enhancing students' AI literacy and enabling them to critically evaluate tools is one of the main contributions of this study. This supports new educational models that integrate both technological and ethical skills.

Third, this work can be useful in the practical field, including in terms of developing university curricula, professional development of teachers, and shaping institutional policies. Informing about the risks of irresponsible reliance on AI tools, such as “cognitive debt” and socio-economic inequality, allows for the development of strategies for education policymakers and leaders (Kosmyrna et al., 2023; Iskandarova et al., 2023).

As a result, this study provides theoretical and practical contributions for the future development of AI in higher education, taking into account not only technological innovations, but also the ethical, pedagogical, and social context. The work shows that artificial intelligence will not only enhance the quality of higher education, but also support democratic knowledge production and responsible learning environments.

Theoretical Basis

The theoretical basis of research on the application of artificial intelligence (AI) in higher education is based on several key concepts and theoretical frameworks. First, the concept of AI literacy is at the heart of the research and refers to the development of individuals' skills to understand, use, and critically evaluate AI tools (Roschelle et al., 2023; Hazari, 2023). AI literacy encompasses not only technical knowledge, but also ethical decision-making, critical thinking, and self-directed learning skills. This framework allows for a conceptual analysis of

students' interactions with AI, the role of teachers in using AI in teaching and assessment, and the data analysis capabilities of researchers (EDUCAUSE, 2023).

The second key theoretical framework is the “personalized learning” model. This model emphasizes the creation of learning paths tailored to students' individual needs and explains the provision of adaptive testing, real-time feedback, and personalized learning plans through AI tools (Crompton & Song, 2023; Cheng et al., 2023). The model provides a theoretical framework for increasing student motivation, improving learning outcomes, and encouraging them to use technology tools effectively.

The third theoretical approach is the ethical and responsible use of AI framework. This approach considers risks such as overreliance on AI tools, plagiarism, and reduced creativity and critical thinking (Kosmyrna et al., 2023; Ganjavi et al., 2023). The ethical AI model integrates variables related to curriculum development, teacher professional development, and institutional policy formulation to ensure the responsible use of AI in higher education.

The conceptual map of the study shows that variables related to the implementation of AI tools – students' personalized learning experiences, teachers' use of AI in teaching and assessment, researchers' data analysis and academic writing support – are interrelated, and AI literacy, ethical and pedagogical skills act as key factors moderating this relationship. Thus, the theoretical foundation creates a conceptual framework for the work and allows for a systematic analysis of the role and impacts of AI in higher education at all stages of the study.

Literature Review

The scientific literature on the application of artificial intelligence in higher education has grown rapidly in recent years. Crompton and Burke (2023) examined the contributions of AI to teaching and learning processes, noting opportunities such as personalized learning, adaptive testing, and teacher support. Hazari (2023) emphasized the importance of AI literacy and showed that it is important to develop students' skills in critical evaluation and ethical use of AI tools. In this regard, AI should be considered not only as a technological tool, but also as an important resource in a pedagogical and ethical framework.

Researchers have also paid attention to the potential risks of AI. Kosmyrna et al. (2023) introduced the concept of “cognitive debt” and explained the negative impact of overreliance on AI on memory, creativity, and critical thinking abilities. Ganjavi et al. (2023) noted that GenAI may cause ethical problems in the academic writing process and increase the risk of plagiarism. These studies show that the irresponsible use of AI can have serious implications for educational quality and academic integrity.

There are also various examples of institutional applications. Goel (2016) examined the use of an AI teaching assistant named Jill Watson at Georgia Tech, demonstrating the effectiveness of AI in interacting with students in augmented online courses. Crompton and Song (2023) provided more systematic information on how AI can enhance personalized learning opportunities for students and support teachers' lesson planning.

Some gaps remain in the existing literature. Previous work has focused mainly on the individual functions of AI, but has not comprehensively examined the integration of AI into ethical, pedagogical, and institutional contexts in higher education (EDUCAUSE, 2023; Farrelly & Baker, 2023). At the same time, further research is needed to develop students' AI literacy and analyze the effects of socio-economic inequality (Iskandarova et al., 2023; Roschelle et al., 2023).

This study systematically assesses the opportunities and risks of using AI in higher education to fill existing literature gaps, providing both theoretical and practical contributions. Thus, the work expands the existing scholarly discourse on AI literacy, ethical and pedagogical integration, and institutional policies, and creates a solid evidence base for the responsible use of AI in higher education.

Methodology

The research model used in this study is a mixed-method approach. That is, both quantitative and qualitative methods were used. The quantitative side was aimed at collecting data on students' AI literacy and use of AI tools through a survey. The qualitative side allowed for an in-depth analysis of their experiences and perspectives through semi-structured interviews with teachers and researchers. The mixed approach allowed for both statistical support of the research results and a contextual and rich understanding of the topic (Creswell, 2014).

Working Group / Sample

The working group of the study consisted of undergraduate and graduate students studying at Azerbaijani higher education institutions, as well as teachers and researchers working in various faculties. Students were included in the sample through random sampling, and teachers and researchers were included through purposive sampling. The total sample size was 250 students and 35 teachers/researchers. This sampling method was considered effective in terms of both representativeness and coverage of different perspectives.

Data Collection Tools

A structured questionnaire was developed for quantitative data and consisted of sections on AI literacy, frequency of use, personalized learning opportunities, and ethical knowledge. A semi-structured interview form was designed for qualitative data. The interviews allowed teachers and researchers to determine how they applied AI tools in their teaching and research processes, and what challenges and benefits they saw.

Data Collection Process

The research process began with prior permission from the relevant university ethics committee. Students and teachers were explained the purpose of the study, the confidentiality of data, and the principle of voluntary participation. The surveys were distributed via an online platform and the data obtained from the participants were collected anonymously. Interviews were conducted in video conference or face-to-face format, and each interview was recorded within the framework of previously agreed ethical guidelines.

Data Analysis

The collected quantitative data were statistically analyzed in SPSS. Descriptive statistics, cross-tabulation, correlation and multiple regression analyses were used. Qualitative data were analyzed using thematic analysis techniques, and main themes and subthemes were extracted from the interview transcripts (Braun & Clarke, 2006). As a result of the mixed methods approach, both statistical results and participants' experiences were combined, resulting in comprehensive and reliable conclusions on the application of AI in higher education.

Findings and Comments

A number of important findings were obtained as a result of the analysis of the quantitative and qualitative data of the study.

1. Students' AI literacy and use

According to the survey results, 68% of students reported using AI tools for teaching and learning purposes. Only 42% of students reported that they critically evaluate AI-generated texts and use them in accordance with ethical principles. These results are consistent with previous research; for example, Hazari (2023) showed that students' AI literacy is limited to technical skills and that ethical training is needed.

2. Teachers' use of AI in teaching and assessment

Interviews showed that 74% of teachers used AI tools in the lesson planning and assessment process. However, only 38% of teachers reported that they fully considered the ethical and pedagogical risks in using AI. This finding is similar to the findings of Farrelly and Baker (2023), but in contrast, some teachers noted that they have not yet fully implemented the adaptive testing and feedback capabilities of AI.

3. Researchers' use of AI and data analysis

Qualitative data showed that 81% of researchers reported using AI tools in data analysis and academic writing. However, some participants emphasized that the results presented by AI can be flawed and that the results should always be critically reviewed. These findings are consistent with the findings of Jarrah et al. (2023) and Cheng et al. (2023), namely that while AI increases productivity, attention should be paid to responsible use.

4. Social and ethical issues

The study also revealed social and ethical aspects. 29% of students and 32% of teachers reported being concerned about inequalities in the use of AI and differences in access to technology. This is consistent with Iskandarova et al. (2023) highlights the digital divide.

Comments

The findings show that AI tools offer significant opportunities in higher education in terms of personalized learning, lesson planning, assessment, and data analysis. At the same time, the results reveal similarities and differences compared to previous literature. Students' AI literacy is still underdeveloped and ethical educational measures are needed (Hazari, 2023; Roschelle et al., 2023). Although teachers and researchers benefit from the capabilities of AI, the importance of responsible and ethical use is still not fully realized (Farrelly & Baker, 2023;

Kosmyna et al., 2023). The issue of socio-economic inequality and access to technology highlights the practical challenges of integrating AI in higher education (Iskandarova et al., 2023).

In conclusion, the findings of the study comprehensively reveal the opportunities and risks of using artificial intelligence in higher education and make a theoretical and practical contribution to the existing literature.

Conclusion

This study systematically explores both the opportunities and risks of using artificial intelligence (AI), particularly Generative AI (GenAI) and Large Language Models (LLMs), in higher education. The findings show that AI tools provide a number of practical benefits for students, teachers, and researchers. Students can learn more effectively through personalized learning paths, adaptive testing, and real-time feedback. Teachers can reduce their workload and improve the quality of teaching by using AI in lesson planning and assessment. Researchers can increase their productivity by using AI tools in data analysis, visualization, and academic writing (Crompton & Song, 2023; Cheng et al., 2023).

However, the study also highlights both ethical and pedagogical aspects. The findings show that only a minority of students are able to critically evaluate and use AI-generated outputs in an ethical manner. Teachers and researchers are not fully committed to responsible use of AI, given its potential risks. These results confirm the risks of AI, such as “cognitive debt”, plagiarism and reduced creativity, as highlighted by Kosmyna et al. (2023), Ganjavi et al. (2023) and Hazari (2023).

The study also draws attention to issues of social and technological inequality. The limited access of some students to technology and instructors creates disparities in the use of AI, which affects educational outcomes (Iskandarova et al., 2023). This highlights the importance of supporting the integration of AI in higher education not only through technological innovations, but also through institutional policies and equitable distribution of resources. As a result, the successful implementation of AI in higher education is not only about the use of technological tools; it is also possible through the development of students’ AI literacy, the application of ethical and pedagogical rules, the professional development of teachers and the provision of institutional support. AI literacy has a direct impact on students’ development of self-directed learning, critical thinking, and ethical decision-making skills, teachers’ optimization of teaching processes, and researchers’ productivity (Roschelle et al., 2023; EDUCAUSE, 2023).

In this regard, artificial intelligence is seen not only as a technological tool, but also as a strategic resource for improving the quality of higher education, supporting democratic knowledge production, and shaping responsible learning environments. The study contributes from both theoretical, practical, and institutional perspectives, and creates a solid knowledge base for the responsible, ethical, and effective use of AI in higher education. These results can play an important role in developing future policy and teaching strategies for integrating AI in higher education.

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The Impact of Ensuring Psychological Well-Being in the Learning Environment on Educational Quality: A Systematic Approach

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Abstract

Ensuring psychological well-being within the learning environment has become a critical determinant of educational quality in contemporary education systems. Growing empirical evidence indicates that students' emotional, social, and psychological states significantly influence their academic achievement, motivation, engagement, and long-term development. This study examines the impact of psychological well-being on educational quality through a systematic, theory-driven approach. Drawing on major theoretical frameworks—including self-determination theory, ecological systems theory, and social-emotional learning—the article synthesizes international research to identify key mechanisms linking well-being and educational outcomes. Using a qualitative systematic literature review and thematic analysis, the study reveals that psychologically supportive learning environments foster stronger teacher–student relationships, positive school climate, enhanced student engagement, and improved academic performance. The findings further demonstrate that educational quality cannot be sustained through cognitive instruction alone but requires integrated policies and practices that prioritize mental health, emotional safety, and social connectedness. The article concludes that systematic investment in psychological well-being is not an auxiliary component of education but a foundational condition for achieving high-quality, inclusive, and effective learning environments.

Keywords: psychological well-being; learning environment; educational quality; school climate; social-emotional learning

Introduction

In recent years, the concept of **psychological well-being** has emerged as a central concern in educational research and policy, reflecting broader societal recognition of mental health as a fundamental component of human development. Schools are no longer viewed solely as institutions for cognitive instruction but as complex social environments that significantly shape students' emotional, psychological, and social experiences. A growing body of research demonstrates that students' psychological well-being is closely linked to academic achievement, motivation, engagement, and overall educational quality (OECD, 2017; Suldo et al., 2011).

Educational quality has traditionally been assessed through indicators such as curriculum standards, instructional effectiveness, and academic outcomes. However, contemporary frameworks increasingly emphasize the role of **school climate**, teacher–student relationships, and emotional safety as critical determinants of effective learning (Thapa et al., 2013; Hattie, 2009). International assessments, including the OECD's PISA studies, highlight that students who report higher levels of well-being tend to demonstrate stronger academic resilience, higher life satisfaction, and more positive attitudes toward learning (OECD, 2017). Despite this growing recognition, many education systems continue to prioritize performance-driven metrics while underestimating the psychological conditions under which learning occurs. This imbalance has prompted scholars to call for a more holistic and systematic approach to educational quality—one that integrates psychological well-being as a core educational objective rather than a supplementary concern (Jennings & Greenberg, 2009; Ryan & Deci, 2017). Against this backdrop, the present study seeks to examine how ensuring psychological well-being within the learning environment influences educational quality and to identify the mechanisms through which this relationship operates.

1. Theoretical Framework

The theoretical framework of this study is grounded in an interdisciplinary synthesis of psychological, educational, and developmental theories that conceptualize well-being as integral to learning and academic success.

A primary foundation is **Self-Determination Theory (SDT)**, which posits that optimal functioning and motivation depend on the satisfaction of three basic psychological needs: autonomy, competence, and

relatedness (Ryan & Deci, 2017). In educational contexts, environments that support these needs promote intrinsic motivation, engagement, and deeper learning, thereby enhancing educational quality.

The framework also draws on **Ecological Systems Theory**, which conceptualizes learning and development as products of dynamic interactions between individuals and their environments (Bronfenbrenner & Morris, 2006). From this perspective, schools function as key developmental contexts where relationships, institutional norms, and emotional climates shape students' psychological well-being and academic trajectories (Eccles & Roeser, 2011).

Another essential component is **Social-Emotional Learning (SEL) theory**, which emphasizes the development of emotional regulation, social skills, and self-awareness as prerequisites for academic success (Durlak et al., 2011; Zins et al., 2007). SEL frameworks position psychological well-being as both an educational outcome and a process that enhances learning capacity.

Finally, theories of **positive education and school climate** underscore the role of supportive relationships, emotional safety, and positive affect in fostering high-quality learning environments (Seligman, 2011; Thapa et al., 2013). Together, these theoretical perspectives provide a coherent foundation for analyzing how psychological well-being operates as a systemic driver of educational quality.

2. Literature Review

Extensive research confirms a strong association between psychological well-being and academic outcomes. Meta-analytical studies indicate that interventions targeting students' social and emotional competencies produce significant improvements in academic performance and behavior (Durlak et al., 2011; Taylor et al., 2017). These findings challenge traditional assumptions that emotional factors are peripheral to learning.

Research on **teacher-student relationships** consistently demonstrates that emotionally supportive interactions contribute to students' engagement, motivation, and achievement (Hamre & Pianta, 2006; Wentzel, 2012). Similarly, studies on **classroom emotional climate** show that positive affective environments enhance attention, persistence, and cognitive processing (Reyes et al., 2012).

The concept of **school climate** has received increasing scholarly attention as a multidimensional construct encompassing safety, relationships, teaching practices, and institutional norms. Reviews indicate that positive school climates are associated with higher academic achievement, lower dropout rates, and improved psychological well-being (Thapa et al., 2013; Konu & Rimpelä, 2002).

International policy-oriented literature further emphasizes that educational quality is inseparable from student well-being. OECD reports highlight that systems prioritizing well-being alongside academic standards achieve more sustainable and equitable educational outcomes (OECD, 2017; OECD, 2019). However, the literature also notes persistent gaps between policy rhetoric and school-level implementation, underscoring the need for systematic approaches.

3. Methodology

This study adopts a **qualitative systematic literature review** design. Peer-reviewed journal articles, scholarly books, and international reports were selected based on relevance to psychological well-being, learning environments, and educational quality.

The analysis followed three stages:

1. thematic coding of well-being dimensions (emotional, social, psychological),
2. identification of mechanisms linking well-being to educational outcomes, and
3. integrative synthesis across theoretical and empirical studies (Ryan & Deci, 2017; Thapa et al., 2013).

Analytical rigor was ensured through theoretical triangulation and cross-source comparison. As a secondary-data study, no ethical approval was required.

4. Findings and Discussion

This section presents the synthesized findings of the systematic literature analysis and discusses how psychological well-being within the learning environment influences educational quality. To ensure analytical clarity, the findings are organized into thematic subsections and summarized in tables, followed by in-depth discussion grounded in empirical and theoretical research.

4.1 Psychological Well-Being as a Determinant of Educational Quality

The first major finding indicates that psychological well-being functions as a **core determinant of educational quality**, influencing both learning processes and outcomes. Across the reviewed studies, educational quality is consistently associated with students' emotional safety, sense of belonging, and mental health.

Table 1. Dimensions of Psychological Well-Being and Educational Quality Outcomes

Dimension of well-being	Key characteristics	Impact on educational quality	Supporting sources
Emotional well-being	Positive affect, low anxiety, emotional regulation	Improved attention, persistence, and academic achievement	Seligman (2011); Reyes et al. (2012)
Social well-being	Sense of belonging, peer support	Higher engagement, reduced dropout risk	Thapa et al. (2013); Konu & Rimpelä (2002)
Psychological safety	Feeling respected and valued	Increased participation and motivation	OECD (2017); Wentzel (2012)
Mental health support	Access to counseling and support systems	Long-term academic resilience	Suldo et al. (2011); WHO (2021)

The findings confirm that educational quality cannot be sustained in environments where students experience chronic stress, anxiety, or social exclusion. Emotional and psychological well-being enhance students' cognitive functioning, enabling deeper learning and higher academic performance (Hattie, 2009). These results align with OECD evidence showing that student well-being predicts both academic success and long-term educational engagement (OECD, 2017).

4.2 Teacher–Student Relationships and Classroom Emotional Climate

A second key finding emphasizes the central role of **teacher–student relationships** and classroom emotional climate in mediating the relationship between psychological well-being and educational quality.

Table 2. Teacher–Student Relationships as a Mechanism of Educational Quality

Relational factor	Description	Educational impact	Key references
Emotional support	Teacher empathy and care	Increased motivation and engagement	Hamre & Pianta (2006)
Trust-based interaction	Mutual respect and fairness	Positive classroom behavior and participation	Wentzel (2012)
Classroom emotional climate	Collective emotional tone	Enhanced academic performance	Reyes et al. (2012)
Teacher well-being	Educator emotional health	Higher instructional effectiveness	Jennings & Greenberg (2009)

Supportive teacher–student relationships foster a learning environment in which students feel secure to express ideas, take intellectual risks, and engage in challenging tasks. Research demonstrates that classrooms characterized by positive emotional climates yield higher academic achievement and stronger self-regulation skills (Reyes et al., 2012). Moreover, teacher well-being emerges as a prerequisite for sustaining such environments, highlighting the systemic nature of educational quality (Jennings & Greenberg, 2009).

4.3 Social–Emotional Learning and Systemic Educational Practices

The third finding highlights **social–emotional learning (SEL)** as a critical pathway through which psychological well-being enhances educational quality.

Table 3. Effects of Social–Emotional Learning on Educational Quality

SEL component	Educational practice	Observed outcomes	Supporting sources
Self-awareness	Reflective learning activities	Improved self-regulation	Durlak et al. (2011)
Social skills	Cooperative learning	Positive peer relations	Zins et al. (2007)
Emotional regulation	Mindfulness and coping strategies	Reduced behavioral problems	Taylor et al. (2017)
Responsible decision-making	Ethical and civic tasks	Long-term academic success	Eccles & Roeser (2011)

Meta-analytical evidence shows that SEL programs produce statistically significant improvements in academic achievement alongside enhanced psychological well-being (Durlak et al., 2011). These findings challenge traditional dichotomies between emotional development and cognitive learning, instead positioning SEL as a central contributor to educational quality. Systematic integration of SEL across curricula yields the strongest and most sustainable outcomes (Taylor et al., 2017).

4.4 School Climate and Whole-School Approaches

Another major finding concerns the influence of **school climate** and whole-school well-being policies on educational quality.

Table 4. School Climate Factors and Educational Quality Indicators

School climate factor	Description	Educational quality indicator	Sources
Emotional safety	Absence of bullying and fear	Increased attendance and retention	Thapa et al. (2013)
Institutional support	Leadership commitment to well-being	Improved academic outcomes	OECD (2019)
Inclusive practices	Equity and respect for diversity	Reduced achievement gaps	Roffey (2012)
Community engagement	Family–school partnerships	Sustained learning outcomes	Bronfenbrenner & Morris (2006)

The findings demonstrate that fragmented interventions are insufficient for achieving lasting improvements in educational quality. Instead, **whole-school approaches** that embed psychological well-being into leadership, policy, and daily practice yield more consistent and equitable outcomes (OECD, 2019). Schools operating as supportive ecosystems enhance not only academic performance but also long-term student development.

4.5 Integrated Discussion

Across all thematic areas, the findings converge on a central conclusion: **psychological well-being is a foundational condition for educational quality**. Emotionally supportive classrooms, strong teacher–student relationships, systematic SEL implementation, and positive school climates collectively create environments conducive to high-quality learning.

From a systemic perspective, the evidence suggests that investments in psychological well-being should be viewed not as auxiliary supports but as strategic drivers of educational effectiveness. Aligning with ecological and self-determination theories, the results underscore that educational quality emerges from the interaction between individual well-being and institutional conditions (Ryan & Deci, 2017; Bronfenbrenner & Morris, 2006).

In summary, ensuring psychological well-being within the learning environment enhances educational quality by improving engagement, academic performance, and long-term student outcomes. These findings support a paradigm shift toward holistic, well-being-centered educational systems capable of meeting the complex demands of contemporary education.

Conclusion

This study has demonstrated that psychological well-being is a fundamental and systemic determinant of educational quality, rather than a supplementary or peripheral factor within the learning environment. Drawing on a comprehensive synthesis of international research, the findings confirm that students’ emotional safety, mental health, and sense of belonging significantly shape their engagement, motivation, academic performance, and long-term educational trajectories.

The analysis shows that learning environments which prioritize psychological well-being foster more effective teaching and learning processes. Supportive teacher–student relationships, positive classroom emotional climates, and structured social–emotional learning (SEL) practices emerge as key mechanisms through which well-being enhances educational quality. These factors collectively enable students to regulate emotions, sustain attention, participate actively, and engage in higher-order cognitive tasks, thereby improving both academic outcomes and overall school effectiveness (Durlak et al., 2011; Hamre & Pianta, 2006; Reyes et al., 2012).

At the institutional level, the study highlights the importance of whole-school approaches that embed psychological well-being into leadership practices, school climate policies, and community partnerships. Fragmented or short-term interventions are shown to have limited impact, whereas systematic strategies that integrate well-being across curricula and school structures lead to more sustainable improvements in educational quality and equity (Thapa et al., 2013; OECD, 2019). This finding underscores the necessity of aligning educational quality frameworks with mental health and well-being policies.

The results also support a broader conceptual shift in how educational quality is defined and evaluated. Traditional performance-oriented models that focus exclusively on academic achievement fail to capture the conditions under which effective learning occurs. In contrast, a well-being-centered approach recognizes that high-quality education emerges from the interaction of cognitive instruction, emotional support, and social connectedness, consistent with ecological and self-determination theories of development (Ryan & Deci, 2017; Bronfenbrenner & Morris, 2006).

In conclusion, ensuring psychological well-being within the learning environment is not merely an ethical or supportive obligation but a strategic imperative for achieving high-quality education. Policymakers, school leaders, and educators are encouraged to adopt integrated, evidence-based approaches that prioritize mental health, positive relationships, and supportive school climates. Future research should extend this work through

longitudinal and empirical studies examining how systematic well-being interventions can be effectively implemented across diverse educational contexts to enhance both learning outcomes and student development.

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The Impact of the Digital Environment on Human Psychology

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Abstract

This article examines the impact of the digital environment on human psychology in the 21st century from various aspects. The rapid development of digital technologies and the widespread use of social media platforms have a significant impact on a person's emotional state, behavioral patterns, attention and memory processes, as well as social relationships. Research shows that the digital environment creates both positive and negative psychological consequences. Social networks and online platforms play a role as a resource in terms of emotional support, increasing educational opportunities, facilitating communication, and maintaining social relationships. At the same time, negative effects such as digital addiction, information overload, FOMO (fear of missing out), attention dispersion, weakening of memory and learning processes, social adaptation difficulties, and emotional disorders are also observed.

The article emphasizes that the psychological effects of the digital environment are closely related to the user's digital literacy and the purposeful nature of technology use. High digital literacy allows the user to correctly set the information filter, manage time, exhibit safe online behavior, and maintain emotional balance. In this regard, increasing digital literacy and psychological awareness are considered necessary measures for modern society.

The results show that the digital environment should be considered as a powerful social ecosystem that has a multifaceted impact on human psychology. Responsible and balanced digital use, increasing digital literacy, and simultaneously developing online and real-world communication skills are essential for maintaining psychological well-being. The article contributes to understanding the psychological effects of the digital environment from both theoretical and practical perspectives and to formulating healthy digital usage strategies for individuals.

Keywords: Digital environment, psychological impact, digital addiction, emotional state, social relationships, attention and learning, digital literacy

Introduction

The 21st century is characterized by the rapid development of information and communication technologies, and the integration of the digital environment into all areas of life. Mobile devices, social networks, online learning platforms, virtual games and other digital tools have significantly changed people's daily activities, social relationships, educational and work processes (Przybylski & Weinstein, 2017). The digital environment not only serves as a platform for communication and information exchange, but also has become a new socio-ecological context that shapes the emotional reactions, behavioral patterns and social skills of the individual. In this regard, the study of the psychological effects of digital technologies emerges as a pressing problem in modern psychology and educational sciences (Odgers & Jensen, 2020).

Studies conducted in recent years show that the use of the digital environment is associated with both positive and negative psychological effects. Positive effects include increasing social support, expanding access to information, developing educational and professional skills, as well as maintaining social ties through distance communication (Valkenburg, Koutamanis, & Vossen, 2017). However, intensive use of digital media can lead to negative consequences such as emotional disorders, attention and memory problems, social adaptation difficulties and digital addiction (Twenge, 2019; Montag et al., 2021). Idealized presentations, filtered images and success stories on social networks increase self-satisfaction, feelings of inadequacy and social comparison stress in individuals (Fardouly, Diedrichs, Vartanian, & Halliwell, 2015). At the same time, the use of digital technologies in education creates conditions for the development of new learning methods and increases the opportunities for acquiring knowledge through interactive textbooks and online courses (Sung, Chang, & Liu, 2016). Thus, the psychological effects of the digital environment are multifaceted, complex and depend on the individual's usage habits.

The relevance of the topic is manifested both at the individual and social levels. The widespread use of digital technologies has created new challenges in the formation of emotional and social development among children,

adolescents and young people. Children's excessive dependence on virtual communication can lead to a weakening of social skills formed through real-life experiences (Uhls et al., 2017). At the same time, in adults, phenomena such as digital information overload and "FOMO" (fear of missing out) lead to stress, sleep disorders, and attention deficit (Przybylski, 2013). Therefore, it is scientifically and practically important to systematically investigate the psychological effects of the digital environment and formulate recommendations for balanced use. The aim of this article is to study the impact of the digital environment on human psychology from various aspects – emotional state, behavioral patterns, social relationships, attention, and the learning process. The study analyzes both positive and negative effects based on scientific sources and correlates the results with modern psychological theories and research. Thus, the article aims to make a theoretical and practical contribution to understanding the impact of the digital environment on human psychology.

Objective

The main objective of this study is to systematically investigate the impact of the digital environment on human psychology in the 21st century from various aspects. Rapidly developing information and communication technologies, social networks, mobile applications and other digital platforms are creating significant changes in the emotional state, behavioral patterns, social relationships, attention and memory processes of individuals. In this regard, the study aims to understand the psychological effects of the digital environment, identify both positive and negative impact mechanisms and ultimately provide a scientific basis for the formation of healthy digital usage strategies.

The sub-objectives of the study are defined as follows:

1. Impact on emotional state: To investigate the impact of the digital environment on individuals' self-confidence, self-esteem, anxiety and depressive symptoms; to analyze the psychological consequences of social comparison on social media platforms.
2. Behavior and digital addiction: To study the impact of addiction to mobile phones, games and social media on behavioral patterns and motivation; to determine the relationship between dopamine levels and behavioral addiction.
3. Social relationships and communication: To analyze the impact of virtual communication on communication skills, empathy levels, and the quality of emotional relationships; to determine the role of digital communication in the social adaptation process of children and adolescents.
4. Attention, memory, and learning: To study the impact of digital stimuli on attention span, memory consolidation, and deep thinking processes; to assess the impact of interactive digital learning tools on learning motivation.
5. Stress and information overload: To analyze the impact of information overload and psychological phenomena such as "FOMO" on stress, sleep disorders, and emotional instability.
6. Digital literacy and psychological well-being: To examine the role of digital literacy in creating opportunities for individuals to use technology in a purposeful and balanced way, and in maintaining psychological well-being and emotional balance.

The research conducted within the framework of these objectives aims to clarify the multifaceted effects of the digital environment on human psychology, as well as to make a theoretical and practical contribution to the formulation of strategies for the healthy use of digital technologies at the individual, social, and educational levels.

Significance

The impact of the digital environment on human psychology is a pressing and complex issue for modern society. The rapid development of information and communication technologies, the widespread use of social networks, mobile applications and other digital platforms have significant impacts on individuals' emotional state, behavioral patterns, attention and memory processes, social relationships and psychological well-being in general (Odgers & Jensen, 2020; Twenge, 2019). Therefore, systematically investigating the psychological effects of the digital environment is important from both theoretical, practical and social policy perspectives.

The scientific significance of this work lies primarily in the comprehensive study of the mechanisms of influence of digital technologies on human psychology. The article identifies both positive and negative effects of the digital environment and analyzes them on various psychological indicators – emotional state, digital addiction, attention, memory and learning, social adaptation and stress level. This brings a new theoretical perspective and systematic approach to the existing literature (Fardouly, Diedrichs, Vartanian, & Halliwell, 2015; Montag et al., 2021).

The practical significance is that the results of the study allow us to develop guidelines and programs to protect the psychological well-being of individuals, increase digital literacy, and formulate balanced digital usage strategies, taking into account the effects of the digital environment. This work can also contribute to the

optimization of curricula and programs related to digital literacy and psychological well-being in the education system, especially for children and adolescents.

From a social policy perspective, this study provides scientifically sound information for the preparation of decisions and recommendations regarding the use of digital technologies. By better understanding the risks and opportunities posed by the digital environment, state and non-state organizations can formulate strategies aimed at protecting the psychological well-being of individuals and society (Valkenburg, Koutamanis, & Vossen, 2017). Consequently, this study enriches scientific knowledge by examining the impact of the digital environment on human psychology at both the theoretical, practical, and policy levels, and makes an important contribution to the protection of psychological well-being and the development of healthy digital usage strategies.

Theoretical Basis

This study, which examines the impact of the digital environment on human psychology, is based on several main theoretical approaches and models. First, Social Comparison Theory (Festinger, 1954) explains how individuals evaluate themselves by comparing themselves with others on social media platforms. According to this theory, self-esteem and emotional state can change as users follow the successes, lifestyles, and achievements of others. The dissatisfaction, feelings of inadequacy, and emotional tension that arise in social media users are explained within the framework of this theory (Fardouly, Diedrichs, Vartanian, & Halliwell, 2015).

Second, Behavioral Addiction Theory and dopamine mechanisms (Montag et al., 2021) explain the psychological and behavioral consequences of addiction to digital technologies. Interactive affirmations (like, comment, view) on mobile phones, online games, and social networks strengthen the reward-motivation relationship by stimulating the dopamine system. This process leads to digital addiction, rapid attention span, and impulsive behaviors in the long term.

The third theoretical framework is related to the Cognitive Load Theory (Sweller, 1988). Continuous visual and audio stimuli in the digital environment strain attention and memory resources, increase information overload, and make learning more difficult. This theoretical approach explains the relationship between short videos, multitasking, and rapid information consumption with attentional fragmentation and the weakening of deep thinking processes.

In addition, the Social Learning Theory (Bandura, 1977) explains the learning of modeled behaviors in the digital environment and the processes of imitation. Children and adolescents form social skills by observing the behavioral models they encounter on virtual platforms. However, excessive virtual communication can lead to a weakening of empathy and social skills in real life (Uhls et al., 2017).

The conceptual framework of the study is based on these theories and includes the relationships between the following variables:

- Independent variables: Digital media use, social media activity, digital literacy level;
- Dependent variables: Emotional state, behavioral patterns, attention and memory functions, social adaptation and psychological well-being;
- Moderation and mediating variables: Digital literacy, individual differences, usage habits and age groups.

Thus, the theoretical foundations of the study explain the impact of the digital environment on human psychology in a multifaceted and systematic way, interpret the relationships between different psychological variables in a scientific perspective and form a conceptual map of the study.

Literature Review

International and local literature on the impact of the digital environment on human psychology has been extensively reviewed. International studies show that social media use and digital technologies have a significant impact on individuals' emotional states, attention and memory processes, behavioral patterns, and social relationships (Odgers & Jensen, 2020; Twenge, 2019). Fardouly, Diedrichs, Vartanian, and Halliwell (2015) showed that idealized lives on social media platforms, through the social comparison mechanism, lead to decreased self-esteem and increased emotional distress in women. At the same time, Montag, Lachmann, Herrlich, and Zweig (2021) analyzed the effect of digital addiction on the brain dopamine system and emphasized its relationship with behavioral changes and impulsive reactions.

Studies investigating the impact of the digital environment on learning and attention show that, within the framework of Sweller's (1988) Cognitive Load Theory, multiple visual and auditory stimuli cause attentional fragmentation and impaired memory consolidation. At the same time, Sung, Chang, and Liu (2016) emphasize

that interactive textbooks and online courses increase learning motivation and the potential benefits of digital technologies in education.

Research on the topic has also been conducted in the Azerbaijani literature. For example, Aliyev (2020) studied the impact of digital technologies on the social behavior and emotional state of young people and showed that digital literacy plays an important role in protecting psychological well-being. Hasanova (2019) examined the impact of social media use on attention and learning processes in adolescents, noting that prolonged online activity increases attention deficit and sleep problems. At the same time, Guliyeva (2021) emphasized the positive impact of developing digital literacy on the psychological health of children and adolescents.

A critical review of the existing literature shows that many studies have identified the emotional and behavioral effects of the digital environment, but do not provide extensive information on the effects of individual differences, age groups, and different digital usage patterns. Also, studies conducted in the Azerbaijani context are mainly based on small samples and local analyses, lacking comparative analysis and conceptual framework with international studies.

The contribution of this work to the literature is that it systematically examines the impact of the digital environment on human psychology in both international and local contexts, presenting multidisciplinary results on emotional states, behavioral patterns, attention and memory, social relationships, and psychological well-being. At the same time, it fills existing knowledge gaps by taking into account factors such as individual differences and the role of digital literacy, and creates theoretical and practical contributions for future research.

Methodology and Analysis of Findings

The study results were analyzed based on both quantitative and qualitative data. Quantitative data were analyzed using SPSS and were evaluated using descriptive statistics, correlation analyses, t-tests, and ANOVA. Qualitative data were coded in NVivo and analyzed using thematic analysis.

1. Emotional state and digital environment

According to the survey and test results, 46% of participants reported that social media use negatively affected their self-esteem and emotional state. In particular, social comparison processes and viewing images of an “ideal life” were associated with increased anxiety and depressive symptoms. Qualitative data obtained from focus groups indicate that although users sometimes find emotional support through social media, long-term use increases stress and anxiety. These results are consistent with the findings of Fardouly et al. (2015).

2. Behavior and digital addiction

According to the survey results, 38% of participants reported high levels of engagement in social media and mobile device use. Behavioral addiction based on dopamine mechanisms distinguishes this group from others. Digital addiction has been associated with increased attention span, decreased productivity in work and learning activities, and sleep disturbances. These findings are consistent with the results of Montag et al. (2021).

3. Social relationships and communication

According to the analysis of focus groups, 54% of participants shared their experiences of digital communication weakening communication skills and reducing empathy. In addition, virtual communication provides access to a large audience and convenience. The results are consistent with the study of Uhls et al. (2017), but the greater mention of a decrease in face-to-face communication among Azerbaijani participants indicates the influence of the local context.

4. Attention, memory, and learning

Quantitative tests show that participants' attention span is reduced due to rapid visual and audio stimuli. Short videos and multitasking weaken attentional focus and make memory consolidation difficult. However, interactive textbooks and online learning tools increased participants' motivation. These findings are consistent with studies by Sweller (1988) and Sung et al. (2016).

5. Stress and information overload

According to the survey results, 41% of participants reported that information overload and the feeling of “FOMO” increased their stress and anxiety levels. Qualitative data obtained from focus groups showed that the constant flow of online information makes decision-making difficult and creates emotional instability. This is consistent with the findings of Valkenburg, Koutamanis, and Vossen (2017).

6. Digital literacy and psychological well-being

The data show that participants with high levels of digital literacy use technology purposefully and are more successful in maintaining emotional balance. This result confirms the relationship between psychological well-being and digital literacy highlighted by Aliyev (2020) and Guliyeva (2021) in the Azerbaijani context.

Discussion

The findings reveal several important conclusions compared to the existing literature. On the one hand, in line with international studies, social media use and digital addiction have a negative impact on emotional state and attention. On the other hand, in the Azerbaijani context, a decrease in face-to-face communication skills and social adaptation difficulties are more pronounced, which indicates the role of cultural and social differences. At the same time, it is confirmed that digital literacy plays a positive role in maintaining psychological well-being, which provides practical contributions for future educational programs and psychological interventions.

Conclusion:

The digital environment has profoundly transformed human psychology, influencing the way we think, communicate, and perceive the world. While it offers significant benefits such as instant access to information, enhanced connectivity, and new avenues for learning, it also presents challenges including increased stress, attention fragmentation, and potential social isolation. Understanding these impacts is crucial for developing strategies that promote healthy digital habits and ensure that technology enhances, rather than undermines, psychological well-being. Future research and conscious engagement with digital tools are essential to balance the advantages and risks of our increasingly digital lives.

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The Influence of Textbook Policy on Teaching Quality in Higher Education in Azerbaijan

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Abstract

Textbook policy plays a pivotal role in shaping teaching quality in higher education by influencing faculty autonomy, resource accessibility, and student engagement. This study examines the impact of textbook policies on teaching quality in Azerbaijani universities and compares national practices with international models implemented in the United States, the European Union, Turkey, and China. In Azerbaijan, textbook selection remains partially centralized under Ministry of Education regulations, which limits faculty flexibility and restricts the integration of innovative and contemporary instructional materials. Survey data collected across six Azerbaijani universities reveal that 45% of students struggle to afford required textbooks, while 60% of faculty members report constraints in adapting materials to diverse learning needs. These challenges negatively affect student participation, academic performance, and course completion rates.

Global evidence, however, demonstrates that institutions adopting Open Educational Resources (OER) and flexible textbook policies achieve notable improvements in teaching quality and student learning outcomes. Case studies from U.S. universities such as Boise State and UMass Amherst show that OER integration significantly reduces financial barriers, enhances student engagement, and supports inclusive pedagogy. Similar policy trends in Turkey and several EU countries highlight the effectiveness of national incentives that encourage faculty adoption of affordable and digital learning resources. Comparative analysis indicates that textbook affordability and faculty autonomy are strongly correlated with higher levels of instructional innovation and improved student success.

The findings underscore the need for Azerbaijani higher education institutions to transition toward OER-based policies, expand institutional autonomy, and invest in modern digital infrastructure. Key recommendations include establishing a national OER repository, providing systematic faculty training, and implementing incentive programs for open content development. By aligning with global best practices, Azerbaijan can enhance teaching quality, promote equity, and strengthen its integration into the European Higher Education Area. This research contributes to ongoing policy discussions by demonstrating the critical link between textbook policy and pedagogical effectiveness across diverse educational contexts.

Keywords: textbook policy, teaching quality, higher education, ministry of education, faculty autonomy, open educational resources.

1. Introduction

Textbooks remain one of the most essential components of higher education worldwide, serving not only as repositories of knowledge but also as instruments that shape curriculum design, pedagogical strategies, assessment practices, and student learning pathways. While the rapid expansion of digital technologies, online learning platforms, and Open Educational Resources (OER) has diversified educational tools, traditional textbooks continue to exert a significant influence on the academic experience of both students and faculty. Their effectiveness, however, is closely linked to the policies that govern their development, approval, distribution, and cost. Textbook policies determine the range of materials available to faculty, regulate the ability to adopt contemporary or interdisciplinary resources, and influence students' access to essential learning content. As such, these policies are a critical factor in shaping the overall quality of teaching and learning in higher education.

In recent decades, many countries have undertaken substantial reforms to their textbook policies in response to globalization, technological innovation, and growing attention to educational equity. For example, the United States, European Union member states, Turkey, and China have implemented flexible frameworks that allow universities to select or develop course materials independently, incorporate digital resources, and reduce the financial burden on students. Empirical research from these contexts consistently shows that such policies foster greater instructional innovation, enhance student engagement, improve learning outcomes, and support inclusive education. The availability of OER and digital content not only lowers costs but also provides instructors with

opportunities to customize resources according to evolving disciplinary knowledge, emerging pedagogical trends, and the diverse needs of learners.

By contrast, Azerbaijan's higher education system continues to operate within a partially centralized framework rooted in Soviet-era governance structures. Although post-independence reforms and participation in the Bologna Process have introduced elements of institutional autonomy, textbook selection and approval remain largely influenced by Ministry of Education regulations. This centralized approach aims to ensure uniformity, maintain academic standards, and prevent disparities between universities. While these objectives are important, the current system often results in slow adoption of new materials, limited curricular adaptability, and constraints on faculty innovation. Faculty members frequently report restricted freedom to select or adapt textbooks to meet the specific needs of their students or to incorporate global academic perspectives into their teaching. Consequently, pedagogical flexibility is reduced, and opportunities for innovative instruction are constrained.

Affordability also emerges as a significant challenge within the Azerbaijani context. National surveys indicate that nearly half of university students experience difficulty in purchasing required textbooks due to high costs and limited availability. Many students resort to outdated print copies, photocopied materials, or informal digital alternatives, which can compromise learning outcomes. This lack of access affects student engagement, participation in class, and completion of assignments, thereby directly impacting overall teaching quality. At the same time, the slow integration of digital resources and OER limits both faculty and student opportunities to benefit from flexible, modern, and cost-effective learning tools, leaving Azerbaijani institutions behind global higher education trends.

Given this context, a systematic examination of textbook policy in Azerbaijan is both timely and necessary. Understanding how policy frameworks shape teaching quality, influence faculty autonomy, and affect student access provides critical insights into structural and systemic barriers within the higher education system. Moreover, comparative analysis with international best practices highlights opportunities for policy innovation, modernization, and alignment with global standards.

The purpose of this study is therefore to analyze the impact of textbook policy on teaching quality in Azerbaijan universities, identify key barriers and challenges, and situate these findings within a broader international context. By integrating national survey data, institutional documents, and global comparative evidence, the research aims to offer evidence-based recommendations for enhancing pedagogical effectiveness, promoting affordability and equity, and supporting institutional autonomy. Ultimately, this study contributes to ongoing educational policy discourse in Azerbaijan, demonstrating that strategic reforms in textbook policy can improve teaching quality, foster innovation, and strengthen the alignment of higher education institutions with the standards of the European Higher Education Area.

2. Literature Review

2.1 Azerbaijan's higher education context

Azerbaijan's higher education system currently comprises 52 institutions operating under public, private, and semi-autonomous governance models (Suleymanov, 2020; World Bank, 2019). Despite reforms introduced since independence, the system retains structural elements inherited from the Soviet model, particularly strong ministerial oversight in curriculum regulation, quality assurance, and textbook approval (Kazimli, 2023; Republic of Azerbaijan, 2020). While selected universities have expanded international partnerships and implemented internal quality frameworks, full institutional autonomy remains limited at the national level (OECD, 2020; Mammadova & Valiyev, 2020).

Studies on post-Soviet educational transitions emphasize that centralized decision-making continues to shape the academic environment in Azerbaijan (Kazimli, 2023). Curricular frameworks, learning outcomes, and textbook lists are often standardized across institutions, reducing variation but also restricting innovation. Universities with greater international engagement or external accreditation tend to introduce contemporary course materials independently, creating disparities between institutions with strong academic capacity and those dependent on top-down directives (Mammadova & Valiyev, 2020).

2.2 Textbook policy and its impact on teaching quality

Textbook policy directly influences pedagogical effectiveness by determining the type and quality of instructional materials available to faculty. Centralized approval processes—common in post-Soviet systems—ensure curricular consistency but simultaneously restrict flexibility (Kazimli, 2023). Research from Russia, Kazakhstan, and Georgia highlights similar patterns: rigid textbook approval systems limit educators' ability to integrate contemporary scholarship, interdisciplinary resources, and global perspectives (OECD, 2020).

In Azerbaijan, Ministry-approved textbooks dominate many public universities, particularly in foundational disciplines (Republic of Azerbaijan, 2020). These standardized materials often undergo revisions slowly and may not reflect rapidly evolving scientific or pedagogical standards (Suleymanov, 2020). Faculty members who wish to incorporate foreign textbooks or develop their own materials must navigate bureaucratic approval procedures, which discourages innovation (World Bank, 2019). Literature on university pedagogy consistently suggests that restricted autonomy in material selection reduces opportunities for active learning, problem-based instruction, and the inclusion of diverse viewpoints—all of which are essential for fostering critical thinking and student independence (Hilton, 2016).

Moreover, textbook policy influences the extent to which instructors can adapt materials for students with varying learning needs. Studies in higher education pedagogy show that flexible material selection enables differentiation, incorporation of culturally relevant texts, and scaffolding of complex topics (Wiley & Hilton, 2018).

2.3 Affordability and student outcomes

Affordability is a critical determinant of students' engagement with academic materials. Global research indicates that rising textbook prices disproportionately affect students from low-income households, leading to reduced access, incomplete preparation, and lower academic achievement (Wittkower & Lo, 2020; Lebens, 2021). In Azerbaijan, surveys and institutional reports reveal that a substantial proportion of students struggle to purchase required textbooks due to high costs and limited availability (World Bank, 2019).

Evidence from comparable middle-income countries shows that insufficient access to required resources reduces course participation, lowers examination performance, and increases dropout risk (OECD, 2020). Azerbaijani students frequently report that outdated or inaccessible textbooks hinder their ability to follow lectures, complete assignments, or engage with supplementary discussions (Suleymanov, 2020). Reliance on informal copies or incomplete scanned versions often results in fragmented learning, diminishing comprehension and long-term retention (Kazimli, 2023).

Economics of education literature emphasizes that textbook affordability is directly linked to educational equity. When students cannot access core materials, teaching quality suffers regardless of an instructor's expertise (Colvard, Watson, & Park, 2018).

2.4 Emerging Global Trends: OER and digital access

In recent years, global higher education has witnessed a significant shift toward Open Educational Resources (OER), digital textbooks, and online learning platforms (UNESCO & Commonwealth of Learning, 2011; Olivier & Rambow, 2023). Institutions in the United States, European Union, and parts of Asia increasingly adopt open-access materials to reduce costs, expand access, and support pedagogical innovation (Atenas, Ebner, Ehlers, Nascimbeni, & Schön, 2021; Hilton, 2016). Studies show that OER adoption contributes to improved learning outcomes, increased student satisfaction, and enhanced faculty creativity in course design (Colvard et al., 2018). National-level OER policies in countries such as Poland, Turkey, and China demonstrate that coordinated government support can accelerate digital transformation in higher education (European Commission, 2022).

Despite these global trends, Azerbaijan's adoption of OER remains limited (Suleymanov, 2020; Kazimli, 2023). Most universities lack dedicated OER repositories, formal policies promoting the use of open materials, or professional development programs for faculty. Digital infrastructure challenges—such as inconsistent access to e-libraries, limited institutional subscriptions, and insufficient technological support—further impede progress (World Bank, 2019). Awareness of OER among faculty remains relatively low, and few instructors have experience in adapting or creating open teaching materials (Mammadova & Valiyev, 2020).

The literature therefore highlights a significant gap between Azerbaijan and international best practices, underscoring the need for strategic investment in digital tools, faculty training, and policy reform (Olivier & Rambow, 2023; Wiley & Hilton, 2018).

3. Methods

This study employs a qualitative descriptive method based entirely on documents. Including national education regulations, university guidelines, international reports, and academic literature on textbook policy and teaching quality. These documents were reviewed to identify how textbook policies are structured, how they influence teaching processes, and what challenges arise for students and faculty. The analysis followed a comparative approach, allowing Azerbaijani practices to be contrasted with international examples from the United States, the European Union, Turkey, and China. This method is appropriate because the research aims to understand and interpret policies, not to measure outcomes through primary data collection.

The purpose of this research is to clarify the relationship between textbook policy and teaching quality in higher education, with a specific focus on Azerbaijan. It explains why textbook policy matters, how it affects learning environments, and what changes could improve educational outcomes. The study is important because it:

- highlights the limitations created by centralized textbook selection;
- shows how affordability issues affect student learning;
- demonstrates the importance of faculty autonomy and modern teaching materials;
- connects Azerbaijan's situation to global developments like Open Educational Resources (OER).

By analyzing existing evidence, the research helps policymakers, universities, and educators understand the broader impact of textbook decisions on teaching effectiveness, equity, and academic success. Ultimately, the study aims to support reforms that align Azerbaijan's higher education system with international best practices.

4. Findings

The analysis of existing policy documents, university guidelines, and secondary research reveals a set of interconnected and systemic challenges within Azerbaijan's textbook policy framework. Collectively, these challenges shape the learning environment and influence the overall quality of teaching in higher education.

4.1 Centralized policy structure and institutional constraints

At the structural level, textbook selection and approval remain highly centralized under the Ministry of Education. Although this model is intended to ensure standardization, control quality, and promote national cohesion across institutions, it significantly limits university autonomy. Most higher education institutions lack the authority to independently choose, update, or diversify their instructional materials. As a result:

- Course content frequently reflects national standards rather than the specific needs of diverse student populations.
- Universities find it difficult to introduce modern, internationally recognized textbooks without lengthy approval processes.
- Faculty are constrained in aligning course materials with industry developments, new research, or contemporary global perspectives.

This highly regulated model often delays the adoption of updated editions or new academic resources, causing discrepancies between local curricula and international academic progress.

4.2 Faculty-level challenges and reduced pedagogical flexibility

Faculty perspectives further illuminate the practical consequences of centralized textbook control. Approximately **60% of instructors** report that they face difficulties in modifying or supplementing approved materials. These constraints manifest in several ways:

- Instructional materials often fail to reflect current disciplinary advancements.
- Faculty cannot easily incorporate case studies, empirical research, or interdisciplinary sources.
- Subjects requiring rapid knowledge updates—such as economics, international relations, education sciences, IT, and business—become outdated more quickly.

The inability to adapt teaching materials discourages faculty from experimenting with innovative instructional methods, such as blended learning, inquiry-based learning, or project-oriented activities. Over time, this reduces teaching dynamism and hinders the development of critical thinking and problem-solving skills among students.

4.3 Student affordability issues and academic impact

Affordability remains a major barrier to student success. Findings indicate that **45% of students** cannot afford required textbooks, particularly in fields that rely on imported academic literature. This economic strain has direct academic consequences:

- Nearly **20% of students** report that lack of access to textbooks negatively affects their performance.
- Many students rely heavily on outdated library copies, photocopied materials, or shared textbooks, which limits independent study.
- Students often struggle to follow lectures, complete assignments, or prepare for assessments without personal copies of required resources.

These patterns reinforce educational inequality, as financially disadvantaged students experience reduced academic participation, lower confidence, and limited engagement in learning activities.

4.4 Digital resource gap and limited OER integration

The study also identifies a significant digital resource gap within Azerbaijani universities. Despite the growing global emphasis on Open Educational Resources (OER), digital textbooks, and online academic platforms, adoption in Azerbaijan remains minimal. Key challenges include:

- Insufficient technological infrastructure in many institutions.
- Lack of institutional strategies for integrating OER into teaching and learning.
- Limited awareness among faculty regarding available digital or open-access materials.
- Absence of national incentives to encourage OER development or use.

Consequently, both instructors and students continue to depend primarily on traditional print materials, which are often expensive, outdated, and less flexible. This reliance reinforces pre-existing barriers and prevents the system from benefiting from global digital innovations.

4.5 Overall implications

Taken together, these findings reveal that Azerbaijan's current textbook policy framework significantly constrains teaching quality. The combination of centralized control, restricted faculty autonomy, financial barriers for students, and underdeveloped digital infrastructure undermines the ability of universities to provide inclusive, modern, and effective instruction. These issues not only affect teaching practices but also shape broader educational outcomes, influencing student achievement, equity, and institutional competitiveness in the global higher education landscape.

5. Discussion

The analysis of Azerbaijan's textbook policy reveals a complex interaction between policy strengths and structural limitations that collectively influence teaching quality in higher education. On the positive side, the centralized approval system plays an important role in maintaining national standards. By ensuring that all universities use officially validated textbooks, the Ministry of Education promotes consistency in curriculum content and minimizes disparities between institutions with differing resources or governance capacities. This standardization is especially beneficial in foundational courses—such as general education, introductory sciences, and national history—where cohesion and reliability of information are crucial for building a common academic baseline. Additionally, Azerbaijan's active participation in the Bologna Process offers a strategic foundation for improving the current system. The Bologna framework encourages student-centered learning, transparency, and institutional autonomy—principles that can guide future reforms in textbook policy. Comparing Azerbaijan's practices with those of the United States, EU member states, Turkey, and China shows that more flexible textbook selection processes and the integration of Open Educational Resources (OER) can enrich teaching, reduce costs, and enhance student engagement. These international experiences demonstrate that reform is both feasible and beneficial.

However, despite these strengths, several structural challenges significantly restrict the effectiveness of teaching and learning. The highly centralized textbook approval mechanism, while intended to ensure quality, limits faculty autonomy to tailor course materials to specific learning needs, new research developments, or interdisciplinary approaches. Survey data indicating that 60 percent of instructors struggle to adapt or supplement materials highlights the practical consequences of this rigidity. When faculty are unable to update texts or introduce contemporary academic debates, teaching becomes less dynamic and less responsive to evolving disciplinary trends. This constraint is particularly problematic in fast-changing fields such as education, technology, economics, and international relations, where up-to-date knowledge is essential.

Students face equally pressing obstacles. Affordability remains a substantial barrier, with 45 percent of students reporting difficulty purchasing required textbooks and nearly 20 percent noting that this directly affects their academic performance. These financial pressures lead many students to depend on shared, borrowed, or outdated copies, limiting their ability to participate fully in classroom discussions, complete assignments independently, or engage in deeper learning beyond the classroom. For students from economically disadvantaged backgrounds, these barriers widen existing equity gaps and may contribute to increased stress, reduced motivation, and lower academic achievement.

Another significant issue is the limited adoption of digital materials and OER. Despite global momentum toward digital learning, Azerbaijani universities continue to rely predominantly on traditional print textbooks. The lack of institutional incentives, digital infrastructure, and faculty training prevents the integration of flexible, low-cost, and customizable online resources. As a result, students miss out on the benefits of multimedia content, interactive learning tools, and updated materials that OER platforms offer. Moreover, the slow approval process often means

that textbooks become outdated by the time they reach classrooms, further widening the gap between Azerbaijani higher education and global academic standards.

Collectively, these findings indicate that Azerbaijan's textbook policy supports national cohesion but simultaneously constrains pedagogical innovation and equitable access to learning. The positive elements—standardization, quality assurance, and alignment with international frameworks—serve as a strong foundation for modernization. However, the challenges—reduced institutional autonomy, affordability issues, outdated resources, and digital limitations—signal the need for targeted reforms. A balanced, two-layer approach appears most appropriate: maintaining national oversight to protect quality, while allowing universities greater freedom to adopt OER, diversify teaching materials, and adapt resources to student needs. Strengthening digital infrastructure, investing in faculty development, and creating incentives for OER adoption would expand opportunities for flexible, innovative, and inclusive teaching. If implemented effectively, such reforms could transform textbook policy from a restrictive mechanism into a catalyst for improved learning outcomes, greater equity, and stronger integration with global higher education standards.

6. Conclusion

This study has demonstrated that textbook policy plays a decisive role in shaping teaching quality in Azerbaijani higher education. The findings reveal that while centralized regulation ensures curricular cohesion and national standards, it simultaneously restricts faculty autonomy, slows the adoption of contemporary materials, and limits opportunities for pedagogical innovation. The financial burden of textbooks on students—nearly half of whom struggle to afford required resources—further undermines equity and academic performance. In addition, the minimal integration of digital resources and Open Educational Resources (OER) highlights a significant gap between Azerbaijan and global higher education trends.

At the same time, the analysis underscores that these challenges are not insurmountable. Azerbaijan's participation in the Bologna Process and its growing engagement with international academic networks provide a strong foundation for reform. Comparative evidence from the United States, European Union, Turkey, and China illustrates that flexible textbook policies, combined with national incentives for OER adoption, can reduce costs, enhance faculty creativity, and improve student engagement. By learning from these models, Azerbaijan has the opportunity to transform its textbook policy into a driver of innovation and inclusivity.

To achieve this, several strategic steps are recommended. Expanding institutional autonomy in textbook selection will empower universities to adapt resources to diverse student needs and evolving disciplinary standards. Establishing a national OER repository and providing systematic faculty training will facilitate the transition toward open and digital resources. Incentive programs for open-content development, coupled with investment in digital infrastructure, will ensure that both students and faculty benefit from accessible, affordable, and modern learning materials. Aligning these reforms with European Higher Education Area standards will not only improve teaching quality but also strengthen Azerbaijan's competitiveness in the global academic landscape.

In conclusion, textbook policy is more than an administrative mechanism; it is a determinant of educational equity, innovation, and effectiveness. By addressing affordability, autonomy, and digital integration, Azerbaijan can move beyond the limitations of its current framework and build a higher education system that is both inclusive and internationally aligned. Such reforms will enhance teaching quality, promote student success, and contribute to the country's broader educational and socio-economic development.

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The Use of Modern Teaching Technologies in Pedagogical Staff Training as a Key Factor in the Quality Indicators of University Instructors

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Abstract

In the 21st-century digital era, higher education institutions must not only transmit theory but also prepare future teachers as technologically competent professionals. This article examines how integrating modern teaching technologies into teacher education affects university instructors' quality indicators. Through a systematic analysis of recent literature (2010–2025), international case studies, and educational statistics, we explore frameworks like TPACK, innovative teaching methods (project/problem-based learning), and emerging digital tools (AI, VR/AR). The findings indicate that teachers with strong TPACK and who employ student-centered methods tend to create more engaging, effective learning environments. For example, AI-driven adaptive systems can personalize training, and VR simulations allow safe practice of classroom management, but both raise ethical and infrastructure challenges. We conclude that increasing technology integration in pedagogy can improve teacher quality by developing digital, pedagogical, and ethical competencies. Key recommendations include mandatory TPACK-based coursework (including AI ethics), sustained reflective professional communities (PLCs), updated quality metrics (e.g., digital resource creation, VR usage), and modernizing infrastructure. Implementing these measures will align Azerbaijan's teacher training with global best practices.

Keywords: TPACK, teacher education, educational technology, professional development, teacher quality.

Introduction

The rapid digitalization of society demands that universities evolve beyond traditional lecturing and cultivate educators who are digitally savvy and pedagogically innovative. Global education reforms have introduced new standards for teacher preparation, placing the Technological Pedagogical Content Knowledge (TPACK) model at the forefront. Mishra and Koehler (2006) define TPACK as the intersection of technology, pedagogy, and subject content knowledge, arguing that “thoughtful pedagogical uses of technology require the development of a complex, situated form of knowledge”. In practice, a high TPACK level means teachers skillfully integrate tools (like multimedia or online platforms) into effective, student-centered instruction.

Concurrently, modern curricula emphasize 21st-century competencies (the “4Cs”: Critical thinking, Communication, Creativity, Collaboration). Project-based and problem-based learning (PBL) are widely recommended to develop these skills in future teachers. For example, incorporating real-world problem-solving tasks with digital tools encourages critical thinking and teamwork. International literature indicates that educators who employ PBL and similar active learning approaches are viewed as having advanced professional competence. However, the pervasive use of technology also introduces challenges: pedagogical training must now address issues like AI ethics, data privacy, and digital equity.

This study investigates the necessity and impact of modern teaching technologies in teacher training on university instructors' performance indicators. We synthesize findings from academic research and educational reports (2010–2025) to assess the current state of technology integration in teacher education. Our goal is to evaluate how these innovations influence teaching quality and to provide concrete recommendations for updating the teacher training system. By examining both opportunities (adaptive learning, VR simulations, micro-credentials) and obstacles (infrastructure gaps, ethical concerns), we aim to chart a path for aligning national teacher education with international best practices.

Aim

The primary aim of this research is to analyze how modern teaching technologies affect the quality indicators of university instructors in teacher education. Specific objectives include:

- 1) evaluating the current integration of technologies (e.g. TPACK framework, AI tools, VR/AR, PBL methods) in pedagogical staff training;
- 2) identifying the impacts of these technologies on teaching effectiveness and teacher competencies;
- 3) formulating evidence-based recommendations for modernizing teacher training curricula and evaluation systems.

These objectives directly address the desired outcomes of improved pedagogical innovation and competitive teacher training. By clarifying how technology use correlates with instructor quality, the study seeks to inform educational leaders and policymakers on where to focus reforms.

Significance

This study contributes to educational research and practice by filling a gap in understanding the role of digital pedagogy in teacher preparation. As nations seek to revitalize education through technology, it is crucial to know how such changes translate into teacher performance and student learning. Our findings will inform curriculum designers, university administrators, and policymakers. For example, aligning teacher education with UNESCO's ICT Competency Framework or national digital literacy standards requires evidence on effective strategies. By systematically reviewing literature and statistical data, we offer practical insights into how enhancing instructors' technological competencies can raise overall education quality.

The work also offers theoretical advancement by connecting TPACK and 21st-century skills frameworks to measurable outcomes. It highlights novel indicators (such as educators' creation of digital content or mastery of AI tools) that extend traditional faculty evaluation criteria. Ultimately, this research underscores the urgency of integrating pedagogy, technology, and ethics in teacher training, thereby supporting the development of a future-ready educator workforce.

Theoretical Framework

The core theoretical lens for this study is the TPACK framework. Building on Shulman's Pedagogical Content Knowledge, Mishra and Koehler (2006) introduced TPACK to explain the specialized knowledge teachers need for technology-integrated instruction. In this model, three primary knowledge domains intersect: Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK). The overlaps of these domains define subareas like Pedagogical Content Knowledge (PCK) and Technological Pedagogical Knowledge (TPK). TPACK itself represents the center where all three overlap, embodying the ability to select and use technology in pedagogically sound ways. This study uses TPACK as a conceptual map to assess educators' competencies.

Another theoretical foundation is the concept of 21st-century skills education. Frameworks from the Partnership for 21st Century Learning emphasize the "4Cs" (Critical thinking, Communication, Creativity, Collaboration) as essential competencies for modern learners. Teacher education programs thus adopt project-based learning (PBL) and problem-based learning to cultivate these skills. In our context, we treat development of 4C competencies as both a goal of training and an indicator of effective teaching. For instance, Sunardi and Doringin (2020) found that a "4Cs" focused PD model increased teachers' enthusiasm and technology use, highlighting the interlink between pedagogy, skills, and tech.

For professional development, we draw on continuous improvement theories. The literature on Professional Learning Communities (PLCs) and reflective practice (e.g. Fullan's coherence model) suggests that collective, ongoing learning cultures improve teaching quality. Dufour and Eaker's PLC model proposes elements like a collaborative learning culture and a commitment to continuous improvement. We adopt this as a guiding principle: that sustainable teacher development requires institutionalized communities of practice. Micro-credentialing and MOOCs are seen as extensions of adult learning theory – providing competency-based, self-directed learning opportunities (constructivist and andragogical underpinnings).

Together, these frameworks (TPACK, 21st-century skills pedagogy, continuous PD theory) shape our analysis. They inform which variables to examine (e.g., teacher tech knowledge, classroom strategies, community practices) and how to interpret their influence on instructor quality.

Literature Review

TPACK and Teacher Quality: Research consistently shows that higher TPACK levels correlate with more effective technology use in teaching. Chai et al. (2013) reviewed dozens of studies and concluded that TPACK-based approaches significantly enhanced teachers' ability to integrate ICT into instruction. In practice, instructors with well-developed TPACK design learning environments that are more student-centered and cognitively engaging. For example, they might employ interactive simulations or adaptive software aligned with lesson content (the Technological Pedagogical Content intersection), rather than using tech as an add-on. Conversely, a narrow focus on technology without pedagogical context often fails to improve outcomes. Thus, literature emphasizes professional development that blends tech skills with content-specific pedagogy.

Project-Based and Problem-Based Learning: Active learning methods like PBL have been championed for promoting 21st-century skills. A substantial body of work (e.g., PBLWorks, ConceptSchools guides) describes how involving pre-service teachers in projects builds their capability to guide real-world, inquiry-driven learning. Project/problem-based tasks require communication, collaboration, and creativity. Recent studies in teacher PD have adopted a “4Cs” model and found it accelerates teachers’ comfort with technology and deepens their instructional skills. In one case, Indonesian researchers showed a 4Cs-focused PD significantly boosted teachers’ tech integration competence and classroom performance. The implication is that universities should incorporate hands-on, tech-rich projects into teacher education curricula. Educators who model these methods in their courses are thus seen as highly competent, since they are building these critical skills in future teachers.

Artificial Intelligence and Adaptive Learning: A frontier in educational technology is the use of AI to personalize learning. Adaptive Learning Systems (ALS) use algorithms to adjust content delivery to each learner’s pace, style, and performance. In teacher training, AI tools can diagnose a trainee’s strengths/weaknesses and suggest customized modules. For instance, if a future teacher struggles with classroom management theory, an AI tutor might provide targeted simulations or readings. Holmes et al. (2019) describe myriad AI applications (from intelligent tutoring to predictive analytics) that promise more individualized learning. These tools also track massive data, which could help instructors refine their teaching strategies (a data-driven pedagogy). However, the literature cautions about ethical challenges: AI use raises issues of data privacy, bias in algorithms, and academic integrity (e.g. plagiarism via generative AI). Studies note that many educators lack experience in digital ethics, so teacher quality increasingly depends on professors’ ability to teach responsible AI use. Thus, universities must address not only technical competence but also digital responsibility.

Virtual and Augmented Reality (VR/AR): Immersive technologies offer transformative opportunities for practice and visualization. VR allows future teachers to rehearse classroom scenarios in a safe, controlled environment. For example, Alvarez et al. (2024) developed a VR classroom simulation (Didascalia Virtual-ClassRoom) where pre-service teachers manage disruptive student behavior. Their study found participants quickly recognized the tool’s usefulness and potential to improve classroom management skills. Similarly, Bailenson (2018) and others argue that realistic VR experiences can build novices’ confidence and empathy without risk to real students. On the content side, AR can enhance understanding of complex subjects: 3D models in science or art lessons reduce cognitive load and make abstract concepts concrete. Buchner et al.’s systematic review (2021) concludes that AR often imposes *lower* cognitive load than traditional methods and tends to improve learning performance. Thus, instructors who integrate AR/VR into their teaching are leveraging cutting-edge methods for deeper learning.

Professional Development Models: Given rapid tech evolution, one-off training is insufficient. Experts like Fullan (2016) and Dufour et al. argue for ongoing, reflective PD. Professional Learning Communities (PLCs) are widely advocated: they bring educators together to apply new methods, share outcomes, and iterate on practice. Dufour et al. list core PLC elements: shared learning goals, collaborative culture, collective inquiry, action orientation, continuous improvement, and results focus. Research shows that when faculty form technology-focused PLCs (even online via forums or MOOCs), adoption rates of new pedagogy increase. Micro-credentials and MOOCs represent another trend: short, competency-based courses allow teachers to upskill flexibly. For example, platforms like Coursera or EdX now offer MOOCs on gamification or data analytics for education, often aligned with micro-credentials (digital badges or certificate programs). Luo and Chen (2023) found that micro-credentials can “effectively meet the needs of working professionals in higher education for teacher professional development” by being competency-based and flexible. The NEA similarly promotes micro-credentials as personalized, performance-based recognitions of mastery. Thus, the literature suggests that sustained, personalized PD systems (not one-time workshops) are key to raising teacher quality.

International Models – Finland and Estonia: Comparative studies highlight best practices abroad. Finland famously prepares teachers with intensive research-based training; technology is woven into education early so that Finnish trainees “perceive technology as a natural learning tool” (Sahlberg, 2011). Jokinen (2010) notes Finnish programs emphasize reflective practice and content mastery alongside tech integration. In Estonia, national policy has driven digital competence. Since the 1990s, the Tiger Leap initiative ensured every school had internet and computers. Today, Estonia’s lifelong learning strategy includes a digital transformation program to continuously develop teachers’ tech skills. Official reports emphasize providing devices, building e-learning materials, and integrating digital literacy standards for educators. The result is an ecosystem where Estonian professors regularly create and use digital content. These international examples show that systemic support (beyond individual willingness) is crucial: strong government and institutional policies can normalize technology use in pedagogy and elevate teacher quality on a national scale.

In summary, the literature consistently finds that technology-rich pedagogies, supported by adequate infrastructure and PD models, lead to higher teacher effectiveness. Gaps remain, however, in evaluating these innovations: few studies track quantitative outcomes like student test gains or teachers' digital portfolios. This review highlights the need to integrate technology-focused metrics into quality assurance (see Section 4).

Methodology

This study employs a qualitative analytical approach, primarily a systematic literature review complemented by analysis of international education reports and statistical indicators. Key methodological steps include:

- **Research Scope and Sources:** We collected scholarly and policy publications from 2010–2025 on teacher training and educational technology. Sources included peer-reviewed journals (e.g. *Teachers College Record*, *Journal of Computer Assisted Learning*), conference proceedings (e.g. ED-MEDIA, AACE), and reports from UNESCO/OECD. We also examined national documents (Estonia's e-education strategy, Finnish education white papers) and case studies (e.g. micro-credentials in higher ed). Databases like ERIC, Web of Science, and Google Scholar were searched with terms: "TPACK", "teacher education technology", "AI in education", "VR teacher training", etc.
- **Selection Criteria:** Included works focused on university-level teacher preparation or professional development in technology integration. Interventions ranged from curriculum design to PD programs. Both empirical studies (surveys, experiments) and conceptual analyses were reviewed. We prioritized recent publications (especially 2020–2025) to capture cutting-edge trends, while foundational works (e.g. Mishra & Koehler 2006) provided theoretical grounding.
- **Data Analysis:** Content from the selected sources was coded thematically around our research questions (e.g. TPACK impact, AI applications, PD models). We synthesized findings under the conceptual framework outlined above. Quantitative data (where available) on technology adoption rates or student outcomes were noted but not analyzed statistically due to heterogeneity of measures. Instead, we critically compared qualitative results and meta-analyses (such as Chai et al. 2013) to identify consensus findings.
- **Limitations and Ethics:** As a desk review, the study did not involve human subjects. We ensured intellectual honesty by citing all sources. Limitations include the reliance on published results and the potential for publication bias (studies showing positive technology outcomes are more likely published). However, by covering diverse geographies (Europe, Asia, North America) and methodologies, we aimed for a balanced perspective.
- **Validation:** To enhance credibility, we cross-referenced findings from multiple sources. For example, claims about AI benefits were supported by both theoretical treatises (Holmes et al., 2019) and practitioner reports (ElearningIndustry 2024). Divergent views (e.g. on AR's cognitive load) were noted from systematic reviews. This triangulation strengthens confidence in the conclusions.

Findings and Discussion

1. **Enhancing Teacher Competence through TPACK:** Across the literature, higher TPACK among instructors is linked with improved teaching quality. Chai et al. (2013) reported that TPACK-based training "yielded positive results in enhancing teachers' capability to integrate ICT" into practice. In real-world terms, this means students in TPACK-informed courses experience more interactive, project-based learning, which boosts engagement and 21st-century skills. For example, a science professor using AR simulations (merging content and pedagogy with tech) can present chemistry molecules in 3D, making abstract concepts concrete and memorable. Anecdotally, faculty who embrace such methods often note that students exhibit deeper understanding and problem-solving ability.

Quantitative studies (though scarce) support this trend. Where measured, classes taught by high-TPACK teachers show higher gains on assessments of critical thinking and collaboration. Thus, we recommend institutions adopt pre/post testing on specific learning outcomes (critical thinking tests, STEM concept inventories) to gauge the impact of tech integration. Over time, tracking such metrics will validate the role of TPACK in raising learning outcomes.

2. **Developing 21st-Century Skills with Active Methods:** The incorporation of PBL and problem-solving tasks in teacher education fosters crucial skills. Sunardi and Doringin (2020) show that embedding a 4Cs framework in PD accelerated teachers' tech competency. In practice, students guide a project from planning to digital presentation, learning communication and creative use of media in the process. Professors who routinely use PBL report that their cohorts demonstrate better teamwork and digital literacy. As a result, instructors using these methods tend to have higher student satisfaction and attainment of soft skills. We therefore consider mastery of PBL methods a quality indicator: professors trained to design and facilitate such projects embody modern pedagogical competence.

3. **AI and Adaptive Technologies:** The review indicates that AI-driven tools can greatly enhance personalization in teacher training. Adaptive platforms monitor a trainee’s responses and immediately adjust content difficulty, much like an intelligent tutor. This approach can boost efficiency; eLearningIndustry (2024) notes AI-driven adaptive learning “enhances learner motivation through customized challenges and rewards”. For example, if a teacher candidate quickly masters a topic, the system can skip basic review and advance them, whereas struggling learners receive extra practice. However, we emphasize a key finding: the effectiveness of AI hinges on ethical use. Multiple sources highlight concerns about algorithmic bias and data privacy. In line with Holmes et al. (2019), faculty must be trained in digital ethics so they can guide students on responsible AI use. Thus, while AI can improve learning outcomes, teacher quality also depends on instructors’ awareness of these new challenges.

4. **VR/AR in Teacher Practice:** Immersive technologies are confirmed as valuable for teacher training. VR simulations enable pre-service teachers to practice classroom management in a realistic yet risk-free setting. In the Didascalia VR study, trainees reported that the immersive experience allowed them to confront common classroom conflicts and immediately reflect on decisions. This kind of “deliberate practice” is otherwise hard to provide in teacher programs. Consequently, instructors who integrate VR into methods courses tend to produce graduates with higher self-efficacy in classroom management. Augmented reality, meanwhile, serves as a visualization aid in subject matter teaching. Systematic reviews (e.g. Buchner et al., 2021) find that well-designed AR can *reduce* cognitive load for learners, making complex science and math content easier to grasp. Thus, faculty who employ AR/VR tools can be judged as innovating effectively: their students learn more deeply and confidently.

5. **Continuous Professional Development:** The dynamic nature of educational technology means professors must keep learning. Our literature review underscores the efficacy of PLCs and other collaborative PD models. When teachers form learning communities around subjects or technologies, they collectively experiment and improve. For example, a university computer science department might hold weekly sessions where faculty demonstrate new educational apps, discuss student feedback, and adjust their practice. Such a PLC aligns with Dufour’s six elements (continuous improvement, collaborative inquiry). The presence of active PLCs can therefore be an institutional quality indicator.

In parallel, micro-credentials and MOOCs offer flexible skill-building. Luo & Chen (2022) observe that credit-bearing micro-courses (like a postgrad certificate in teaching and learning) allowed faculty to integrate new strategies and tools into their classrooms. Educators benefit from choosing bite-sized courses on topics like gamification or data analysis for teaching. The NEA highlights that micro-credentials are personalized and performance-based. We suggest that tracking faculty engagement with such credentials is a modern metric of professional growth. A professor who has earned micro-credentials in AI ethics or AR pedagogy demonstrates initiative in meeting contemporary demands.

6. **International Comparisons:** Finland’s model shows that deeply integrating tech and pedagogy from the start produces teachers who see technology as natural in instruction (Sahlberg, 2011). Estonian examples illustrate the importance of state support: national initiatives (like Tiger Leap in the 1990s) ensured universal connectivity, and current policies provide devices and training to educators. The outcome in Estonia is a resilient, digitally literate teacher corps—evidenced by rapid pivot to remote learning during crises. These cases reveal that institutional backing (e.g. funding, standards, infrastructure) greatly amplifies the impact of pedagogical technology use. In Azerbaijan, this suggests a need for coordinated efforts (see Recommendations).

7. **Quality Indicators and Challenges:** Traditional faculty evaluation (publications, teaching hours, supervision) does not capture digital innovation. New quantitative indicators should include: (a) measured impact of technology-enhanced teaching on student skills (using pre/post tests of critical thinking, problem-solving); (b) volume and quality of digital teaching resources authored by instructors (video lectures, interactive modules, MOOC content); (c) scholarly output in educational technology (number of relevant publications and citations). For instance, Najdawi & Shwede (2025) argue for linking bibliometric metrics (H-index on ed-tech topics) to teaching competence.

Nonetheless, we also identify organizational obstacles. In line with Larry Cuban’s insights, even enthusiastic teachers face “technological resistance” if infrastructure is poor. Outdated computers, slow internet, or lack of licensed software can nullify individual efforts. For example, a professor might design an innovative online lab simulation, but if students cannot access it, the potential is lost. Administrative support is thus crucial. Incentives (such as grants for developing digital projects or recognition for innovative teaching) play a decisive role. Without institutional commitment, investments in teacher tech skills will have limited effect.

In summary, our analysis confirms that effectively using modern technologies is strongly linked to higher teacher quality. The review of literature and case studies consistently shows that integrating TPACK, fostering 21st-century skills, and providing ongoing PD lead to more competent, adaptive instructors. However, success depends on supportive policies and culture. The next section turns these insights into actionable recommendations.

Conclusion and Recommendations

This study underscores that technological competence is a core component of contemporary teaching quality. By raising instructors' TPACK levels and embedding innovative methods, higher education institutions can produce teachers who are ready to educate digital-age learners. Our findings show that blended pedagogies (combining technology, sound pedagogy, and rich content) result in more engaging, outcome-focused education. Moreover, tools like AI and VR, when used thoughtfully, can greatly enhance learning. These advances develop not only technical skills but also ethical and reflective dimensions of teaching.

To align with international standards and national goals, we recommend the following concrete measures:

Structured TPACK-based Courses: Teacher education curricula should include mandatory, practice-oriented modules on TPACK. These courses would train future professors in selecting and applying educational technologies as part of their pedagogy. Specific topics should cover integrating AI (including hands-on use of tools like ChatGPT), as well as didactic issues such as detecting AI-generated plagiarism and ensuring data privacy. By formalizing TPACK education, institutions ensure all graduates reach a baseline digital fluency.

Continuous Reflective PLCs: Universities should facilitate ongoing Professional Learning Communities. This could involve allocating time and resources for faculty groups (by subject area or technology interest) to meet regularly. These PLCs would share best practices (e.g. new software, VR exercises) and peer-review each other's teaching materials. Providing support (such as small grants or credit) for these communities emphasizes collective reflection on instructional innovation. Evidence shows that such collaborative cultures lead to more sustained improvements than isolated training sessions.

Innovation-Focused Quality Assurance: Institutional evaluation systems must evolve. Annual reviews should credit faculty contributions to digital pedagogy. For example, instructors could report on newly created online modules, interactive simulations, or successful use of VR in lectures. Evaluation rubrics might include indicators like "integration of educational technology in teaching portfolio" or "student 21st-century skill development outcomes". Celebrating these achievements (through awards or promotion criteria) will incentivize technology adoption. This aligns with the notion that micro-credentials and MOOCs earned by faculty reflect their commitment to growth.

Modernizing Infrastructure: To remove barriers, institutions must invest in up-to-date equipment. Computers and devices should be refreshed at least every 5 years; high-speed internet should be guaranteed campus-wide. Software licenses for key educational tools (e.g. VR platforms, AI analytics) should be procured. Administrative policies should ensure technical support is available for faculty. If the groundwork is laid, professors will be far more willing and able to implement innovative methods. This addresses the "technological resistance" noted in the literature (Cuban, 2015) by ensuring the environment facilitates rather than impedes change.

Implementing these recommendations will accelerate the digital transformation of teacher preparation in Azerbaijan. It will help bridge the gap between current practice and global benchmarks exemplified by leaders like Finland and Estonia. In the long run, higher TPACK levels and a culture of innovation will produce university instructors who can deliver future teachers with the skills needed in a digitalized world.

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