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Scoping Review on the Role of Learning Analytics in Assessing and Fostering Creativity in Educational Contexts

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Abstract

Learning Analytics (LA) is increasingly applied to assess and foster creativity in educational settings. Whereas existing applications have shown promise in STEM contexts, less is known about the diversity of approaches across educational domains. Therefore, we conducted a scoping review that systematically mapped LA applications for creativity in educational contexts. Searches returned 278 articles, with 41 studies meeting eligibility criteria. Analysis revealed five fundamental mechanisms through which LA fosters creativity: process visualization, adaptive feedback, automated pattern recognition, behavioural analytics, and real-time intervention. Computational creativity (10 studies) was the most prevalent conceptualization, with log data as the primary source (12 studies) and automated assessment via platform-based metrics as the leading approach (10 studies). Programming platforms represented the main technological applications (11 studies), while collaborative learning was the most common pedagogical strategy (7 studies). Problem-solving emerged as the most frequently linked complementary skill (17 studies). However, research showed extensive STEM focus; methodological fragmentation, with 38 studies lacking specified study duration; and theoretical gaps, with nine studies missing explicit theoretical frameworks. These findings highlight LA's transformative potential for creativity assessment and fostering while revealing opportunities for interdisciplinary expansion and methodological standardization.

Notes for Practice

- LA enables creativity assessment through five core mechanisms: process visualization, adaptive feedback, automated pattern recognition, behavioural analytics, and real-time intervention. Programming platforms like Kodetu demonstrate how these mechanisms transform creativity evaluation from static to dynamic analysis.
- Log data analysis and automated assessment show scalability for creativity evaluation, but the field requires stronger theoretical grounding and explicit study design specifications to advance methodological rigour.
- Current research shows predominant STEM focus despite creativity's historical emphasis on arts and humanities. This reflects LA tool limitations rather than data absence, as digital art platforms offer unexplored opportunities.
- Educational designers should prioritize developing LA frameworks for non-STEM creative domains while maintaining methodological rigour across diverse educational contexts.

Keywords: Learning analytics, automatic analysis, educational data mining, creativity assessment, computational creativity, process visualization, educational contexts

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1. Introduction

1.1. Rationale

Creativity is a fundamental cognitive capacity for generating novel ideas, challenging conventional thinking, and driving innovation through unique solutions. Despite extensive research across cognitive science and education, creativity's integration into educational practices remains inconsistent, highlighting the urgent need for systematic approaches to assess and foster this critical 21st-century competency (Sun et al., 2019).

Traditional creativity assessment approaches face significant limitations that hinder systematic educational integration. Conventional psychometric measures such as the Torrance Tests of Creative Thinking (TTCT) (Torrance, 1972) provide valuable insights but capture only static snapshots of creative ability, missing the dynamic, process-oriented nature of creative thinking as it unfolds in real learning contexts (Reiter-Palmon et al., 2019). Moreover, these traditional approaches struggle with scalability and real-time application in diverse educational settings, creating barriers to widespread implementation. The complexity of creativity as a multifaceted construct that encompasses cognitive, social, and contextual dimensions requires assessment approaches capable of capturing and analyzing multiple data streams simultaneously, a capability beyond traditional measurement paradigms.

Addressing these limitations, learning analytics (LA) emerges as a promising solution that leverages computational techniques and data-driven methods (Gašević et al., 2015) to capture and analyze creative processes across diverse learning environments (Marrone & Cropley, 2022). Unlike traditional static assessments, LA enables continuous monitoring of creative behaviours through log data analysis, behavioural tracking, and multimodal analytics, revealing previously hidden patterns in creative thinking and problem-solving processes. By examining vast amounts of real-time educational data, LA can identify creative development trajectories, provide adaptive feedback, and enable educators to design targeted interventions that support individual creative growth (Giannakos et al., 2012; Luan et al., 2020). This computational approach can also transform creativity assessment from occasional evaluation to continuous, embedded analysis that occurs naturally within learning activities.

The implementation of innovative assessment approaches is particularly crucial as creativity is increasingly recognized as essential for addressing 21st-century complexities, supporting innovation, problem-solving, and self-expression (Collard & Looney, 2014). The recent inclusion of creative thinking assessment in PISA (Programme for International Student Assessment) by the Organisation for Economic Co-operation and Development (OECD, 2023) highlights its growing importance, defining it as student ability to productively generate, evaluate, and improve ideas leading to original and effective solutions. However, realizing this educational outcome requires assessment approaches capable of capturing creativity's dynamic, contextual, and process-oriented nature, precisely the capabilities that LA methodologies offer.

In fact, in this scenario, LA has emerged as a powerful tool for understanding complex competencies beyond traditional academic achievement, with its capacity to capture real-time behavioural data enabling process-oriented analyses that reveal underlying mechanisms of creative and critical thinking (Blikstein, 2011). Multimodal analytics further enriches this understanding by integrating diverse data sources, providing comprehensive insights into student engagement and competency development. Recent advances demonstrate LA's potential for assessing socio-emotional competencies through innovative data-driven approaches (Joksimović et al., 2022), while predictive modelling enables proactive interventions addressing both cognitive and non-cognitive learning dimensions (Krumm et al., 2018). The integration of computational thinking with creativity assessment through LA platforms demonstrates promise, with studies showing how programming environments can capture creative problem-solving processes while providing real-time feedback that enhances both CT and creative capabilities. Similarly, the emerging role of generative AI in creativity assessment offers new possibilities for evaluating both originality and flexibility through automated scoring systems that complement traditional psychometric approaches (Organisciak, Acar et al., 2023; Hadas & Hershkovitz, 2024).

However, LA applications specifically targeting creativity remain limited and fragmented. While isolated studies have shown promise in STEM contexts, such as block-based programming platforms capturing computational creativity (Israel-Fishelson & Hershkovitz, 2020), systematic understanding of LA's role in creativity assessment and fostering is lacking. Current research remains narrow in scope, primarily focused on computational domains, with limited exploration of broader interdisciplinary applications. Furthermore, the field faces significant challenges in terminological consistency, with researchers employing a variety of terms for similar computational approaches to creativity analysis (Romero & Ventura, 2020; Siemens & Gašević, 2012). This fragmentation, combined with the historical evolution from traditional psychometric assessment toward computational methods (Dumas et al., 2016; Organisciak, Acar et al., 2023; Reiter-Palmon et al., 2019), creates gaps between established creativity research communities and emerging LA applications (Gajda et al., 2017; Plucker & Makel, 2010). A comprehensive mapping is therefore essential to identify integration opportunities and establish methodological standards that can advance both theoretical understanding and practical implementation (Gašević et al., 2015; Krumm et al., 2018).

This scoping review systematically maps the existing literature on LA applications for creativity in educational contexts. It identifies the theoretical frameworks employed, the data sources and analytical methods used, and the pedagogical approaches implemented while also examining the effectiveness of different LA techniques in assessing and fostering creative competencies. By analyzing current research and identifying methodological gaps, this review aims to inform the development of LA-driven creativity fostering tools and highlight key considerations for their educational implementation.

Given the emerging nature of this intersection and the diversity of approaches employed across studies, a scoping review was selected as the most appropriate methodology. Unlike systematic reviews that focus on evidence quality assessment, scoping reviews provide comprehensive mapping of research areas, making them particularly suited to topics with evolving theoretical frameworks and diverse applications (Tricco et al., 2018).

1.2. Objectives

Review questions were developed using the PCC framework (Population, Concept, and Context) recommended by the Joanna Briggs Institute (Peters et al., 2020; Pollock et al., 2023) to establish clear objectives and eligibility criteria. Table 1 provides an overview of the PCC framework elements applied to this study.

Table 1. PCC Framework Table for the Scoping Review

Component	Description
Population	Students, educators, researchers, and practitioners in educational contexts, spanning K–12 to higher education levels
Concept	Applications of LA for human creativity assessment and fostering, including multimodal analytics, automated assessment tools, and real-time enhancement systems
Context	Educational settings globally, encompassing various educational levels and learning environments

In this review, “fostering creativity through LA” refers to the process by which LA makes visible typically hidden creative behaviours and thinking patterns, enabling educators to provide targeted feedback, personalized interventions, and pedagogical adjustments that support creative development, rather than LA directly generating creativity itself.

The review questions guiding this scoping review are:

RQ1. How is creativity defined, conceptualized, and measured within studies that explore its relationship with LA?

RQ2. What additional skills or competencies are identified as being closely related to creativity in these studies?

RQ3. What types of data are extracted for LA in the context of creativity, and which specific LA methods and tools are employed?

RQ4. What pedagogical approaches and educational contexts are associated with the use of LA to foster creativity?

2. Methods

2.1. Protocol and Registration

This scoping review adhered to the PRISMA-ScR guidelines (Tricco et al., 2018) to ensure systematic and transparent methodology throughout all phases, including search procedures, selection criteria, and data synthesis. The review protocol was registered on Open Science Framework (https://osf.io/xycjb).

2.2. Eligibility Criteria

Eligibility criteria were established to ensure relevant literature was identified and that review parameters were well-defined, aligned with the PCC framework. To meet eligibility, each study was required to: 1) be a peer-reviewed journal article, review, or conference proceeding written in English; 2) investigate the use of LA to assess or foster creativity within educational contexts; 3) focus on learners across all educational levels, from K–12 to higher education and vocational training; 4) be situated in formal or informal educational settings, including online platforms and blended learning environments; and 5) employ LA approaches such as computational analysis (e.g., log data analysis, algorithmic assessment), real-time feedback, or data-driven strategies aimed at assessing and/or fostering creative skill development.

Studies were excluded if they: 6) focused exclusively on educators without incorporating student data; 7) were limited to institutional-level analyses (e.g., enrolment patterns, administrative metrics); or 8) lacked empirical components. Selective exceptions were made for high-quality theoretical contributions that offered foundational frameworks or methodological insights essential to understanding LA-creativity intersections.

2.3. Information Sources and Search Strategy

The study used Scopus and Web of Science (WoS) for comprehensive searches across all collections, employing tailored search strings for each database. In Scopus, the TITLE-ABS-KEY field was used, while WoS relied on the TS field, both incorporating keywords related to LA and creativity in education. Table 2 provides a detailed breakdown of the search strings used. A bibliographic search was conducted on June 4, 2025, covering publications up to December 31, 2024, and identified 134 relevant records in Scopus and 144 in WoS. All records retrieved from database searches are reported in dataset A.1 (https://osf.io/znfmw).

Table 2. Databases and Search Strings Used

Database	String used
Scopus	(TITLE-ABS-KEY ("learning analytics" OR "automatic analysis" OR "educational data mining" OR edm) AND TITLE-ABS-KEY (creativ* OR "divergent thinking" OR "remote association") AND ALL (education* OR classroom OR "online learning" OR "blended learning" OR teaching OR school))
WoS	((TS=("learning analytics" OR "automatic analysis" OR "educational data mining" OR EDM)) AND TS=(creativ* OR "divergent thinking" OR "remote association")) AND ALL=(education* OR classroom OR "online learning" OR "blended learning" OR teaching OR school)

2.4. Screening and Selection of Sources of Evidence

All returns were exported in RIS format and uploaded to a shared RAYYAN project for screening. Author names, journal titles, and institutional affiliations remained visible to reviewers throughout the screening process, with no blinding procedures applied. Following the removal of duplicates (n=72), a total of 206 unique records remained for title and abstract screening.

A calibration exercise was conducted as recommended by Tricco et al. (2016), where both researchers independently screened a subset of 20 records to establish consistent application of inclusion and exclusion criteria. Following calibration, both researchers independently reviewed the titles and abstracts of all remaining articles, with any disagreements resolved through consensus meetings.

Records not meeting PCC criteria were excluded, resulting in 125 exclusions due to wrong publication type (n=3), wrong population (n=13), wrong concept (n=96), and wrong context (n=13). This screening process left 81 reports for full-text evaluation.

2.5. Data Charting Process and Data Items

Data from each study were extracted independently by both researchers using a standardized data charting form developed in Microsoft Excel. All entries were cross-checked and reconciled through an iterative process to ensure consistency and reliability, with any disagreements resolved through discussion.

Extracted data included 1) author name(s) and year of publication; 2) document type and country of origin; 3) sample characteristics and educational levels; 4) study design and data collection methods; 5) creativity definitions and theoretical frameworks; 6) complementary skills and competencies; 7) LA methods and tools employed; 8) pedagogical approaches and educational contexts; and 9) outcome measures related to creativity assessment and fostering.

Before formal data extraction, both researchers cross-checked extraction forms for a random sample of studies to establish consistency in data interpretation and categorization.

2.6. Synthesis of Results

A qualitative content analysis methodology was employed to systematically examine and classify the findings (Elo & Kyngäs, 2008). Initially, a preliminary synthesis of findings was undertaken where the first author conducted line-by-line readings of the results from included studies and generated codes representing creativity conceptualizations, LA methods, and educational applications. Codes were then grouped into broader overarching themes aligned with the four research questions. Only codes containing findings from two or more studies were included to ensure robustness.

After collating studies and findings for each theme, relationships within and between studies were explored to identify factors that might explain variations in creativity assessment approaches and outcomes across different educational contexts (e.g., STEM vs. interdisciplinary settings, K–12 vs. higher education).

3. Results

3.1. Selection of Sources of Evidence

A total of 81 records were sought for full-text retrieval, with three unavailable due to access limitations. Of the remaining 78 full texts screened, 37 articles were excluded: 36 did not examine LA with explicit focus on creativity assessment or fostering, and one had inappropriate scope. As a result, 41 studies met all inclusion criteria and were retained for data extraction and synthesis. Figure 1 shows the PRISMA flow diagram outlining the screening process, exclusions, and final sources. Studies screened at both title/abstract and full-text levels, along with their primary PCC-based exclusion reason, are reported in dataset A.2 (https://osf.io/r27nv).

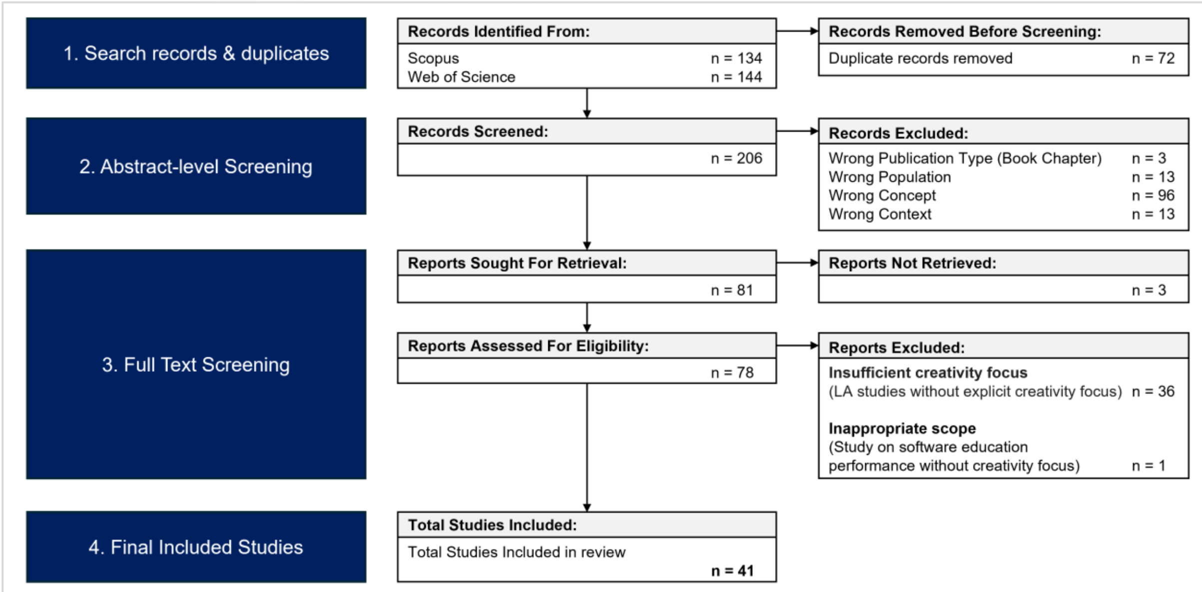

Figure 1. PRISMA flow diagram outlining the screening process, including reasons for exclusions and final sources of evidence.

3.2. Characteristics of Sources of Evidence

Key characteristics of the studies reviewed are summarized in dataset A.3 (https://osf.io/8mpqb), organized by data items relevant to the use of LA in assessing and fostering creativity within educational contexts. Research was conducted across 21 countries, with Spain (n=10), USA (n=8), and Israel (n=7) being most represented. Studies spanned 2011–2024, with 27 conducted in 2020–2024. Educational contexts balanced between higher education (n=15) and K–12 (n=13), predominantly in digital environments (n=15) and mixed settings (n=18). The majority employed short-term designs (n=38), with only two longitudinal studies, highlighting a significant methodological gap.

3.3. Results of Individual Sources of Evidence

The analysis reveals how technology transforms creativity evaluation from static measurement to dynamic, process-oriented analysis. Table 3 provides an overview of LA applications for creativity assessment and fostering across the 41 studies, demonstrating how different LA approaches enable educators to support creative development through automated log analysis, behavioural tracking, data fusion, and assessment protocols. These technological mechanisms capture creative activities in programming, collaborative work, design processes, and problem-solving contexts, making visible previously hidden creative behaviours and enabling targeted educational interventions. A more detailed version of this analysis is presented in dataset A.4 (https://osf.io/7xsrg).

Table 3. Learning Analytics Applications and Creativity Outcomes Across Included Studies

Author, year	LA methods	Key Outcome
Avital et al., 2023	Automated logs	Gender interventions (ρ=0.38–0.41)
Berland & Kumar, 2023	Joint Choice Time analytics	Collaborative patterns (Simpson's=0.74 vs 0.54)
Berland et al., 2014	Multimodal analytics	70% expertise classification accuracy
Britain et al., 2020	Design fluency analytics	Real-time process feedback (43 submissions)
Bubenkova & Pietrikova, 2024	Flexible assessment	90% exceeding requirements
Cheng et al., 2020	Group leadership analytics	Targeted interventions (M=4.02, η^2=0.08)
Chien et al., 2020	Text mining + clustering	93% creativity prediction accuracy
Chiu & Hsiao, 2023	Google Docs analytics	Collaboration tracking (p=0.002)
Chniter et al., 2024	Moodle analytics	5x longer texts post-intervention
Chou et al., 2024	AST code analysis	Originality measurement (κ=0.533)
de Paula et al., 2022	Real-time mood tracking	Team creativity interventions
Domalis et al., 2022	Data fusion + ontologies	ML competency identification
Gal et al., 2017	Programming logs	Automated creativity scoring (M=7.9)
Giannakos et al., 2012	Multimodal analytics	Spatial reasoning + creativity tracking

Author, year	LA methods	Key Outcome
Gibson, 2018	Digital behavioural tracking	Continuous assessment vs static
Hernández-Leo, 2023	ChatGPT integration	Human–AI collaboration guidance
Hershkovitz et al., 2019	Platform analytics	Creativity correlations (ρ=0.30–0.55)
Hicks et al., 2016	Automated content analysis	Scalable creative assessment
Israel-Fishelson & Hershkovitz, 2022	Log analysis + clustering	Five-cluster student profiling
Israel-Fishelson et al., 2021a	Targeted feedback logs	Originality improvement (M=0.68→0.92)
Israel-Fishelson et al., 2020	Log analysis	Creativity–CT correlations (ρ= –0.16 to –0.18)
Israel-Fishelson et al., 2021b	Log analysis	Gender-differentiated interventions
Kim et al., 2011	Exercise logs	70% enhancement (fluency +0.86)
Lee et al., 2024	Prompt analytics	Divergent/convergent patterns (ρ=0.58–0.70)
Manske & Hoppe, 2014	Multi-agent system	Programming creativity (α=0.552–0.729)
Menchaca Sierra & Doran, 2019	3-step assessment	Design thinking tracking (800+ students)
Nacu et al., 2016	Automated log coding	Creative patterns (203k actions analyzed)
Olivares-Rodríguez et al., 2017	Query diversity analysis	Creative problem-solving (78.43% sensitivity)
Olivares-Rodríguez et al., 2018	Query pattern analysis	Automated prediction (80% sensitivity)
Organisciak, Newman et al., 2023	Child-specific modelling	Elementary creativity assessment (r=.388)
Romero et al., 2017	Expert + automated assessment	Creative diversity measurement (M=0.469)
Saleeb, 2021	VR learning analytics	Creative engagement tracking (R>0.7)
Shabani et al., 2022	Knowledge graphs	Creative pattern identification (480 students)
Shabani et al., 2023	Rule-based SPARQL	Three behavioural categories (480 students)
Shettar et al., 2020	Moodle event logs	Convergent/divergent classification (71 students)
Sopher, 2020	KCA model	Design decision tracking (366 decisions)
T et al., 2020	VR + reinforcement learning	Creative thinking across difficulty levels
Sun et al., 2020	Click stream analysis	Five behavioural patterns identified
Wang, 2014	Facebook analytics	Creative behaviour detection
Zaki et al., 2020	APPS-STEM model	Systematic creativity assessment
Zhu et al., 2021	Energy3D logs	Evaluation-reformulation tracking (β=0.209–0.791)

3.4. Synthesis of Results

Overall, findings from 41 studies were organized into four thematic areas corresponding to the research questions. These themes comprised: 1) creativity conceptualizations and measurement approaches, including theoretical frameworks and assessment methods; 2) complementary skills and competencies linked to creativity, such as critical thinking, collaboration, and problem-solving; 3) LA data sources and analytical methods, encompassing log data, multimodal analytics, and automated assessment tools; and 4) pedagogical approaches and educational contexts integrating LA for creativity enhancement, spanning STEM education, creative arts, and interdisciplinary learning environments.

3.4.1. Preliminary Synthesis: Core LA Fostering Mechanisms

Before addressing the specific research questions, the comprehensive analysis reveals five fundamental mechanisms through which LA enables creativity fostering:

- **Process visualization and transparency.** Studies demonstrate how LA makes visible typically hidden creative processes across diverse educational contexts, providing the foundational capability for all other fostering mechanisms. Examples include Avital et al. (2023) who used automatic logs to make visible hidden creative behaviours during programming, enabling targeted feedback on originality and problem-solving strategies, and Berland et al. (2014) who employed log analysis to reveal hidden constructionist learning processes, enabling precise formative assessment of complex creative constructs while maintaining pedagogical richness.
- **Adaptive feedback systems.** Sophisticated platforms provide personalized creative support based on individual behavioural patterns and learning trajectories. Britain et al. (2020) developed an integrated ideation-assessment environment enabling contextual creative feedback through dashboard analytics that support instructor insights into student design processes, while Israel-Fishelson et al. (2021a) implemented targeted feedback on creative programming strategies achieving significant originality improvement (M=0.68→0.92).
- **Automated pattern recognition.** Advanced algorithms identify hidden creative behaviours and thinking patterns previously invisible to educators, enabling scalable creativity assessment and intervention. Chien et al. (2020) achieved real-time discussion analysis enabling timely teaching guidance through vocabulary pattern recognition that allows

intervention when superficial terms are detected, while Shabani et al. (2022, 2023) developed algorithms achieving 85% accuracy in creative student identification through contextualized educational data analysis using knowledge graphs.

- **Behavioural analytics and interaction mining.** Comprehensive analysis of user interactions, click streams, and digital behaviours reveals fine-grained creative thinking patterns and problem-solving approaches. Sun et al. (2020) implemented click stream analysis tracking five behavioural patterns that revealed improved creativity in programming students, while Nacu et al. (2016) developed an automated log coding framework analyzing 203k actions to reveal patterns of creative production, self-directed learning, and social collaboration.
- **Real-time intervention systems.** Dynamic platforms capture creative activities as they unfold, enabling immediate pedagogical adjustments and timely support during critical creative moments. Zhu et al. (2021) implemented Energy3D logs enabling targeted creativity interventions through automated evaluation-reformulation tracking with predictive relationships (β=0.209–0.791), while de Paula et al. (2022) developed InnoPulse for real-time team mood tracking through micro-surveys enabling collaborative creativity interventions.

An emerging sixth mechanism, **collaboration intelligence**, represents a growing area where LA specifically targets group creative dynamics and social creativity construction. Examples include Berland and Kumar (2023) using Joint Choice Time metrics to understand collaborative meaning-making in interactive exhibits, and Chiu and Hsiao (2023) implementing Google Docs analytics for tracking collaborative creative writing processes (p=0.002). This mechanism shows particular promise for future development as educational contexts increasingly emphasize collaborative creativity and social innovation skills.

3.4.2. RQ1: Conceptualization of Creativity

Creativity definitions and conceptualizations. Computational creativity emerged as most prevalent (10 studies); for example, Avital et al. (2023), Hershkovitz et al. (2019), and Israel-Fishelson et al. (2020, 2021a, 2021b) explored programming creativity emphasizing solution originality and iterative problem-solving. Problem-solving definitions were equally prominent (9 studies), with Bubenkova and Pietrikova (2024) focusing on independent problem-solving in game development and Cheng et al. (2020) integrating creative problem-solving with leadership skills. Domain-specific creativity received significant attention (6 studies), while Torrance's four-dimensional model remained influential (4 studies); Avital et al. (2023) and Chien et al. (2020) have combined traditional psychometric measures with computational metrics. Collaborative creativity approaches (4 studies) emphasized group dynamics, as reported by Berland and Kumar (2023) and Chien et al. (2020). Other approaches included divergent thinking (3 studies), AI-enhanced frameworks (1 study), and design thinking with Britain et al. (2020) demonstrating design curation.

Theoretical frameworks underpinning creativity conceptualization. Significant theoretical diversity emerged, with nine studies lacking explicit frameworks, thus highlighting gaps in consistency. TTCT provided the most common foundation (6 studies), while computational thinking models were used as frameworks in five studies, particularly Israel-Fishelson et al. (2020, 2021a, 2021b) and Hershkovitz et al. (2019), who extended traditional creativity theories into digital contexts. Research using divergent-convergent thinking models (3 studies) includes Sopher (2020), who applied them to architectural design. Social and collaborative models (3 studies) emphasized socio-constructivist perspectives. Less common frameworks included constructionism (2 studies) with Berland et al. (2014), and single-study frameworks including the 4P creativity model by Chiu and Hsiao (2023) and design curation theory by Britain et al. (2020).

Creativity assessment approaches. Platform-based metrics emerged as most common (10 studies), leveraging Kodetu, Minecraft, and Moodle to capture creative behaviours through log data and interaction patterns. TTCT remained significant (6 studies) but frequently combined with digital analytics; for example, Avital et al. (2023) integrated TTCT with Kodetu platform data and Israel-Fishelson et al. (2020, 2021a, 2021b) combined psychometric measures with computational creativity scores. Process-based assessment (3 studies) captured iterative behaviours, with Britain et al. (2020) demonstrating design curation processes and Berland et al. (2014) using educational data mining for real-time analysis. Automated scoring (3 studies) included Manske and Hoppe (2014) and Nacu et al. (2016). Additional approaches involved self-report questionnaires (2 studies), expert evaluation (2 studies), and specialized originality metrics (2 studies).

3.4.3. RQ2: Complementary Skills Related to Creativity

Exploration of complementary skills. Problem-solving emerged as most central (17 studies), with Avital et al. (2023) emphasizing interplay with computational thinking and visuospatial skills in coding tasks, Romero et al. (2017) integrating problem-solving with computational thinking in programming, and Bubenkova and Pietrikova (2024) highlighting independent problem-solving in game development. Critical thinking frequently complemented creativity (10 studies): Britain et al. (2020) emphasized its role in iterative design processes and Shettar et al. (2020) linked it with divergent and convergent thinking. Computational thinking was significant in STEM contexts (7 studies), with Israel-Fishelson et al. (2020, 2021a, 2021b) and Hershkovitz et al. (2019) demonstrating strong creativity–CT associations in programming environments. Collaboration and communication were essential in group settings (5 studies); Sun et al. (2020) reinforced this in pair programming and

Cheng et al. (2020) explored leadership as complementary skill. Additional skills included emotional self-regulation by T et al. (2020) and spatial reasoning by Giannakos et al. (2012).

Methods for joint assessment of creativity and related skills. TTCT combined with platform data represented the primary approach (4 studies); for example, Avital et al. (2023) combine TTCT with Kodetu data to measure verbal fluency and computational creativity, and Israel-Fishelson et al. (2020, 2021a, 2021b) employed TTCT with computational creativity scores from programming logs. Machine learning and statistical models were increasingly used (3 studies), with Chien et al. (2020) applying clustering algorithms and text mining for discussion analysis, and Kanuru and Priyaadharshini (2020) using neural networks for prediction. Expert evaluation combined with automated assessment (2 studies) included Romero et al. (2017) integrating human and automated evaluations. Self-report instruments with performance data (3 studies) featured Cheng et al. (2020) using 15-item questionnaires with LA data. Multimodal data collection (4 studies) included Berland et al. (2014) and Giannakos et al. (2012) who employed interaction logs, emotional responses, and performance metrics for comprehensive assessment.

3.4.4. RQ3: LA Methods and Data Sources

Data sources utilized for creativity evaluation. Log data and interaction logs were most prevalent (12 studies), capturing detailed user behaviours and iterative problem-solving processes across digital environments. Avital et al. (2023), Israel-Fishelson et al. (2020, 2021a, 2021b), and Hershkovitz et al. (2019) leveraged Kodetu platform logs to measure computational creativity through programming behaviours and solution originality. Platform-generated data served as a crucial complement (8 studies), providing structured datasets capturing learning environment activities. Student artifacts represented another significant source (7 studies); Berland et al. (2014) and Britain et al. (2020) analyzed student-created artifacts through constructionist approaches, while Romero et al. (2017) examined Scratch project files using automated tools and expert evaluation. Performance metrics (8 studies) provided quantitative indicators including completion rates and creativity assessment outcomes. Survey and questionnaire data (3 studies) captured learner perceptions, with Cheng et al. (2020) and Bubenkova and Pietrikova (2024) who combined self-report measures with objective performance data. Additional sources included collaborative data (3 studies) and emerging multimodal datasets combining behavioural, cognitive, and emotional indicators.

LA methods and analytical approaches employed. Automated assessment emerged as most prevalent (10 studies), with Gal et al. (2017), Gibson (2018), and Hershkovitz et al. (2019) implementing automated scoring systems evaluating creativity through originality metrics and innovation indicators. Statistical analysis methods were widely employed (8 studies), with Israel-Fishelson et al. (2020, 2021a, 2021b) using correlation analysis and regression modelling for creativity–computational thinking associations, while Chiu and Hsiao (2023) applied statistical methods to collaborative creative writing analysis. Educational data mining techniques (5 studies) included Berland et al. (2014) implementing prediction, clustering, and relationship mining for creative learning processes. Clustering algorithms (5 studies) were used by Chien et al. (2020) and Chniter et al. (2024) for discussion content analysis, and by Israel-Fishelson and Hershkovitz (2022) for computational creativity profiling. Machine learning approaches (4 studies) enabled predictive modelling; for example, Kim et al. (2011) applied supervised learning for creative outcome prediction. Specialized methods included text mining and natural language processing (2 studies), visualization tools (3 studies), and real-time analytics with dashboard implementations.

3.4.5. RQ4: Pedagogical and Technological Applications

Pedagogical strategies integrating LA for creativity. Collaborative learning emerged as most prevalent (7 studies), with Cheng et al. (2020) implementing collaborative strategies with LA to examine leadership development and creative problem-solving in group settings, while Chiu and Hsiao (2023) leveraged collaborative writing tasks with real-time analytics to assess group creativity. Game-based learning represented another significant approach (6 studies), particularly effective in STEM contexts, with Avital et al. (2023) and Hershkovitz et al. (2019) employing game-based methods within the Kodetu platform to encourage iterative solution development, while Israel-Fishelson et al. (2020, 2021a, 2021b) demonstrated how game-based environments scaffold creativity through progressive challenge levels and immediate feedback. Project-based learning (2 studies) provided authentic contexts: Berland et al. (2014) applied constructionist principles for meaningful artifact creation and Zhu et al. (2021) implemented engineering design tasks combining iterative processes with real-time LA. Design-based learning (2 studies) emphasized iterative design processes, with de Paula et al. (2022) implementing design thinking methodologies supported by mobile analytics. Flipped classroom approaches (2 studies) provided flexible environments combining online resources with face-to-face creative activities. Additional pedagogical approaches included constructionist, problem-based, inquiry-based, scaffolded, experiential, and self-directed learning.

Role of educational technologies in creativity fostering. Programming platforms emerged as most prominent (11 studies), with the Kodetu platform being particularly significant for enabling detailed programming behaviour capture by Avital et al. (2023), Gal et al. (2017), and Hershkovitz et al. (2019) to track solution originality and measure creative problem-solving through iterative code development. Game environments represented another crucial category (7 studies): Berland and Kumar (2023) used interactive game exhibits for collaborative choice-making studies, Bubenkova and Pietrikova (2024) employed game development environments for creative project assessment, and Sun et al. (2020) leveraged Minecraft for collaborative programming experiences combining creative world-building with computational thinking. Mobile applications (6 studies) provided flexible platforms, with de Paula et al. (2022) developing mobile analytics tools for real-time team mood tracking and Giannakos et al. (2012) implementing tabletop and mobile interfaces for spatial reasoning support. Learning management systems (3 studies) served as foundational platforms, with Chien et al. (2020), Chniter et al. (2024), and Shettar et al. (2020) leveraging Moodle capabilities for discussion pattern tracking and creative discourse analysis. Virtual reality environments (2 studies) included Saleeb (2021) implementing VR-based learning spaces and T et al. (2020) developing VR programming courses. Emerging technologies included AI tools with Hernández-Leo (2023) exploring generative AI applications, and specialized design tools like CAD software used by Zhu et al. (2021).

4. Discussion

4.1. Summary of Evidence

This scoping review identified 41 studies addressing LA applications for creativity assessment and fostering in educational contexts (2011–2024), revealing a rapidly evolving field with significant potential alongside notable limitations.

Theoretical advancement and persistent fragmentation. Our findings confirm Reiter-Palmon et al.'s (2019) observation about creativity assessment variability, considering the different theoretical frameworks used, ranging from Torrance's traditional four-dimensional model to emerging computational creativity approaches. However, the field is highly fragmented in theoretical terms, with a substantial number of studies lacking explicit frameworks, contradicting calls for greater theoretical coherence in creativity research. This fragmentation reflects broader challenges in creativity science, as noted by Gajda et al. (2017), where assessment approaches fundamentally shape research outcomes and educational implications. The theoretical landscape reveals a discipline still searching for unified conceptual foundations, exemplified by the contrast between traditional psychometric approaches like the TTCT and innovative computational frameworks emerging from programming education research.

From static to dynamic assessment paradigms. Our analysis reveals LA's transformative impact on creativity evaluation, representing a fundamental shift from traditional static psychometric measures toward sophisticated real-time assessment systems. Log data emerged as the predominant source, with automated assessment representing the most common approach, signalling a methodological revolution in creativity measurement. This transformation aligns with Blikstein's (2011) vision of process-oriented analysis but extends significantly beyond, demonstrating how LA enables comprehensive understanding of creative thinking mechanisms through multimodal analytics that combine behavioural, cognitive, and social dimensions. The evolution shows a shift from instantaneous assessment of creativity to continuous monitoring of creative processes as they develop naturally within learning environments.

STEM dominance versus interdisciplinary potential. The predominant focus on computational contexts (particularly programming platforms and computational creativity) contrasts strongly with creativity's historical roots in arts and humanities. This concentration reflects LA tool availability and computational tractability rather than comprehensive field representation, creating an artificial narrowing of creativity research scope. While exemplary studies such as that by Avital et al. (2023) demonstrate compelling associations between computational thinking and creativity, this narrow focus limits understanding of the broader manifestations of creativity across disciplines. The gap directly contradicts OECD's (2023) inclusive definition of creative thinking as the ability of students to generate, evaluate, and improve ideas across all domains, suggesting significant untapped potential for LA applications in non-STEM creative contexts.

Methodological innovation with persistent gaps. Studies reveal significant advancement in joint assessment methodologies, with hybrid approaches combining traditional psychometric tools like TTCT with platform-generated data representing major methodological innovation. These developments demonstrate the sophisticated evolution of creativity research toward multiple-source assessment approaches. However, the field exhibits a critical temporal limitation, with the vast majority of studies employing cross-sectional designs; only a few studies explore longitudinal creative development. This gap prevents understanding of the trajectories of creativity development and contradicts the inherently process-oriented nature of creative skill development emphasized in contemporary creativity theory and educational practice.

Fostering mechanisms (from theory to practise). Our analysis identifies five core mechanisms through which LA enables creativity fostering: 1) process visualization making hidden creative behaviours visible, 2) adaptive feedback systems providing personalized support, 3) automated pattern recognition identifying creative thinking signatures, 4) behavioural analytics revealing fine-grained interaction patterns, and 5) real-time intervention systems enabling dynamic pedagogical adjustments. These mechanisms represent a paradigm shift from passive creativity assessment toward active creativity enhancement through technology-mediated interventions. Significant examples, such as the targeted feedback systems developed by Israel-Fishelson et al. (2021a), which achieved significant improvements in terms of originality, confirm the transformative potential of LA to enhance creative development beyond the boundaries of traditional assessment.

Skills integration and 21st-century competencies. The substantial integration between creativity and complementary skills (particularly problem-solving, critical thinking, and computational thinking) aligns closely with current educational emphasis on 21st-century competencies and interdisciplinary learning. This integration highlights the role of creativity as a skill that connects different cognitive domains, supporting holistic educational approaches. However, this integration of competencies remains limited mainly to STEM contexts, despite collaboration and the recognized importance of critical thinking across all academic disciplines and professional fields.

5. Conclusion

5.1. Implications

By summarizing the available knowledge, this review offers food for thought to researchers, educators, and technology developers, supporting future research and the effective integration of LA in creativity-centred education.

The results confirm the multifaceted nature of creativity, while highlighting the urgent need to develop more theoretical coherence in research on creativity in LA. Furthermore, the emergence of computational creativity as a dominant paradigm suggests that new theoretical frameworks may be needed to link traditional theories of creativity with educational contexts in the digital age. LA demonstrates transformative potential for moving creativity assessment from static evaluation toward dynamic, process-oriented analysis. However, realizing this potential requires addressing methodological fragmentation through shared and clearly defined frameworks, while maintaining flexibility for different educational contexts.

For educators, findings highlight specific pedagogical strategies that effectively integrate LA for creativity enhancement, including collaborative learning with real-time analytics and game-based approaches with iterative feedback. Technology developers should prioritize creating LA tools for non-STEM creative domains while establishing interoperable assessment frameworks.

Critical needs include: 1) expanding applications beyond STEM dominance to arts and humanities contexts; 2) conducting longitudinal studies to understand sustained creativity development; 3) developing ethical frameworks for AI-enhanced creativity assessment; 4) establishing theoretical coherence through interdisciplinary collaboration between creativity researchers and LA practitioners; and 5) exploring specialized approaches for different learner populations, as recent advances in child-directed language models demonstrate improved accuracy in analyzing younger learners' creative expressions (Organisciak, Newman et al., 2023), suggesting that age-appropriate computational approaches could enhance LA applications across educational levels.

5.2. Limitations

Limitations of this study include restriction to English-language sources potentially excluding diverse cultural perspectives, emphasis on specific platforms limiting generalizability, and the cross-sectional nature of most studies, preventing understanding of developmental trajectories. The predominant computational focus reflects tool availability rather than comprehensive field representation.

5.3. Future Directions

This review demonstrates LA's significant potential for transforming creativity assessment and fostering through sophisticated methodological approaches that make visible typically hidden creative processes. However, realizing this potential requires addressing theoretical fragmentation, expanding beyond STEM contexts, and developing longitudinal understanding of creative development. The focus in computational domains suggests systematic review remains premature until evidence expands across other creative disciplines. Future research should prioritize interdisciplinary applications, standardized methodological frameworks, and ethical guidelines for AI-enhanced assessment to fulfill LA's transformative potential for 21st-century creativity education.

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