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Reframing the Role of the Curriculum Planner in the Age of Artificial Intelligence: A Systematic Qualitative Evidence Synthesis and Provisional Framework for Intelligent Learning Ecosystems

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ABSTRACT

Objective: This research was designed to organize recent literature on AI-related curriculum-planning functions, competencies, and barriers into a provisional framework for intelligent learning ecosystems.

Methods: This article reports a qualitative evidence synthesis of 71 sources published during 2023-2025. The revision clarifies the design and supplies a provisional bibliography, reconstructed search specifications, and illustrative category mappings. Original selection, appraisal, extraction, and coding records were not supplied. Moreover, corpus membership and numerical results have not been independently revalidated. Six preprint or webpage descriptions are presented separately as supplementary illustrations.

Results: Five provisional layers are presented with the original reported counts: their intended distinct-source frequencies are as follows: learning data analyst, 61.71 (85.9%); human-AI collaboration designer, 59.71 (83.1%); ethical regulator, 56.71 (78.9%); adaptive curriculum designer, 53.71 (74.6%); and technological ecosystem architect, 48.71 (67.6%). Competency domains comprise data literacy, AI ethics, learning architecture, human-AI interaction, and technical literacy. The reported 28-source barrier analysis emphasizes infrastructure, professional competence, and ethical or legal frameworks, but subset membership remains unverified.

Conclusions: The framework proposes a reconfiguration of curriculum-planning responsibilities; it does not establish occupational transformation or causal interdependence. Applications to professional preparation, job descriptions, and institutional readiness require practitioner review and limited field testing. It is suggested that complete methodological verification require the original research records or a documented new audit.

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Introduction

Recent advances in artificial intelligence (AI), particularly generative artificial intelligence (GenAI), have expanded the range of educational tasks that can be automated or supported. AI-enabled systems can generate draft content, analyze learning data, suggest instructional activities, personalize feedback, and support educational decisions. These capabilities create new design and governance questions for curriculum work, but they do not by themselves determine educational aims or justify a new professional model (Chiu, 2024; Giannakos et al., 2025; Crompton & Burke, 2023).

Curriculum planning has not historically been confined to content development. Objectives-based approaches assign curriculum workers responsibility for defining educational purposes, selecting and organizing learning experiences, and evaluating results (Taba, 1962; Tyler, 1949). The practical and deliberative tradition further emphasizes situated judgment and negotiation among subject matters, learners, teachers, and institutional contexts (Schwab, 1973). AI should therefore be understood as redistributing tasks within a broad field of curricular responsibility, rather than replacing a narrowly defined content-producing role. The relevant question is which decisions may be supported by AI, which require routine human approval, and which remain non-delegable.

An intelligent learning ecosystem is used here to mean a coordinated arrangement of learners, educators, curricula, data practices, digital platforms, and governance mechanisms in which feedback can inform the continuing adjustment of learning opportunities. Within this arrangement, curriculum planners may connect educational purposes with data interpretation, instructional design, technology selection, evaluation, and ethical oversight. This definition treats technological capability as one component of curriculum planning and retains human responsibility for value-laden and context-sensitive decisions (Miao & Holmes, 2023; OECD, 2023).

Recent reviews report opportunities for personalization, feedback, and data-informed decision making, while also documenting uneven effects, dependence on instructional design, and risks involving privacy, bias, transparency, and access (Bond et al., 2024; Deng et al., 2025; Xia et al., 2025). Persian-language scholarship similarly discusses adaptive and AI-supported curriculum design and the institutional conditions required for its use (Aliakbari & Pour Karimi, 2024; Eynypour, 2025). These sources justify examining changes in curriculum-planning functions, but they do not establish a uniform occupational transformation has already occurred.

The proposed contribution is adjacent to, but distinct from, established approaches. Tyler and Taba provided a structure for curricular aims, experiences, organizations, and evaluations; deliberative approaches explain contextual judgment; UNESCO's AI competency frameworks identify human-centered and ethical competencies for teachers and students; Intelligent-TPACK models the professional knowledge teachers need to integrate AI ethically; and the OECD emphasizes the coordination of digital education ecosystems (Celik, 2023; OECD, 2023; Schwab, 1973; Taba, 1962; Tyler, 1949; UNESCO, 2024a, 2024b). None of these compared frameworks, on its own, specifies a meso- or macro-level curriculum-planning role that integrates learning-data use, human-AI task allocation, ethical governance, adaptive curriculum design, and technological ecosystem coordination. The present framework is intended to organize those functions, not to replace the earlier approaches.

The gap addressed by this study is, therefore, narrower than the absence of any prior curriculum or AI framework. Within the reviewed 2023-2025 corpus, the relevant functions and competencies

were dispersed across research on curriculum design, teachers, learning analytics, AI governance, and operational systems. A traceable synthesis was needed to determine which functions recur across sources, how evidence about classroom actors can inform broader curriculum-planning responsibilities, and where the resulting interpretation remains provisional.

This study systematically synthesized English- and Persian-language evidence to: (1) identify recurring AI-related functions attributed to curriculum-planning work; (2) identify the competencies associated with those functions; and (3) examine implementation barriers and human-AI collaboration arrangements. The resulting five-layer framework is presented as an analytically derived proposal for subsequent practitioner review and field validation, rather than as a validated job model.

Review Questions

RQ1. Which AI-related functions of curriculum-planning work are reported in the recent literature?

RQ2. Which competency domains are associated with those functions, and under what conditions can evidence about teachers or classroom lesson planning inform conclusions about curriculum-planning responsibilities?

RQ3. Which implementation barriers and human-AI collaboration arrangements are reported, and how can the findings be organized into a provisional framework for intelligent learning ecosystems?

Materials and Methods

Research Design and Reporting Framework

This applied-developmental review used a systematic qualitative evidence-synthesis design for heterogeneous documentary sources. It was not a classical meta-synthesis restricted to primary qualitative studies: the corpus combined review-level syntheses, other peer-reviewed studies, and institutional guidance. Sandelowski and Barroso's (2007) staged logic informed question formulation, searching, appraisal, extraction, synthesis, and reporting, while PRISMA 2020, PRISMA-S, and ENTREQ informed transparent reporting (Page et al., 2021; Rethlefsen et al., 2021; Tong et al., 2012). No effect sizes were pooled, and the final framework is an interpretive synthesis rather than an estimate of intervention effectiveness.

Definition and Scope of the Curriculum-Planner Role

In this study, curriculum planner denotes a professional role or team function rather than a single occupational title. At meso and macro levels, the role includes responsibility for curricular aims, scope and sequence, learning design, assessment architecture, implementation, evaluation, and governance across a program, institution, or education system. Teachers, instructional designers, curators, and platform users were not automatically treated as curriculum planners. They were considered curriculum-planning actors only when the reported activity corresponded directly to one or more of these responsibilities.

Classroom-level evidence was transferable only when it concerned an analogous curriculum function, such as needs analysis, alignment of objectives and assessment, sequencing, adaptation, contextualization, or accountable review of AI-generated designs. Findings limited to classroom enactment, tool attitudes, or teacher identity were retained as contextual evidence and were not generalized to broader curriculum-planning authority. Tables 6-8 therefore use the term curriculum-planning actor when the source describes teachers, curators, or other human participants rather than a formally designated curriculum planner.

Information Sources and Search Strategy

The search covered publications dated first January 2023 through 31 December 2025. January 2023 was selected because the public release and rapid educational uptake of generative-AI systems after late 2022 created a distinct body of literature on AI-supported design, governance, and professional practice; earlier foundational curriculum and methodological works were used for conceptual comparison but were not part of the 71-source synthesis. Searches covered Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, Google Scholar, Scientific Information Database (SID), Noormags, the Comprehensive Portal of Humanities, and Civilica. The exact historical execution dates were not supplied with the manuscript; this reporting gap is acknowledged in the Limitations rather than reconstructed retrospectively.

The original method description reports the English concepts artificial intelligence, generative AI, curriculum planning/design, curriculum planner/developer, and intelligent learning ecosystem, together with their Persian counterparts. It does not provide the verbatim historical Boolean strings. To permit a transparent update, Supplementary Table S2 reports database-adapted rerun specifications reconstructed from those concepts and clearly labels them as reconstructions; these strings are not presented as verbatim records of the original searches.

For a reproducible rerun, Scopus is specified with TITLE-ABS-KEY fields, Web of Science with Topic, ScienceDirect with title/abstract/keywords, SpringerLink with title, IEEE Xplore with All Metadata, and Persian databases with title/abstract/keyword fields where supported. The historical Google Scholar screening limit, ordering rule, and exact execution dates were not supplied. Backward reference-list checking was described as a completeness check, but its retrieval count and unique contribution to final inclusion cannot be determined from the supplied manuscript. These unresolved reporting gaps are carried into Supplementary Table S2 and the Limitations rather than filled retrospectively.

Eligibility Criteria, Evidence Roles, and Study Selection

The revised eligibility definition covers sources addressing at least one review question, published during 2023-2025 as peer-reviewed research or review articles or authoritative OECD/UNESCO guidance, available in full text, and relevant to a curriculum-planning function, competency, or implementation condition. Theses, dissertations, non-research commentary, inaccessible full texts, and irrelevant sources are excluded under this definition. Supplementary Table S1 is a provisional reconstruction from the manuscript bibliography, not a recovered screening or inclusion log. It lists 71 candidate corpus entries, including one OECD and three UNESCO documents. These counts describe the reconstructed list; correspondence with the original included corpus requires confirmation against the original selection records.

Six operational-system descriptions-Dennison et al. (2025), Gonnermann-Müller et al. (2025), Learning Genie (2025), Nova Escola (2025), Shafi (2025), and Zhang et al. (2025)-are presented separately as supplementary illustrations in the revision. They comprise four preprints and two organizational webpages. Their purpose is to illustrate reported workflows and possible human-control arrangements in Tables 7 and 8, without establishing effectiveness. This separation is a reporting decision in the revision; their absence from the original thematic calculations cannot be verified without the original extraction and coding matrix.

The original manuscript reports importing records into reference-management software, removing duplicates, screening titles and abstracts, and assessing full texts. Figure 1 reorganizes the reported totals for clarity, placing the 12 relevance exclusions with eligibility exclusions. This is a retrospective regrouping for presentation, not evidence that screening was rerun or that the

historical order of decisions was different. The underlying record-level selection log was not supplied for this revision.

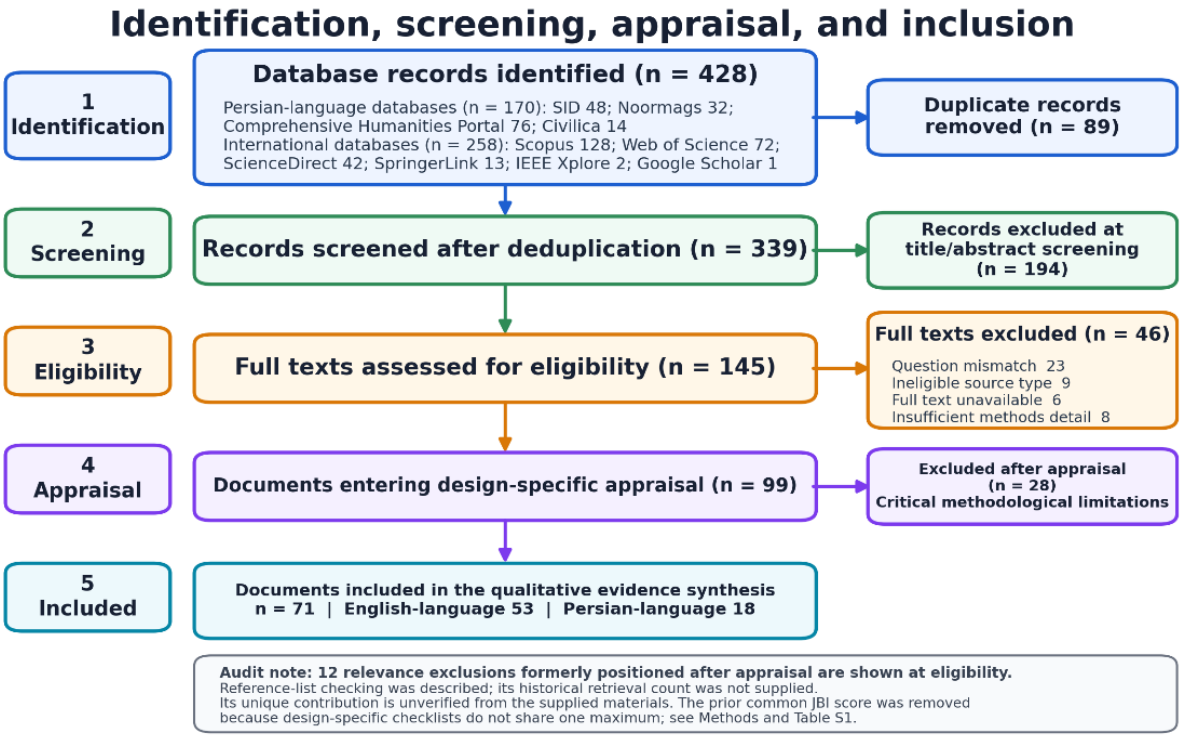


Figure 1. Reorganized presentation of the reported selection totals. Moving 12 relevance exclusions to eligibility is a reporting adjustment; the original decision log and unique yield of reference-list searching were not supplied.

Methodological Appraisal and Data Extraction

The original method states that peer-reviewed sources were assessed with design-specific Joanna Briggs Institute (JBI) instruments (Aromataris & Munn, 2020). The applicable routes in the 2017 tool set and 2020 JBI Manual include the 11-item checklist for systematic reviews and research syntheses, the 10-item qualitative-research checklist, the 8-item analytical cross-sectional checklist, the 9-item quasi-experimental checklist, and the 6-item text-and-opinion checklist. For OECD and UNESCO documents, the appropriate grey-literature route is the six AACODS domains: authority, accuracy, coverage, objectivity, date, and significance (Tyndall, 2010). JBI responses are "Yes, No, Unclear, or Not applicable"; these design-specific instruments do not share one maximum score.

The earlier common threshold (JBI < 28) has been removed because a cross-design numerical rule was not justified. The original figure attributed 28 exclusions to insufficient methodological quality, but individual checklist responses, handling of Not-applicable items, and decision rules were not supplied. Neither individual scores nor the validity of those exclusions can therefore be re-established here. The routes in Supplementary Table S1 are suggestions for a documented reappraisal, not evidence that those particular instruments were applied historically. The original manuscript describes a nine-domain extraction form covering bibliographic information,

objectives, methods, population and sample, concepts, role-related findings, theoretical framework, limitations, and recommendations; the completed matrix was not supplied.

Data Analysis, Translation, Overlap, and Trustworthiness

For the revised analytical description, a source-specific meaning unit is the finding, the conclusion, or formal recommendation addressing a review question. Reported frequencies are interpreted at the level of distinct sources: multiple segments from one source should count once within a category, although a source may contribute to different categories. The original binary source-by-category matrix was not supplied, so this counting rule and the reported totals could not be independently checked. Qualitative content analysis informed by Hsieh and Shannon (2005) is described through initial coding, consolidation into categories, and organization into provisional role layers. These are descriptive operations rather than a claim to grounded-theory generation, theoretical sampling, or saturation. The research reports MAXQDA 2022 for evidence management; the project file and exports were not supplied, so detailed software operations and frequency settings cannot be verified.

The original manuscript reports 315 initial codes and 22 axial categories, whereas its figure displays 21 subcomponent labels. This revision consistently presents those 21 visible categories in Figure 3 and Supplementary Table S3. The discrepancy is resolved at the level of presentation; without the original codebook it is not possible to determine whether the earlier count reflects duplication or an omitted category. Table 3 and S3 supply illustrative analytical mappings and paraphrases, not a recovered passage-level audit trail. The original Persian coding language, translation sequence, translator role, and equivalence checks were not documented in the supplied material; no particular translation workflow is claimed retrospectively.

Evidence classes are separated in the revised inventory, and no review is explicitly weighted by its number of constituent studies. Counting documents does not remove dependence where a primary study is also represented within one or more reviews. An overlap matrix and a sensitivity analysis were not supplied or performed for this revision, so the influence of such dependence remains unquantified. The added definitions, inventory, and illustrative mappings improve reporting but do not substitute for the missing codebook, extraction matrix, or external audit. The original Author Contributions statement assigns formal analysis to the sole author, while the Methods refer to two independent researchers. The supplied material does not resolve their identities, the extent of independent coding, or the calculation of 78.5%. No independently verified dual-coding or agreement claim is therefore made in this revision. Faculty review of the extraction form is reported in the original manuscript, but additional reviewer roles require author confirmation.

Results

Descriptive Profile of the Included Sources

Table 1 and Figure 2 describe the provisional bibliographic reconstruction in Supplementary Table S1. Their totals have been made internally consistent. The entries and evidence classes remain subject to verification against the original inclusion log and full texts; bibliographic reconciliation alone does not establish the original synthesis corpus.

The reconstructed list contains 71 entries: 13 dated 2023, 36 dated 2024, and 22 dated 2025; 53 are identified as English-language and 18 as Persian-language. Provisional bibliographic classifications comprise 26 review-level syntheses, 41 other studies, and four institutional guidance

documents. These totals describe S1 and are not a newly verified account of the original screening or coding process.

Table 1. Characteristics of the 71 entries in the provisional bibliographic reconstruction.

Indicator	Category	n	%
Publication year	2023	13	18.3
	2024	36	50.7
	2025	22	31.0
Evidence class	Review-level synthesis	26	36.6
	Other peer-reviewed study	41	57.7
	Institutional guidance/report	4	5.6
Language	English	53	74.6
	Persian	18	25.4

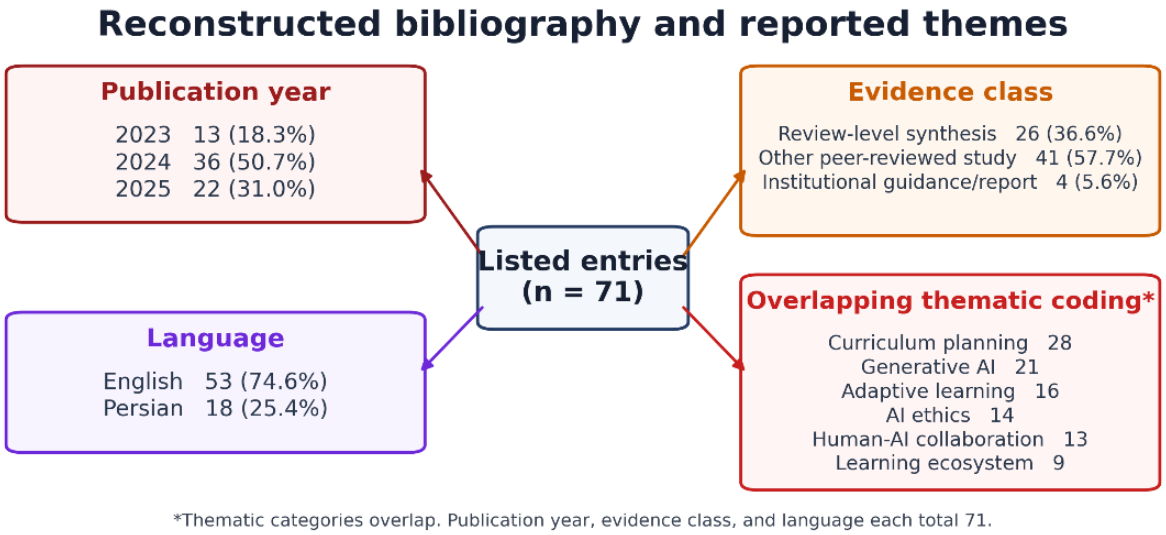


Figure 2. Profile of the 71 entries in the reconstructed bibliography. Year, language, and provisional evidence classes refer to S1; original thematic totals are retained and have not been revalidated against a coding matrix.

Within this reconstructed list, 2024 accounts for the largest share (50.7%), and provisionally classified review-level syntheses account for 36.6%. Unsupported country totals have been removed. These corrections establish consistency between the displayed list, table, and figure; confirmation of original inclusion and evidence type remains necessary.

Table 2. Distribution of overlapping thematic areas.

Thematic area	Distinct sources (n)	% of 71
Curriculum planning	28	39.4
Generative AI	21	29.6
Adaptive learning	16	22.5
AI ethics	14	19.7
Human-AI collaboration	13	18.3
Learning ecosystem	9	12.7

Note. Thematic categories are not mutually exclusive. Each document could be counted once in more than one thematic area; consequently, percentages do not sum to 100%.

As shown above, curriculum planning was coded in 28 sources (39.4%), generative AI in 21 (29.6%), and adaptive learning in 16 (22.5%). These values describe thematic coverage in the included corpus. They do not measure effect magnitude, methodological quality, or the practical importance of a theme.

Coding Structure and the Provisional Five-Layer Framework

Table 3 displays some instances of tracing source findings throug initial descriptive codes axial categories, and role layers.

Table 3. Examples tracing source findings through initial descriptive codes, axial categories, and provisional role layers.

Source finding (analytical paraphrase)	Initial descriptive code	Axial category	Provisional role layer
Reviews link learning analytics to continuing curriculum improvement (Bond et al., 2024).	Use ongoing learning evidence to revise curriculum	Data-driven curriculum development	Learning data analyst
AI literacy and trust shape educators' capacity to interpret and use AI outputs (Al-Abdullatif, 2024).	Interpret AI-generated evidence critically	Learning analytics and prediction	Learning data analyst
Human-machine teaming retains human judgment for contextual and evaluative decisions (Bedington et al., 2024).	Allocate generative and judgment tasks	Human-machine collaboration	Human-AI collaboration designer
Teachers are not viewed as substitutable where contextual judgment and responsibility are required (Chan & Tsi, 2024).	Require human authority at review points	Autopilot/copilot task allocation	Human-AI collaboration designer
AI policy should specify privacy, fairness, transparency, and responsibility (Chan, 2023).	Embed governance requirements in curriculum design	Privacy and fairness management	Ethical regulator
Guidance emphasizes protection of human agency and accountable oversight of AI use (Miao & Holmes, 2023).	Preserve contestability and human accountability	Accountability and sustainability	Ethical regulator
Generative AI can support personalization when aligned with instructional purpose and human guidance (Chiu, 2024).	Adjust learning paths under pedagogical control	Personalized learning-path design	Adaptive curriculum designer
Reported applications differ by task and pedagogy, requiring design-specific adaptation (Qian, 2025).	Match adaptive activity to learning design	Learning-activity design	Adaptive curriculum designer
Effective digital education depends on coordinated data, platforms, standards, and governance (OECD, 2023).	Coordinate systems and standards around curricular aims	System-factor integration	Technological ecosystem architect
The curriculum is framed as a systemic and culturally situated platform (translated analytical paraphrase; Fathi et al., 2024b).	Integrate technology with educational and cultural purposes	Technology selection and management	Technological ecosystem architect

The reported 315 initial codes and the 21 displayed categories are organized under five provisional layers: learning data analyst, human-AI collaboration designer, ethical regulator, adaptive curriculum designer, and technological ecosystem architect. Layer denotes an analytical grouping, not a rank or organizational level. Table 3 and S3 illustrate the proposed organization. They do not document all 315 codes or verify the original consolidation decisions.

Table 4. Five provisional role layers, functions, and document-level source frequencies.

No.	Role	Principal Functions	Documents n (%)	Supplementary Illustrations*
1	Learning data analyst	Knowledge modeling, learning analytics, risk signals, learner profiling	61 (85.9)	EduPlanner; SmartTutor AI
2	Human-AI collaboration designer	Task allocation, control-point design, interaction protocols, accountable review	59 (83.1)	Shiksha Copilot; FACET
3	Ethical regulator	Privacy, fairness, security, transparency, contestability, accountability	56 (78.9)	OECD and UNESCO guidance
4	Adaptive curriculum designer	Learning pathways, assessment adaptation, content delivery, activity design	53 (74.6)	Curriculum Genie; Nova Escola
5	Technological ecosystem architect	System integration, interoperability, technology selection, data governance, evaluation	48 (67.6)	EduPlanner multi-agent architecture

Note. Percentages use the reported denominator of 71 sources and are intended as distinct-source frequencies, not empirical confirmation, effect magnitude, evidence quality, or occupational prevalence. A source should contribute at most once per layer. The original source-by-layer matrix was not supplied; the retained numerators and application of this rule have not been independently revalidated.

The learning data analyst layer was reported in 61 of 71 sources (85.9%), the human-AI collaboration designer in 59 (83.1%), the ethical regulator in 56 (78.9%), the adaptive curriculum designer in 53 (74.6%), and the technological ecosystem architect in 48 (67.6%). This ordering shows how widely each role was discussed in the documentary corpus; it cannot establish relative importance or mutual dependence (The proposed relationships among layers are argued separately and displayed in Panel B of Figure 3).

Competency Domains

Table 5. Competency domains, operational scope, and links to the role layers.

No.	Competency domain	Operational scope	Linked layers	Analytical function
1	Data literacy	Learning-data analysis, knowledge modeling, dashboard interpretation, pattern detection	1, 4, 5	Supports evidence-informed curricular decisions
2	AI ethics	Bias detection, privacy, transparency, fairness, accountability, contestability	2, 3, 4, 5	Sets governance conditions across role layers
3	Learning architecture	Alignment, adaptive design, personalization, assessment, learning pathways	1, 4, 5	Connects educational aims to adaptive structures
4	Human-AI interaction	Task allocation, approval gates, collaboration protocols, agent communication	2, 3, 4	Specifies human control and joint-work arrangements
5	Technical literacy	Working knowledge of models, agents, APIs, data flows, and platform limitations	1, 2, 5	Enables informed requirements and oversight

Note. The earlier Very high, High, Moderate, Core, and Enabling labels were removed because no reproducible weighting procedure was documented in the supplied material. The table describes competency domains and their analytical functions without assigning validated priorities.

Five competency domains recurred across the role framework: data literacy, AI ethics, learning architecture, human-AI interaction, and technical literacy. Data literacy supports interpretation of learning evidence; AI ethics supports governance and accountability; learning architecture connects aims, learning pathways, assessment, and adaptation; human-AI interaction supports task allocation and review; and technical literacy enables informed communication with platforms and technical specialists. Both learning architecture and human-AI interaction are therefore represented explicitly in Table 5.

Implementation Barriers

Table 6. Implementation barriers reported by the 28-source barrier subset.

No.	Barrier	Distinct documents (n)	% of 28	Illustrative sources
1	Inadequate technological infrastructure	22	78.6	Denecke et al., 2023; Mottaghi Dastenaei et al., 2024
2	Insufficient professional or digital competence	20	71.4	Ghodrati et al., 2024; Kohnke et al., 2023
3	Incomplete ethical and legal frameworks	18	64.3	Chan, 2023; Miao & Holmes, 2023
4	Organizational and cultural resistance	15	53.6	Denecke et al., 2023; Mutanga et al., 2024
5	Privacy and data-security concerns	14	50.0	OECD, 2023; UNESCO, 2024a
6	Implementation and maintenance costs	12	42.9	OECD, 2023; Denecke et al., 2023
7	Research-practice gap	10	35.7	Bond et al., 2024; Giannakos et al., 2025

Note. The original manuscript reports a 28-document barrier subset. Counts are presented as intended distinct-source frequencies, not coded-occurrence totals, severity, or effect estimates. The source-to-barrier matrix was not supplied, so the 28 members and the counting rule cannot be verified from the manuscript. S1 therefore marks original barrier membership as unverified. The proposed inclusion rule for a future audit is explicit identification of an implementation constraint in a source finding, synthesis conclusion, or formal recommendation.

Within the 28-source subset, inadequate technological infrastructure was reported in 22 documents (78.6%), insufficient professional or digital competence in 20 (71.4%), and incomplete ethical or legal frameworks in 18 (64.3%). Organizational resistance, privacy and security, cost, and the research-practice gap were less frequently coded. Because the subset combines empirical studies, reviews, and guidance documents, these counts indicate the visibility of barriers in the literature and should not be read as comparative estimates of prevalence or causal influence

Comparison of Operational Systems and Initiatives

Table 7 separates reported workflow descriptions from author interpretations.

Table 7. Supplementary comparison of operational systems and initiatives.

System/Initiative	Setting	Documented Workflow	Human Curriculum-Planning Actor	Author-Mapped Layers	Evidence Status/Source
EduPlanner	China	Multi-agent task automation; final human review described, but whether routine or exceptional is unverified	Defines goals and reviews the final design	1, 2, 4, 5	Supplementary preprint; Zhang et al., 2025
Shiksha Copilot	India	Iterative human-in-the-loop drafting and contextualization	Curators and teachers contextualize, evaluate, and revise	1, 2, 3	Supplementary preprint; Dennison et al., 2025
Curriculum Genie	United States	AI-assisted generation with human editing	Reviews, edits, and localizes generated lessons and units	1, 4	Supplementary webpage; Learning Genie, 2025
SmartTutor AI	International	Closed-loop adaptation within human-defined alignment and governance constraints	Defines alignment, assessment structure, and constraints	1, 3, 4	Supplementary preprint; Shafi, 2025
Nova Escola AI planner	Brazil	WhatsApp-based copilot that generates lesson-plan options	Selects grade and subject and adapts output locally	1, 2, 4	Supplementary webpage; Nova Escola, 2025
FACET	Germany	Teacher-facing multi-agent generation with iterative review	Defines learner profiles and reviews personalized materials	1, 2, 4, 5	Supplementary preprint; Gonnermann-Müller et al., 2025

The six initiatives are presented as supplementary cases. Their cited descriptions concern generation, adaptation, and human review, but provide no common effectiveness measure. EduPlanner can be classified as human-in-the-loop if final human review is mandatory before use; the description available in the manuscript does not establish whether review is routine or exceptional. Its assignment is therefore conditional, pending source-level verification of that control point.

Human-AI Collaboration Patterns in Curriculum Planning

Table 8 gives interpretive control-point definitions and provisional applications, not validated performance classifications.

Table 8. Operational criteria for human-AI collaboration patterns in curriculum-planning work.

Pattern	Operational Criterion	Human Control Point	Provisional Application	Illustration/Status
Human-in-the-loop	Output cannot enter curriculum use until routine human approval, rejection, or revision	Mandatory approval gate	Context-sensitive or high-stakes curriculum decisions	EduPlanner conditionally, if pre-use approval is mandatory; Shiksha Copilot as described
Human-on-the-loop	System completes a bounded task; human monitors and intervenes by exception	Exception-based intervention	Low-stakes, standardized, reversible tasks after validation	SmartTutor mapping is interpretive, not explicit
Human-alongside-the-loop	Human and AI work concurrently through repeated exchange without one fixed final gate	Continuous joint review	Complex design requiring iterative contextual judgment	FACET mapping is interpretive

As displayed, high-stakes aims, assessment, learner rights, and culturally sensitive content require accountable human review; wider use of these arrangements needs practitioner and field evaluation. Figure 3 separates retained descriptive frequencies from proposed functional relationships.

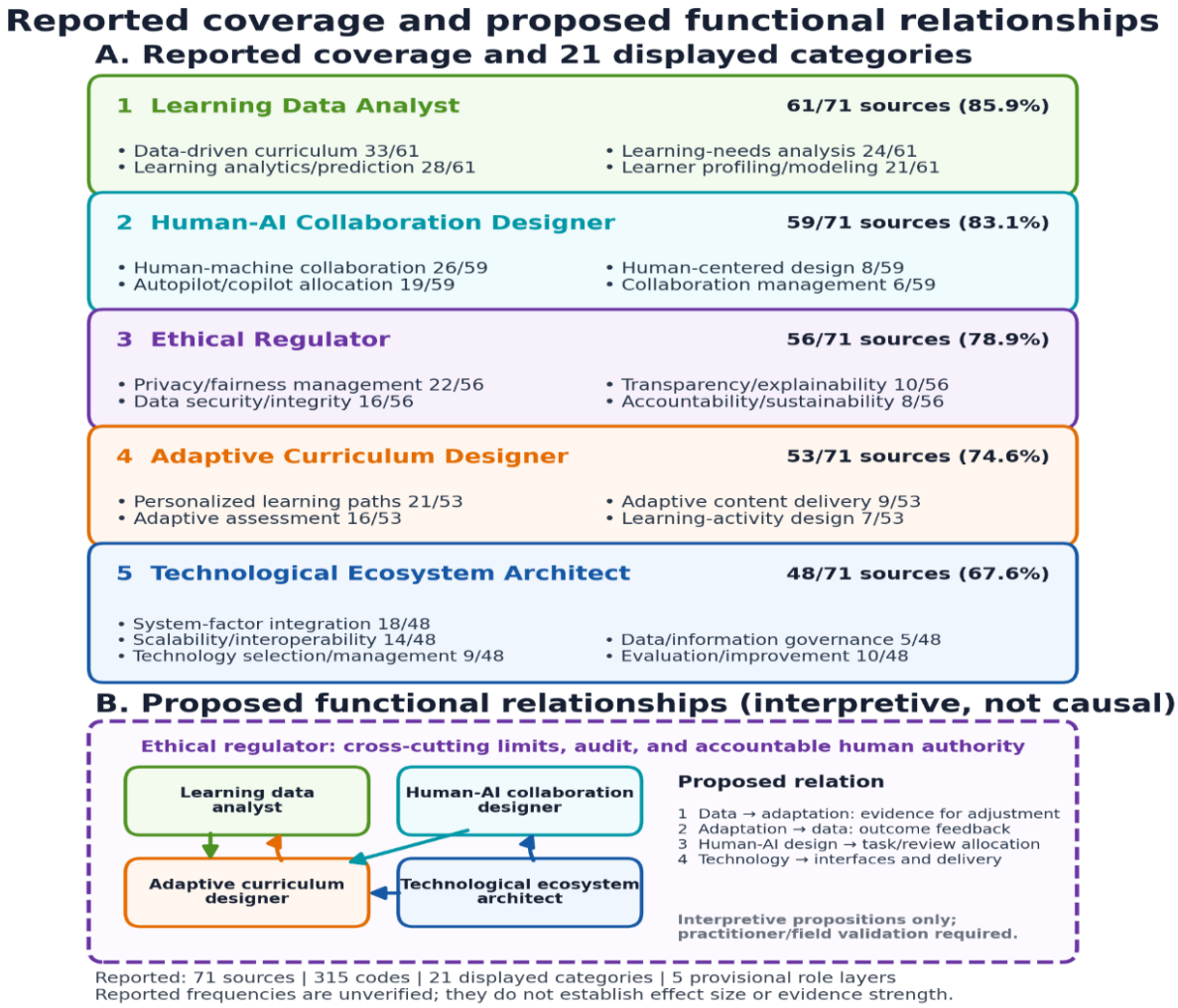


Figure 3. Twenty-one displayed categories and five provisional role layers. Frequencies are retained reported values; arrows represent proposed functional relationships. The original 22-category count and complete coding trail remain unverified.

Discussion

The synthesis suggests a reconfiguration of emphasis within curriculum-planning work, not a proven replacement of the conventional role. Established curriculum approaches already assign responsibility for aims, learning experiences, organization, evaluation, and contextual deliberation. The proposed framework extends that foundation by making five AI-related functions explicit: interpreting learning data, allocating work between humans and AI, governing ethical risk, designing adaptive curricula, and coordinating the technological environment. Its contribution is therefore integrative and prospective. The heterogeneous documentary corpus supports the relevance of these functions, but not a claim that every curriculum-planning position has already adopted them.

The two most frequently reported layers were learning data analyst (61 sources; 85.9%) and human-AI collaboration designer (59; 83.1%). These frequencies show broad attention across

documents rather than stronger effects. Their proposed relationship with adaptive design is functional: data interpretation can inform adjustments to pathways and assessment, while the outcomes of those adjustments create new data for review. Human-AI collaboration design specifies which analytical or generative tasks may be delegated and where human approval is required. The technological layer supplies interoperable data and delivery arrangements, and the ethical layer sets cross-cutting constraints involving privacy, fairness, transparency, contestability, and accountability. These arrows are the author's functional propositions from category comparison; they are not results of a preserved co-occurrence analysis and do not demonstrate causal or mutually dependent relations.

The ethical-regulator and adaptive-designer layers illustrate why frequency cannot substitute for evaluative judgment. Governance documents place privacy, bias, transparency, and human oversight at the design stage, while empirical and review sources show that the outcomes of AI-supported adaptation vary with instructional design, task type, context, and the degree of human guidance (Chan, 2023; Deng et al., 2025; Miao & Holmes, 2023; Qian, 2025; Wang et al., 2025; Xia et al., 2025). The framework therefore treats ethical review as a design condition and adaptation as a monitored cycle, rather than assuming that personalization is inherently effective or equitable.

The technological ecosystem architect layer concerns integration, interoperability, technology selection, data governance, and continuing evaluation. Its lower source frequency (48; 67.6%) should not be interpreted as lesser practical importance. The competency analysis also clarifies the boundary between teachers and curriculum planners. Intelligent-TPACK describes teachers' professional knowledge for ethical AI integration, whereas the present framework transfers only functionally analogous evidence to program- or system-level curriculum work (Celik, 2023). Curriculum planners need sufficient technical literacy to question system assumptions, communicate requirements, and interpret limitations, but the proposed role does not require programming expertise. Data literacy, learning architecture, human-AI interaction, and ethical judgment connect technical capabilities to curricular purposes (Al-Abdullatif, 2024; Fathi et al., 2024a; Kohnke et al., 2023).

Conclusion

This systematic qualitative evidence synthesis organizes recent literature into a provisional five-layer account of AI-related curriculum-planning work: learning-data analysis, human-AI collaboration design, ethical regulation, adaptive curriculum design, and technological ecosystem architecture. The document-level frequencies show that each function appears across a substantial portion of the reviewed corpus, but they do not prove a completed occupational transformation, rank the layers, or establish causal interdependence. The framework's main contribution is to make the proposed functions and their control relationships explicit while retaining human responsibility for educational aims, contextual judgment, limits on automation, and final accountability. Applications to professional preparation, job descriptions, institutional readiness, or system procurement should be treated as hypotheses for practitioner review and limited field testing.

Practical and Policy Implications

The barrier subset places infrastructure, professional competence, and ethical or legal frameworks among the most frequently discussed implementation constraints. This pattern suggests that technology procurement should be accompanied by capacity development and data governance, but the documentary counts do not establish which investment has the largest effect. Evidence concerning teachers and language instructors is used here to identify transferable competencies and

organizational conditions, not to claim that those groups hold identical authority to curriculum planners (Ahmadi et al., 2024; Azimpour et al., 2024; Ghodrati et al., 2024).

The supplementary systems in Tables 7 and 8 show why automation needs to be described through control points. A system can automate drafting while requiring human approval before use, but the mandatory or optional status of that gate must be documented before a classification is treated as established. The system mappings and suggested applications are interpretations of the cited descriptions, not independently verified properties. Uses of Figure 3 in preparation programs, job descriptions, readiness assessment, or technology selection remain provisional and require evaluation with relevant practitioners and institutions.

A defensible implementation sequence begins with limited pilots. Institutions should specify the curricular decision being supported, the human actor who remains accountable, the data that may be used, the required review gate, and the criteria for stopping or revising the pilot. Evaluation should address learning quality, equitable access, data security, explainability, stakeholder experience, workload, and preservation of human agency. Expansion should follow only when practitioners judge the arrangement educationally useful and governance requirements have been met (UNESCO, 2024a, 2024b).

Limitations

Six limitations constrain the interpretation of the findings. First, the 2023-2025 window omits earlier research, and exact search dates, historical strings, Google Scholar limits, and the unique reference-list yield were not supplied. Second, the original inclusion log is unavailable for this revision: S1 is a provisional bibliography, its evidence classes require verification, and overlap between primary and review evidence is unquantified. Third, individual appraisal responses and decision rules were not supplied; removing a common JBI cutoff does not validate the original exclusions. Fourth, the full extraction matrix, 315-code record, category history, Persian translation procedure, coder identities, and agreement calculation were not supplied; the 21 displayed categories resolve presentation but cannot explain the original 22-category claim. Fifth, source and barrier frequencies are retained reported values, not independently reproduced results; the 28 barrier-subset members remain unverified. Sixth, the framework and its arrows lack practitioner and field validation, and the supplementary system classifications remain interpretive. These gaps preclude a claim that methodological reproducibility or evidential independence has been established by the revision.

Directions for Future Research

Future research should proceed in three linked stages. First, interviews and a Delphi study with curriculum planners, teachers, educational technologists, learners, administrators, and legal experts should test the role definition, the boundaries of transferred classroom evidence, the 21 axial categories, and the proposed relationships in Figure 3. Second, the refined competency domains should be converted into a validated instrument, followed by confirmatory factor analysis or structural equation modeling in clearly defined curriculum-planning populations. Third, design-based and longitudinal pilots should compare human-in-the-loop, human-on-the-loop, and human-alongside arrangements for decisions of different risk, measuring curriculum quality, equity, workload, trust, data protection, and learning outcomes. Updates of the evidence synthesis should preserve full search logs, publish the extraction and appraisal matrices, and quantify overlap among review-level and primary sources.

Author Contributions

The original Author Contributions statement assigns conceptualization, methodology, investigation, formal analysis, drafting, revision, and approval to the sole author. The revised article follows that attribution without treating it as proof that no other coding took place. The identities and scope of the two researchers mentioned in the original Methods, and any contribution warranting acknowledgement or authorship, require confirmation from the author. No independently verified duplicate-coding or agreement result is claimed.

Data Availability Statement

Supplementary Tables S1-S3 contain a provisional bibliographic inventory, suggested appraisal routes, reconstructed search specifications, and illustrative category mappings prepared for the revision. They are not recovered original extraction, appraisal, or coding records. Original database exports, execution dates, verbatim queries, selection decisions, item-level appraisals, the source-to-code and source-to-barrier matrices, overlap analysis, codebook history, translation records, agreement calculations, and the MAXQDA project were not supplied. Original inclusion, the 28-member barrier subset, source frequencies, and the full coding trail therefore cannot be independently verified from the current package. Recovery or a transparently documented new review is required to provide those materials. No participant-level data were collected for this review.

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Ethical Considerations

This study synthesized publicly available documents and did not involve human participants, animals, interventions, or identifiable personal data. Institutional ethics approval and informed consent were therefore not required. The distinction between included evidence, supplementary system descriptions, and the author's interpretations is reported throughout the manuscript.

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Conflict of Interest

The author declares no conflict of interest.

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