Integrating CIPP, Technology Acceptance, and Media System Dependency Theories: A Conceptual Framework for Evaluating AI-Driven Teaching Resource Repositories in Vocational Journalism and Communication Education

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ABSTRACT

Teaching resource repositories have become central infrastructure for vocational education, yet the artificial intelligence (AI) functions now embedded in these platforms, including intelligent recommendation, natural language processing (NLP) classification, learning analytics, algorithmic governance and, increasingly, generative content production, have outpaced the frameworks used to evaluate them. This conceptual paper develops an evaluation framework for AI-driven teaching resource repositories in vocational journalism and communication education, a discipline whose students are trained to work within, and critically upon, algorithmically mediated media systems. Three theories are assigned distinct and non-overlapping roles rather than being combined eclectically. The Context-Input-Process-Product (CIPP) model supplies programme-evaluation logic and generates the evaluation structure; the Technology Acceptance Model (TAM) specifies a mediating acceptance mechanism on one designated path rather than a general conditioning factor; and Media System Dependency (MSD) theory specifies goal-oriented dependency as a moderator whose valence is dual, amplifying adverse as well as beneficial repository effects. The framework was developed through an integrative, theory-driven review conducted under a stated search and selection protocol, and its derivation is made inspectable through a theory-to-dimension matrix. It specifies five evaluation dimensions, namely resource quality, technological adaptability, instructional integration, learning and vocational competence outcomes, and ethical and professional compliance, with the context component of CIPP retained as an evaluative frame rather than as a scored dimension, and with overall repository performance specified as a second-order construct comprising the dimensions rather than as a separate outcome predicted by them. Generative AI functions are brought explicitly within scope through criteria for generation accuracy, provenance, human verification and copyright, and the compliance dimension is extended to the discipline-specific concerns of misinformation, source attribution, synthetic media, algorithmic amplification and editorial accountability. Seven propositions are advanced, each stated without presupposing untested weight hierarchies and each accompanied by a proposed test. A staged validation pathway proceeds from Delphi indicator development and Analytic Hierarchy Process weighting to construct-validity testing, structural equation modelling of the mediated path, and multigroup comparison of dependency effects across resource-rich and resource-constrained institutions. The framework is developed primarily for the discipline-specific national repository systems characteristic of the Chinese vocational college sector, with the Malaysian technical and vocational education system as a secondary reference, and it aligns with United Nations Sustainable Development Goal 4 (Quality Education).

Keywords: AI-driven teaching resource repository; conceptual framework; vocational journalism and communication education; CIPP-TAM-MSD integration; second-order construct; Quality Education

INTRODUCTION

Digital teaching resource repositories, curated and searchable collections of courseware, case libraries, media assets, assessment items, and industry materials, have moved from the periphery to the centre of vocational education infrastructure over the past decade. In parallel, artificial intelligence (AI) has been extensively applied across educational practice, opening new opportunities for personalisation, resource recommendation, automated assessment, and decision support (Chen et al., 2020; Ouyang & Jiao, 2021; Zhang & Aslan, 2021). Contemporary repositories are therefore no longer static digital libraries: they increasingly embed intelligent recommendation engines, natural language processing (NLP)-based content classification, learning analytics dashboards, and automated quality-control mechanisms. This transformation has been documented across successive systematic reviews of AI in higher education, which report rapid growth in adaptive and personalised systems alongside persistent concerns about ethics, rigour, and pedagogical grounding (Zawacki-Richter et al., 2019; Ouyang et al., 2022; Crompton & Burke, 2023; Bond et al., 2024).

Vocational journalism and communication education occupies a distinctive position within this transformation. The discipline prepares students for media industries that are themselves being restructured by algorithmic curation, automated content generation, and platform intermediation. Teaching resources in this field must consequently satisfy a double requirement: they must be current and technically authentic with respect to fast-moving industry practice, and they must cultivate the critical, ethical dispositions that responsible media work demands (Miao & Holmes, 2023). A repository that recommends outdated newsroom software tutorials, or that classifies content through opaque algorithms students are never invited to interrogate, fails the discipline in ways that a generic quality checklist cannot detect.

Yet the instruments available for evaluating teaching resource repositories remain poorly matched to this task. Most existing evaluation schemes were calibrated to general higher education and to pre-AI digital libraries; they emphasise catalogue completeness, storage capacity, and interface usability while remaining silent on algorithmic recommendation quality, data governance, and the discipline-specific fit of AI functions (Holmes & Tuomi, 2022; Chiu et al., 2023). The broader literature on AI in education has likewise been criticised for weak theoretical grounding: reviews repeatedly find that a large share of empirical studies proceed without any explicit theoretical framework, limiting the cumulative and explanatory value of the field (Zawacki-Richter et al., 2019; Chen et al., 2022; Bearman et al., 2023; Bond et al., 2024). Evaluation practice inherits this weakness. When indicators are assembled ad hoc, evaluators cannot explain why a given dimension matters, how dimensions relate to one another, or what mechanism connects repository characteristics to educational outcomes. Critical scholarship further cautions that enthusiasm for educational AI frequently outruns evidence of educational benefit, making principled evaluation more, not less, necessary (Selwyn, 2022).

This paper responds to that problem conceptually. Its purpose is to construct a theory-driven framework for evaluating AI-driven teaching resource repositories in vocational journalism and communication education by assigning three complementary theoretical traditions distinct and non-overlapping roles. The Context-Input-Process-Product (CIPP) model contributes a comprehensive programme-evaluation logic that organises what should be evaluated across a repository's life cycle (Stufflebeam & Zhang, 2017). The Technology Acceptance Model (TAM) explains whether and why teachers and students adopt the repository's AI functions, since perceived usefulness and perceived ease of use are robust predictors of educational technology acceptance (Davis, 1989; Scherer et al., 2019; Granic, 2022). Media System Dependency (MSD) theory, originating in communication scholarship, conceptualises the goal-oriented dependency relations that individuals form with media systems (Ball-Rokeach & DeFleur, 1976); it is peculiarly apt for a journalism and communication repository, whose users are simultaneously consumers of an information system and apprentices of the media professions.

The context of application requires statement at the outset, because a framework of this kind is not context-neutral. The framework is developed primarily for discipline-specific national teaching resource repositories of the type that constitute an established policy instrument in the Chinese vocational college sector, where such repositories are centrally commissioned, shared across institutions, and subject to periodic quality appraisal. The Malaysian technical and vocational education system serves as a secondary reference context, and Malaysian evidence on AI adoption in higher education informs the acceptance and ethics components of the framework (Kamrozzaman et al., 2020; Liew & Kamrozzaman, 2024; Kamrozzaman et al., 2025). The two systems differ in their repository governance and resource endowments, and that difference is treated in the framework as an object of analysis rather than as noise: the evaluative frame and the dependency moderator exist precisely to make such variation visible. Claims of wider transferability are deferred to the boundary conditions and are not assumed here. Three research questions guide the conceptual development. First, what evaluation dimensions follow from an integration of CIPP, TAM, and MSD perspectives on AI-driven teaching resource repositories, and how can that derivation be made inspectable rather than asserted? Second, how are these dimensions related to one another and to overall repository performance, and what is the conceptual status of acceptance and dependency within those relationships? Third, what propositions can be derived to guide subsequent empirical operationalisation and testing without presupposing results that have not yet been obtained?

In answering these questions, the paper makes three contributions. Theoretically, it offers an integration of CIPP, TAM, and MSD into a single evaluation architecture for discipline-specific, AI-driven educational repositories, in which each theory is confined to a defined explanatory role. The novelty claimed is one of combination and role assignment rather than of any individual component, and it is set out against the existing traditions in Table 1 rather than asserted; the claim rests on the search reported in Table 2 and not on an exhaustive systematic review of every evaluation instrument in circulation. Practically, the paper supplies repository managers, vocational educators, and policymakers with an organised set of evaluation dimensions, a transparent derivation matrix, and testable propositions that can inform diagnosis and improvement planning. In policy terms, it connects repository evaluation to the agenda of equitable, quality education articulated in United Nations Sustainable Development Goal 4 (SDG 4), and to national digitalisation strategies for vocational education (UNESCO, 2023; OECD, 2023; Chan, 2023).

LITERATURE REVIEW

AI-Driven Teaching Resource Repositories

The application of AI in education has developed along a trajectory that Ouyang and Jiao (2021) characterise as three paradigms: AI-directed systems in which learners receive pre-structured content; AI-supported systems in which learners collaborate with responsive technologies; and AI-empowered systems in which learners exercise agency while AI augments their capabilities. Teaching resource repositories have traced a parallel path. Early repositories functioned as digital warehouses, offering organised storage with keyword search. Second-generation platforms introduced metadata standards, learning-object models, and interoperability protocols. Contemporary AI-driven repositories represent a third stage: they profile users, recommend resources adaptively, classify and tag content through NLP, monitor usage through learning analytics, and in some cases generate or remix content (Hwang et al., 2020; Zhang & Aslan, 2021).

Systematic reviews confirm that adaptive systems and personalisation constitute the dominant AI application in higher education, followed by assessment, prediction, and intelligent tutoring (Zawacki-Richter et al., 2019; Zhai et al., 2021; Ouyang et al., 2022; Crompton & Burke, 2023). Recommender systems, the AI function most central to repositories, have themselves become a substantial research field in education, with reviews documenting rapid growth in content-based, collaborative, and hybrid approaches for suggesting learning resources (Urdaneta-Ponte et al., 2021). These functions materially change what it means for a repository to be good. A recommendation engine can amplify high-quality resources or entrench popularity biases; NLP classification can make a sprawling collection navigable or can systematically mislabel discipline-specific genres; learning analytics can inform teaching or can surveil students. Bond et al. (2024), synthesising sixty-six prior reviews, call explicitly for increased attention to ethics, collaboration, and methodological rigour in AI in education research, an admonition that applies with equal force to how AI-enabled platforms are evaluated. Kamalov et al. (2023) similarly argue that the new era of AI in education must be assessed as a multifaceted, sustainability-oriented transformation rather than as a set of isolated technical features.

Generative AI has intensified these questions. Large language models offer substantial opportunities for content creation, feedback, and personalised support, while raising well-documented concerns about accuracy, bias, and academic integrity (Kasneci et al., 2023; Dwivedi et al., 2023). Guidance issued by UNESCO stresses that generative tools must be embedded in educational settings only with human-centred governance, age- and context-appropriate validation, and transparent data practices (Miao & Holmes, 2023). For repositories, this implies that evaluation must now encompass not only the stock of resources but the algorithmic behaviour of the platform itself, what Tlili et al. (2023) frame as the dual character of AI systems that may act simultaneously as guardian angel and devil in educational use.

Vocational Journalism and Communication Education

Vocational education differs from general higher education in its tight coupling to occupational competence: curricula are organised around work processes, industry certification, and employability, and learning resources must track industry practice closely. In journalism and communication, that industry is undergoing algorithmic restructuring. Automated news writing, platform-mediated distribution, data journalism, and AI-assisted editing have altered the competence profile graduates require. Teaching resources must therefore be refreshed at the tempo of the media industry, must incorporate authentic production tools and case materials, and must foster the ethical judgement that media work demands (Miao et al., 2021; Ng et al., 2021). AI literacy, understood as the capacity to use, understand, and critically evaluate AI, has itself become a graduate attribute in the discipline (Ng et al., 2021; Su & Yang, 2023). At the same time, Malaysian evidence shows that higher education students encounter genuine difficulties when integrating AI into their learning, including overreliance, uneven digital readiness, and uncertainty about appropriate use, which underlines that platform intelligence does not automatically translate into learning benefit (Liew & Kamrozzaman, 2024).

These disciplinary characteristics generate distinctive requirements for teaching resource repositories. First, currency and industry alignment dominate resource quality judgements to a degree unusual in more stable disciplines. Second, the repository's own AI functions constitute pedagogical content: a recommendation algorithm operating on journalism students is a live specimen of the algorithmic curation they study. Third, ethical compliance is doubly consequential, because failures of fairness, transparency, or privacy in the platform contradict the professional norms the curriculum seeks to instil (Nguyen et al., 2023; Celik, 2023). Existing repository evaluation schemes, developed for general higher education, capture none of these disciplinary specificities systematically.

Existing Evaluation Approaches and The Research Gap

Evaluation of educational technology has drawn on several traditions, each of which contributes something the present problem requires and each of which omits something else. Because the contribution claimed in this paper is one of integration, the traditions and their omissions must be set out explicitly rather than summarised in a sentence; a claim to combine existing work is only as credible as the account it gives of that work. Table 1 therefore states, for each tradition, what it evaluates, what it omits for the object of interest here, and how the present framework departs from it.

Table 1. Existing evaluation traditions, their omissions for AI-driven repositories, and the departure claimed here

Tradition and representative sources	What it evaluates	What it omits for this object	Departure taken in the present framework
Learning-object and digital-repository quality instruments	Metadata completeness, catalogue coverage, findability, interface usability, storage and delivery reliability.	Predate the embedding of AI functions; silent on algorithmic behaviour, on disciplinary fit, and on educational outcomes.	Content merit is retained as one dimension (D1) rather than as the whole of quality, and is joined by algorithmic, instructional, outcome and governance dimensions.
AI-in-education ethics and policy frameworks	The ethical and governance adequacy of	Are principle statements rather than	Supplies much of the content of the compliance

(Miao et al., 2021; Holmes et al., 2022; Nguyen et al., 2023; Miao & Holmes, 2023; OECD, 2023; UNESCO, 2023)	AI systems used in education, and the principles institutions should apply.	evaluation architectures for a specific artefact, and specify no mechanism connecting platform properties to educational value.	dimension (D5), but embedded within a structure that also specifies mechanism, process and outcome.
Technology-acceptance research applied to educational technology (Davis, 1989; Scherer et al., 2019; Granic, 2022; Wang et al., 2021; Al-Adwan et al., 2023)	Individual adoption of a technology, explained through perceived usefulness and perceived ease of use.	Silent on content quality, on educational product, and on governance; treats acceptance as a terminal outcome rather than as an intermediate mechanism.	Acceptance is retained but relocated as a mediator on one designated path, rather than functioning as a general conditioning factor over the whole framework.
CIPP applications in educational technology evaluation (Stufflebeam & Zhang, 2017)	Programme-level evaluation across context, input, process and product, oriented to improvement rather than accountability alone.	Generic across programmes; contains no account of user psychology, no criteria for algorithmic behaviour, and no disciplinary calibration.	CIPP is retained as the generative logic of the structure, with two departures declared and justified rather than left implicit.
Evaluation of educational recommender systems (Urdaneta-Ponte et al., 2021)	Algorithmic performance of recommendation, typically through accuracy, coverage and diversity metrics.	Evaluates the algorithm rather than the educational platform; accuracy metrics do not speak to curriculum fit, instructional integration or professional ethics.	Recommendation quality becomes a set of indicators within the technological dimension (D2), rather than the object of evaluation in its own right.
Media-dependency scholarship (Ball-Rokeach & DeFleur, 1976)	Variation in media effects as a function of structural dependency on an information system.	Is an explanatory theory rather than an evaluation framework, and has not previously been applied to educational resource repositories.	Supplies the moderator of the framework, and is extended here with an explicit dual valence that the original formulation leaves undeveloped.
Hybrid acceptance-and-evaluation models in specific settings	Combine an acceptance model with an evaluation structure, usually for a named platform or course.	Typically combine two traditions, are seldom discipline-specific, and do not address algorithmic governance or dependency.	The contribution claimed here is the three-way assignment of non-overlapping roles for a discipline-specific AI artefact, not the novelty of any single component.

Three gaps follow from this comparison. The first is a theoretical integration gap: the traditions address different levels of the problem and are seldom combined, so that evaluators possess either an architecture without a mechanism or a mechanism without an architecture, despite repeated calls for stronger theoretical grounding in research on AI in education (Chen et al., 2022; Bearman et al., 2023; Bond et al., 2024).

The second is a disciplinary specificity gap: evaluation instruments for teaching resource repositories are calibrated to general higher education and neglect the currency, authenticity, and professional-ethical demands specific to vocational journalism and communication education. The third is an AI-function gap: most instruments predate the embedding of recommendation, NLP classification, analytics and generative capability into repositories, and thus contain no indicators for algorithmic quality, fairness, provenance or transparency (Holmes & Tuomi, 2022; Ifenthaler et al., 2024). The strength of the novelty claim should be calibrated to the evidence available for it. The search reported in Table 2 located no framework that assigns programme-evaluation logic, an acceptance mechanism and a dependency moderator distinct roles within a single evaluation architecture for a discipline-specific AI-driven repository. That is a claim about a combination, made on the basis of a documented but non-exhaustive search, and it should be read as such. Each component of the framework is well established; what is offered here is an argued arrangement of them, and the arrangement is made inspectable in the derivation matrix presented later so that readers can judge it for themselves.

What “AI-Driven” Includes: The Scope of The Repository Concept

The term AI-driven repository is used in the literature to cover a range of functions of quite different character, and a framework that does not delimit its referent cannot specify appropriate criteria. Four function classes are distinguished here. Retrieval and recommendation functions rank and surface existing holdings. Classification and organisation functions, typically NLP-based, tag, cluster and route content. Analytic functions profile use and report on it. Generative functions produce new content, including summaries, item variants, translations, illustrative media and question banks, whether at the point of ingestion or at the point of retrieval.

The first three classes are well represented in existing repository scholarship; the fourth is newer and raises evaluation questions the others do not (Kasneci et al., 2023; Dwivedi et al., 2023; Su & Yang, 2023). Where a repository generates content, evaluation must address the factual accuracy of what is generated and the risk of confident fabrication, the provenance and labelling of generated material, the copyright status both of training data and of outputs, the behaviour of prompt-based retrieval interfaces that may return synthesised answers in place of located resources, and the arrangements for human verification before generated material enters instructional use (Miao & Holmes, 2023). For journalism and communication education these questions are not peripheral: synthetic media and unattributed content are precisely the phenomena the curriculum trains students to detect and resist (Wardle & Derakhshan, 2017; Diakopoulos, 2019). The framework developed below therefore treats generative capability as within scope, and supplies explicit criteria for it in the technological and compliance dimensions rather than leaving it to be inferred. Where a repository has no generative function, those criteria are simply not scored, and the framework reduces accordingly; this is stated among the boundary conditions.

METHODOLOGY

Research Design

This is a conceptual paper, and its design is an integrative, theory-driven review culminating in framework construction. Rather than testing hypotheses against primary data, the paper synthesises established theory and recent empirical literature to build an evaluation architecture whose components, relationships, and boundary conditions are explicitly warranted. This design is appropriate because the identified problem is theoretical in nature: evaluation instruments for AI-driven repositories exist in fragments across separate research traditions, and what is missing is a principled integration rather than additional isolated measurement.

Theory Selection and Literature Base

Three criteria governed the selection of theories. First, complementarity of explanatory level: candidate theories had to address distinct, non-overlapping questions, covering the programme level, the individual-psychological level, and the system-structural level. Second, empirical pedigree: each theory required a substantial record of validation or productive application in education or communication research (Ball-Rokeach & DeFleur, 1976; Stufflebeam & Zhang, 2017; Scherer et al., 2019). Third, disciplinary resonance: at least one theory had to originate in communication scholarship so that the framework would be intelligible within, and faithful to, the discipline being served. CIPP, TAM, and MSD jointly satisfy these criteria.

Search And Source-Selection Protocol

An integrative review is not a systematic review, but it is not exempt from the requirement of transparency: a reader cannot judge whether a derived framework is warranted without knowing how its evidence base was assembled (Torraco, 2005; Snyder, 2019; Jaakkola, 2020). The protocol followed here is therefore reported in Table 2, including the respects in which it falls short of a systematic procedure.

Table 2. Search and source-selection protocol for the integrative review

Protocol element	Specification
Source categories	Systematic reviews and meta-reviews of AI in higher education; primary research on educational recommender systems and repositories; technology-acceptance research in education; scholarship on the ethics and governance of educational AI; international and national policy guidance; and foundational theoretical works on CIPP, TAM and MSD.
Databases and channels	Scopus and Web of Science as primary indexes, supplemented by Google Scholar for forward and backward citation chaining from the retrieved reviews, and by direct retrieval of policy documents from the issuing bodies (UNESCO, OECD).
Search period	Empirical and review literature from 2019 to 2025, a window chosen because it spans the period over which AI functions became standard in educational platforms and over which generative models entered educational use. Foundational theoretical works were retrieved irrespective of date, since they are the objects of the synthesis rather than evidence within it.
Key concept clusters	Cluster A, the artefact: teaching resource repository, learning object repository, digital learning resources, educational recommender system. Cluster B, the technology: artificial intelligence in education, recommendation, natural language processing, learning analytics, generative artificial intelligence. Cluster C, evaluation: evaluation framework, quality indicators, CIPP, technology acceptance, media dependency. Cluster D, the setting: vocational education, journalism education, communication education, technical and vocational education and training. Searches combined A with B, A with C, and A with D.
Inclusion logic	Sources were retained where they contributed one of four things: evidence about the state and effects of AI functions in educational platforms; an evaluation structure or set of quality criteria; a theoretical mechanism capable of explaining why a repository property should matter educationally; or authoritative governance requirements. Empirical studies of AI applications unrelated to resource provision were excluded, as were technical papers reporting algorithm performance without an educational referent.
Judgement of saturation	Searching continued until additional retrieval within a concept cluster returned no criteria, mechanisms or governance requirements not already represented in the assembled base. Saturation was judged separately for each of the four dimensions and for the compliance layer, and the judgement was made against the derivation matrix rather than against a target number of sources.

Corpus and its status	The retained corpus is the reference list of this paper. Screening was conducted by the authors without independent duplication and no formal appraisal of study quality was applied, since the synthesis extracts constructs and criteria rather than effect estimates. The procedure is therefore reported as an integrative, theory-driven review in the sense of Torraco (2005) and Snyder (2019), and not as a systematic review.

Two features of the protocol carry consequences for the framework. The restriction of the search window to 2019 onward means that the framework is calibrated to platforms with operative AI functions, and its technological dimension will be partly inapplicable to earlier repository generations. And because saturation was judged against the emerging derivation matrix rather than against a fixed corpus size, the procedure is vulnerable to confirmation of the structure it was building; the derivation matrix is published in full for exactly this reason, so that a reader may test whether the mapping is forced.

Framework Construction Procedure

Framework construction proceeded in five analytical steps. Step one assigned each theory a defined explanatory role and mapped its constructs onto the object of evaluation, an AI-driven teaching resource repository serving vocational journalism and communication programmes. Step two derived candidate evaluation dimensions by locating the intersections between the input-process-product logic of CIPP, the governance requirements identified in the ethics and policy literature, and the disciplinary requirements established in the literature review.

Step three subjected the candidate dimensions to a discriminant test, asking of each pair whether the two could vary independently and whether an indicator could belong unambiguously to one rather than the other. This step is the reason the framework departs from its own first draft: an initial dimension combining instructional process with learning outcome failed the test, since instructor efficiency and vocational competence attainment are constructs at different levels that can move in opposite directions, and the dimension was accordingly separated into a process dimension and a product dimension. The same test established that an overall performance construct defined as educational value delivered could not be held distinct from the dimensions said to predict it, which led to its respecification as a second-order construct.

Step four recorded the resulting derivation in a matrix connecting each dimension to its CIPP component, its associated TAM construct where applicable, its MSD relevance, the discipline-specific requirement it answers, the AI governance principle it enforces, and illustrative indicators. Step five articulated propositions specifying expected relationships, formulated so as to be falsifiable and, in particular, so as not to assert relative importance among dimensions in advance of the weighting exercise that the validation pathway assigns to the Analytic Hierarchy Process. The resulting framework is presented in the next section.

The Integrated Conceptual Framework

Theoretical Foundations and Their Integration

The Context-Input-Process-Product (CIPP) model, developed by Stufflebeam and refined over five decades, is among the most widely applied frameworks in programme evaluation (Stufflebeam & Zhang, 2017). Its four components ask complementary questions. Context evaluation examines needs, problems, and environmental conditions. Input evaluation appraises the resources, strategies, and designs marshalled to meet those needs.

Process evaluation monitors implementation, and product evaluation judges outcomes, both intended and unintended. Crucially, CIPP is improvement-oriented rather than merely accountability-oriented. Applied to an AI-driven repository, context evaluation interrogates the fit between the platform and programme needs; input evaluation appraises holdings and technical capability; process evaluation follows the repository in real instructional use; and product evaluation asks what educational value results.

The Technology Acceptance Model (TAM) holds that two beliefs, perceived usefulness (PU) and perceived ease of use (PEOU), jointly determine attitudes toward a technology and, through behavioural intention, actual use (Davis, 1989; Venkatesh & Davis, 2000).

In education, TAM has proved exceptionally durable: meta-analytic structural equation modelling across teacher samples confirms the model's core paths (Scherer et al., 2019), a systematic review documents its dominance in educational technology adoption research (Granic, 2022), and recent studies extend it to AI-based applications and immersive learning platforms (Wang et al., 2021; Al-Adwan et al., 2023).

A repository produces educational value only through use, and use is contingent on acceptance beliefs; AI functions sharpen this contingency, since recommendation and intelligent search are the platform properties most directly experienced by users as usefulness and ease of use. Evidence that students face real challenges in using AI productively reinforces the point that acceptance cannot be assumed (Liew & Kamrozzaman, 2024).

Media System Dependency (MSD) theory proposes that individuals form dependency relations with media systems to the extent that those systems control information resources needed to attain personal goals, and that dependency intensifies when alternative resources are scarce (Ball-Rokeach & DeFleur, 1976).

A teaching resource repository is, functionally, a media system for its users: it controls access to the materials teachers need to attain teaching goals and students need to attain learning and employability goals. Dependency will therefore vary systematically with users' goals and with the availability of alternatives.

A repository serving resource-scarce institutions will command deeper dependency, and hence exert stronger effects, than one duplicating abundant local provision, which connects repository evaluation directly to educational equity (UNESCO, 2023). It is important, however, not to read dependency as a benign amplifier. Dependency magnifies whatever the system delivers, and a dependent user has fewer means of correcting what it delivers badly;

The same structural condition that makes a good repository more valuable makes a deficient one more damaging. This dual valence is developed below and is written into the propositions. In journalism and communication education, MSD carries the additional distinction of being curriculum content: students study audience-media dependency as professional knowledge, and the repository instantiates the theory they study.

Integration proceeds by assigning each theory a defined role and, equally important, by denying it the others, as summarised in Table 3 and depicted in Figure 1. The input-process-product logic of CIPP generates the evaluation structure. TAM specifies an acceptance mechanism on one designated path and does not condition the framework as a whole. MSD specifies a moderator of dimension-outcome relationships, with the dual valence just described.

A theory that has been given a jurisdiction can be shown to have been misapplied, which is what distinguishes integration from assembly (Zawacki-Richter et al., 2019; Chen et al., 2022): every dimension and proposition in the framework is anchored in an explicit theoretical warrant.

Table 3. Complementary roles of the three theories, and the roles each is denied

Theory	Level of analysis	Core question answered	Role in the framework
CIPP model (Stufflebeam & Zhang, 2017)	Programme level	Across which domains must the repository be judged?	Generates the four evaluation dimensions from input-process-product logic
TAM (Davis, 1989)	Individual-psychological level	Through what belief mechanism do platform characteristics become sustained use?	Specifies the acceptance mechanism linking technological adaptability to use and outcomes

MSD theory (Ball-Rokeach & DeFleur, 1976)	System-structural level	Why do user groups depend on the repository more or less deeply, with what consequences?	Specifies dependency conditions that amplify or attenuate repository effects; links evaluation to equity

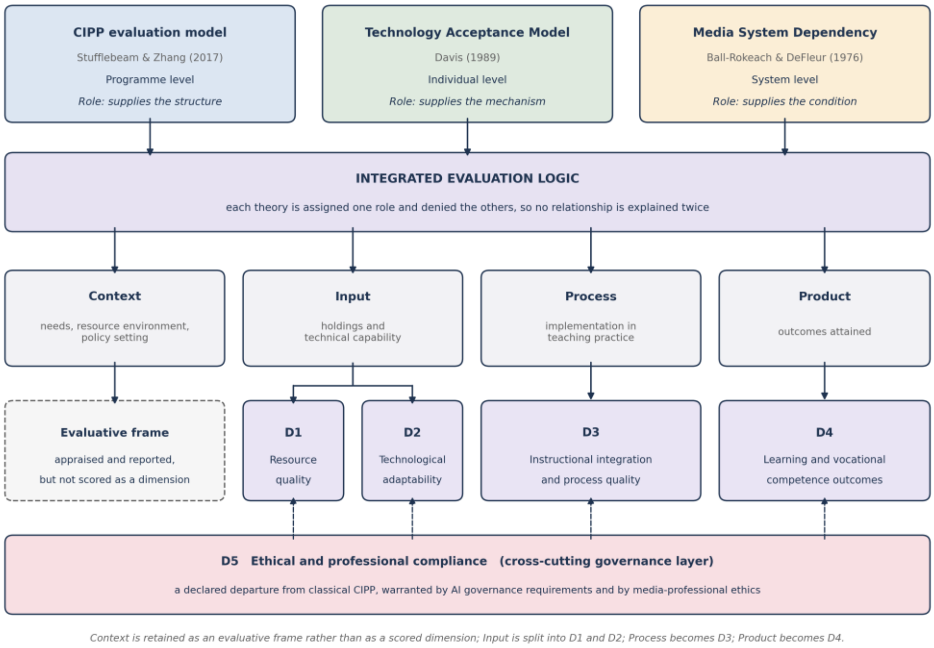

Figure 1. Derivation of the framework: the three theoretical lenses, their assigned roles, and the mapping of CIPP components onto five evaluation dimensions and one evaluative frame

Two Declared Departures From the CIPP Structure

If the framework claims CIPP as its generative logic, then the points at which it departs from CIPP must be declared rather than left for a reader to detect. There are two, and both are deliberate.

The first concerns the context component. Context evaluation in CIPP examines needs, problems and environmental conditions, and it is ordinarily one of four evaluative domains. In this framework, context is not scored as a dimension. The reason is that the institutional resource environment, the national repository policy regime and the programme's needs profile are not properties of the repository being evaluated; scoring them would confound the quality of the artefact with the circumstances of its deployment, and would mean that an identical platform received different quality scores in different institutions for reasons having nothing to do with the platform. Context is therefore retained as an evaluative frame: it is appraised and reported, it determines how the other dimensions are weighted and interpreted, and it enters the propositions as a moderator, but it does not contribute to the performance construct. Figure 1 represents this distinction directly.

The second concerns ethical and professional compliance. Compliance is not one of CIPP's four components, and it could in principle be distributed among them, with data governance treated as an input property, algorithmic fairness as a process property, and so on. It is treated here as a cross-cutting layer instead, for two reasons. Distributing it would make compliance invisible as a category, and the AI-in-education literature is close to unanimous that ethics must be constitutive of quality rather than dispersed among technical criteria (Holmes et al., 2022; Akgun & Greenhow, 2022; Nguyen et al., 2023; Bond et al., 2024). And compliance functions logically as a condition on the others rather than as a parallel contributor: a repository whose recommendation engine is demonstrably biased does not have good technological adaptability and separately poor ethics, it has a technological capability whose educational value is compromised. The framework is therefore CIPP-derived at its structural core and CIPP-extended at its governance layer, and it should be described in those terms rather than as a straightforward application of the model.

The Conceptual Status of Acceptance and of Dependency

Two constructs in the framework are neither dimensions nor outcomes, and their status must be specified precisely if the propositions are to be testable. User acceptance, in the TAM sense of perceived usefulness and perceived ease of use, is specified here as a mediator, and specifically as the mediator of the path from technological adaptability to instructional integration. The restriction is deliberate. Acceptance beliefs are formed about the functions users interact with, which are the recommendation, search, analytic and generative functions constituting the technological dimension; it is through those beliefs that technical capability becomes instructional use (Davis, 1989; Scherer et al., 2019). Acceptance is not specified as a general moderator of every dimension, because no theoretical account is available of why acceptance beliefs about platform functions should condition the relationship between, for example, the accuracy of holdings and learning outcomes. Treating acceptance as both a specific mechanism and a general conditioner, as earlier formulations of this framework did, made it untestable, since a construct that appears everywhere in a model can be neither confirmed nor disconfirmed at any particular point.

Goal-oriented dependency, by contrast, is specified as a moderator, and as one whose valence is dual. The dependency literature has most often been read in education as a claim about magnitude: where alternatives are scarce, effects are larger. That reading is incomplete. Dependency magnifies the consequences of system properties in whichever direction those properties run, and it simultaneously removes the corrective that alternatives would supply. Table 4 sets out this dual valence for each of the principal repository functions, since an evaluation framework that treated dependency only as an amplifier of benefit would systematically under-weight risk in exactly the institutions least able to absorb it.

Table 4. The dual valence of goal-oriented dependency and its evaluative implications

Repository function	Beneficial amplification under high dependency	Adverse amplification under high dependency	Implication for evaluation
Access to current, industry-aligned material	Users in institutions without comparable alternatives gain access to resources they could not otherwise obtain, and the equity return on repository investment is greatest where dependency is highest.	Where the repository is the only realistic source, its coverage decisions become curricular decisions by default, and topics it does not cover may simply go untaught.	Coverage breadth and gap analysis should be weighted more heavily in resource-constrained settings than in resource-rich ones.
Algorithmic recommendation	Consistent surfacing of high-quality material raises the floor of resource selection for less experienced instructors.	Popularity and homogeneity biases are absorbed without correction, since dependent users have no comparison set against which to notice narrowing.	Recommendation diversity and the visibility of ranking logic acquire greater evaluative weight as dependency rises.
Currency of holdings	Central curation can update faster than individual institutions could, which matters acutely in a discipline with a short resource half-life.	Outdated material propagates further and persists longer, because no local alternative is consulted that would reveal it as outdated.	Update latency should be treated as a risk indicator rather than an efficiency indicator where dependency is high.
Data collection and analytics	Aggregate usage data can inform curriculum	Privacy exposure concentrates, and users	Privacy and data-governance indicators

	improvement across institutions.	with no alternative cannot exercise meaningful refusal; consent becomes nominal.	should be scored more stringently for high-dependency deployments.
Generative functions	Rapid production of localised examples, translations and practice items where institutional capacity to author them is limited.	Fabricated or unattributed content enters instruction unchecked, and the discipline's own professional norms are contradicted by the platform that teaches them.	Human verification requirements should scale with dependency rather than being uniform across deployments.
Institutional lock-in	Shared infrastructure lowers duplication and cost across a system.	Switching costs rise, local curation capability atrophies, and the evaluator loses the counterfactual against which repository quality could be judged.	Evaluation should record the availability of alternatives explicitly, as a property of the deployment rather than of the platform.

The evaluative conclusion is that dependency is not a bonus attaching to repositories in under-resourced settings but a condition raising the standard to which they must be held. This reading gives MSD a critical rather than a merely explanatory function within the framework, and it is reflected in the sign-neutral formulation of the dependency proposition.

Overview of the Framework

The framework specifies five evaluation dimensions and one evaluative frame, and defines overall repository performance as a second-order construct comprising the dimensions rather than as a separate outcome predicted by them. The five dimensions are resource quality (D1), technological adaptability (D2), instructional integration (D3), learning and vocational competence outcomes (D4), and ethical and professional compliance (D5). Figure 2 presents the framework and its seven propositions.

The respecification of performance requires justification, since the earlier formulation of this framework treated performance as an outcome that the dimensions predicted. That formulation was untenable. If overall performance is defined as the educational value a repository delivers, and if one of the predictors is defined as the learning and competence outcomes it produces, then predictor and criterion are not distinct constructs and any estimated relationship between them is tautological rather than empirical. The framework therefore adopts the specification that its own definitions require: performance is a formative second-order construct whose facets are D1 to D5, so that a repository performs well by being good along these dimensions rather than by causing something further called performance (Jarvis et al., 2003). This has a direct methodological consequence, taken up in Proposition 1 and in the validation pathway: the dimensions are not interchangeable reflective indicators of a latent quality, and a formative measurement model is therefore required.

The dimensions are conceptually distinct but causally ordered. D1 and D2 are input-side properties of the platform: what it holds and what it can do. D3 is the process dimension: what actually happens in teaching when the platform is used. D4 is the product dimension: what students learn and become able to do. D5 is a cross-cutting governance layer conditioning the others. The separation of D3 from D4 corrects an earlier conflation. Instructor efficiency, course integration and student engagement are process constructs at the level of the teaching encounter; learning gains and vocational competence are product constructs at the level of the student, measured on different instruments, on different timescales, and capable of moving in opposite directions, as when a repository is enthusiastically integrated and produces no measurable competence gain.

Treating them as facets of one dimension would guarantee construct-validity problems at the point of measurement, and the Delphi stage of the validation pathway is accordingly asked to test whether the retained indicators load as the framework predicts.

Table 5 records the derivation of each dimension. It is included because a framework asserting theoretical grounding should allow readers to verify that grounding rather than accept it: each row states which CIPP component the dimension realises, what role if any TAM plays in relation to it, why dependency matters for it, which discipline-specific requirement it answers, which AI governance principle it enforces, and what indicators would express it.

Table 5. Theory-To-Dimension Derivation Matrix

Dimension	CIPP component	Role of TAM	Relevance of dependency (MSD)	Discipline-specific requirement	AI governance principle	Illustrative indicators
D1 Resource quality	Input	Object of perceived usefulness judgements, but not the designated mediated path.	Coverage decisions become curricular decisions where alternatives are scarce.	Currency and industry authenticity, because the resource half-life in media practice is short.	Accuracy and non-deception; diversity of representation.	Content accuracy and authority; update latency; industry-standard alignment; coverage of core vocational competencies; diversity of sources and perspectives.
D2 Technological adaptability	Input	The antecedent of perceived usefulness and perceived ease of use; origin of the mediated path.	Recommendation bias is absorbed uncorrected by dependent users.	The platform's algorithms are themselves objects of study for students of algorithmic media.	Transparency and explainability; robustness; accessibility.	Recommendation precision and diversity; NLP classification accuracy over disciplinary vocabulary; analytic utility; interoperability; accessibility; generative function quality (Table 6).
D3 Instructional integration	Process	The outcome of the mediated path: acceptance converts capability into use.	Where the repository is the default, integration is shaped by what it affords rather than by curriculum design.	Integration must accommodate studio, newsroom-simulation and workplace-based	Human agency and oversight in instructional decisions.	Depth of integration into course design; instructor workflow efficiency; frequency and character of repository-

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				teaching formats.		mediated tasks; student engagement with those tasks.
D4 Learning and vocational competence outcomes	Product	No direct role; acceptance operates upstream.	Outcome gains and outcome harms are both magnified.	Competence must be certified against industry expectations, including AI literacy as a graduate attribute.	Beneficence: demonstrable educational benefit rather than assumed benefit.	Assessed learning gains; vocational competence attainment; AI and media literacy; graduate employability indicators; unintended outcomes.
D5 Ethical and professional compliance	Cross-cutting (declared extension)	Conditions the credibility of usefulness judgements.	Privacy exposure concentrates and refusal becomes nominal.	Professional media ethics are curriculum content, so platform conduct either models or contradicts them (Table 7).	Privacy; fairness; transparency; accountability; intellectual property.	Data protection compliance; algorithmic fairness auditing; explainability provision; IP status of holdings and of generated content; accountability and redress mechanisms.

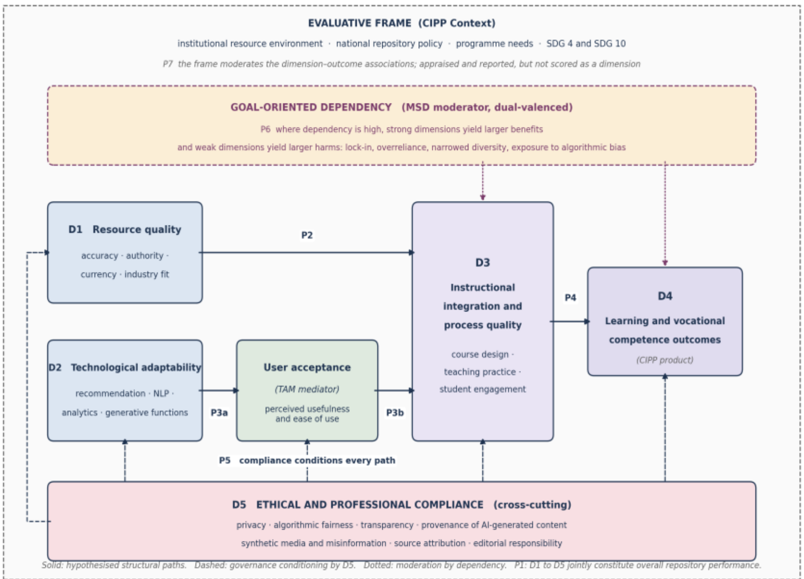

Figure 2. The integrated conceptual framework: five evaluation dimensions within a second-order performance construct, the evaluative frame, acceptance as mediator, and dependency as a dual-valenced moderator (P1-P7)

Evaluation dimensions

Resource quality (D1)

Resource quality denotes the intrinsic merit of the repository's holdings: accuracy, authority, pedagogical soundness, media richness, curriculum coverage, and, decisive in this discipline, currency and alignment with contemporary media industry practice. Within CIPP it is the core of input evaluation. In vocational journalism and communication education the half-life of resources is short: production tools, platform conventions and regulatory environments change rapidly, and repositories must incorporate authentic industry cases and data journalism materials that reflect present practice (Miao et al., 2021). Resource quality also encompasses diversity and inclusiveness of content, consistent with evidence that inclusive design conditions the educational benefits of AI-mediated systems (Xia et al., 2022). Illustrative indicators are listed in Table 5.

Technological Adaptability (D2)

Technological adaptability denotes the platform's technical capability, with emphasis on its AI functions: the precision and pedagogical relevance of intelligent recommendation; the accuracy of NLP-based classification and semantic search over discipline-specific vocabulary; the usefulness of learning analytics; interoperability with institutional systems; system stability, responsiveness and accessibility; and, where present, the quality of generative functions. Reviews of educational recommender systems show that recommendation quality varies widely with technique and context, underscoring that intelligent functions require evaluation rather than presumption of benefit (Urdaneta-Ponte et al., 2021). The dimension deliberately treats AI capability as adaptability rather than sophistication: the evaluative question is not whether the platform deploys advanced models, but whether its intelligent functions adapt to the users, curriculum and workflows of the discipline (Hwang et al., 2020; Holmes & Tuomi, 2022). D2 is also the origin of the mediated path: recommendation precision and search intelligence are the platform properties most directly experienced by users as usefulness and ease of use, and it is through those beliefs that capability reaches instruction (Davis, 1989; Wang et al., 2021).

Where the repository possesses generative capability, the criteria set out in Table 6 apply within this dimension and, for their governance aspects, within D5. They are stated separately because they are not reducible to the retrieval and classification criteria that repository evaluation has conventionally used, and because a framework claiming to address AI-driven repositories cannot leave the fastest-moving class of AI function to be inferred.

Table 6. Evaluation criteria applicable where the repository has generative capability

Criterion	What is evaluated	Why it matters in this discipline
Generation accuracy and fabrication	Rate of factually incorrect or fabricated statements in generated summaries, explanations and item stems; behaviour of the system when asked about matters outside its holdings.	A confidently fabricated case detail entering a journalism teaching resource is not a technical defect but a professional-ethical one.
Provenance and labelling	Whether generated content is machine-readable as generated, whether the generating model and date are recorded, and whether generated and human-authored holdings are distinguishable to users.	Provenance is the discipline's own core competence; a repository that obscures it teaches by counter-example.
Grounding and source attribution	Whether generated output is linked to identifiable holdings, and whether attributions are verified rather than plausible-looking.	Unverifiable attribution is the mechanism by which misinformation acquires credibility.

Prompt-based retrieval behaviour	Whether a conversational interface returns located resources or synthesised answers in place of them, and whether users can tell which they have received.	Substituting synthesis for retrieval silently removes the student from contact with primary material.
Copyright and training data	Licensing status of holdings used for adaptation or fine-tuning; rights position of generated outputs; compliance of generated media with third-party rights.	Intellectual property is both a legal exposure and a professional norm in media production.
Synthetic media generation	Whether the repository can generate images, audio or video; what controls govern that generation; whether outputs are watermarked.	Synthetic media capability inside a journalism repository requires stricter controls than in a general educational platform.
Human verification and oversight	Whether generated material passes human review before instructional release, who performs it, and whether the review is recorded.	Human oversight is the requirement most consistently stated in international guidance (Miao & Holmes, 2023).

Instructional Integration (D3)

Instructional integration denotes what actually happens in teaching when the repository is used: the depth to which its resources and functions are built into course design rather than offered alongside it, the efficiency of instructor workflows, the frequency and character of repository-mediated learning tasks, and student engagement with those tasks. Within CIPP this is process evaluation, and the dimension is deliberately confined to process. It does not include learning gains, which belong to D4.

This confinement is a correction to an earlier version of the framework, in which a single teaching effectiveness dimension combined instructor efficiency, course integration, student engagement, learning outcomes and vocational competence. Those indicators operate at different levels and on different timescales, they are measured by different instruments, and they can diverge: a repository may be deeply integrated and well liked while producing no detectable competence gain, and the evaluative significance of that pattern is destroyed if the two are averaged into one score. Separating process from product also restores the CIPP distinction that the earlier formulation had collapsed. Whether the retained indicators of D3 are themselves unidimensional is an open question, and it is put to the Delphi stage of the validation pathway rather than assumed here.

Learning and Vocational Competence Outcomes (D4)

The product dimension denotes what students learn and become able to do: assessed learning gains, attainment of the vocational competences the programme certifies, AI and media literacy as graduate attributes, and employability-relevant capability. Reviews of AI in higher education consistently identify learning-outcome evidence as the ultimate warrant for AI-enabled systems while cautioning that such evidence is thin relative to technical claims (Zawacki-Richter et al., 2019; Selwyn, 2022; Crompton & Burke, 2023). Retaining outcomes as a distinct dimension is what prevents the framework from certifying a repository as excellent on the strength of its technical and process properties alone. The dimension should also register unintended outcomes, including deskilling of resource selection among instructors and narrowing of the material students encounter, both of which are predicted by the dependency analysis in Table 4.

Ethical and Professional Compliance (D5)

Ethical and professional compliance denotes the repository's conformity with the ethical and regulatory requirements of AI in education: data privacy and protection; algorithmic fairness and the mitigation of bias in recommendation and classification; transparency and explainability of AI functions; intellectual property compliance; and accountability structures for algorithmic decisions. The dimension responds to a substantial literature establishing ethics as constitutive of, not incidental to, educational AI quality (Holmes et al., 2022; Akgun & Greenhow, 2022; Nguyen et al., 2023; Celik, 2023; Bond et al., 2024), and to policy guidance requiring human-centred governance (Miao et al., 2021; Miao & Holmes, 2023; OECD, 2023). Recent expert-consensus work on AI-enabled learning environments likewise ranks ethics and safety among the highest-priority design domains (Kamrozzaman et al., 2025). Generic AI ethics criteria are, however, insufficient for this discipline, and a framework that stopped at privacy, fairness and transparency would be a general AI-in-education instrument wearing a disciplinary label. Journalism and communication education is defined by a professional ethics of information, and the platform that serves it either models that ethics or contradicts it. Table 7 therefore extends the compliance dimension with criteria drawn from the discipline itself.

Table 7. Discipline-specific ethical and professional criteria for journalism and communication repositories

Criterion	What is evaluated	Principal warrant
Misinformation resilience	Whether holdings and generated content are checked against reliable sources; whether corrections propagate to derived materials; whether the repository surfaces contested claims as contested.	Wardle and Derakhshan (2017)
Source attribution and verification	Whether resources model professional attribution practice, and whether case materials retain identifiable sourcing rather than anonymised paraphrase.	Professional reporting standards
Provenance of AI-generated media	Whether the origin of synthetic images, audio and video in the collection is recorded and disclosed to users.	Miao and Holmes (2023)
Deepfake and manipulation material	Whether manipulated media are held for pedagogical analysis under controlled conditions, and whether their status is unambiguous.	Media forensics teaching requirements
Editorial responsibility	Whether an identifiable editorial authority is accountable for holdings, and whether an appeals or correction route exists.	Diakopoulos (2019)
Algorithmic amplification	Whether recommendation concentrates attention on a narrow set of resources, and whether concentration is monitored and reported.	Algorithmic accountability scholarship
Content moderation of user contributions	Where the repository accepts user-generated material, whether moderation criteria are published and consistently applied.	Platform governance norms
Alignment with professional codes	Whether platform conduct is consistent with the professional media ethics codes that the curriculum teaches.	Nguyen et al. (2023); Celik (2023)

Compliance is treated as a condition on the other dimensions rather than as a parallel contributor to them, for the reasons given earlier. A repository whose recommendation engine concentrates attention on a narrow and stale subset of holdings does not possess strong technological adaptability alongside weak ethics; its technological capability is educationally compromised, and the framework represents that relationship as conditioning rather than as addition.

Theoretical Propositions

Seven propositions articulate the framework's expected relationships and render it empirically testable. Two features of their formulation should be noted, because both correct defects in an earlier version. First, noproposition asserts the relative importance of one dimension over another. The earlier formulation claimed that resource quality and teaching effectiveness would outweigh the infrastructural and governance dimensions; that is a weight hierarchy, it had not been established by the literature synthesis, and asserting it in advance would prejudge the very exercise that the validation pathway assigns to the Analytic Hierarchy Process. Relative importance is therefore left as an empirical question. Second, each proposition states the type of relationship it asserts, so that a reader can see what evidence would count against it. Table 8 presents the set.

Table 8. Propositions of the framework, by relationship type, with proposed tests

No.	Proposition	Relationship type	Proposed test
P1	Overall repository performance is constituted by, rather than caused by, the five dimensions: it is a second-order construct whose facets are D1 to D5.	Measurement specification	Comparison of a formative second-order specification against a specification in which performance is an outcome predicted by the dimensions, using fit and construct-validity criteria (Jarvis et al., 2003).
P2	Resource quality (D1) is positively associated with instructional integration (D3).	Direct	Structural path, estimated with the evaluative frame entered as a covariate.
P3a	Technological adaptability (D2) is positively associated with user acceptance, comprising perceived usefulness and perceived ease of use.	Direct	Structural path from repository-function indicators to a validated acceptance measure.
P3b	User acceptance mediates the association between technological adaptability (D2) and instructional integration (D3).	Mediating	Bias-corrected bootstrapped indirect effect; partial rather than full mediation is expected, since some technical properties affect integration without passing through belief.
P4	Instructional integration (D3) is positively associated with learning and vocational competence outcomes (D4).	Direct	Structural path estimated on outcome data collected independently of the integration measure, to avoid common-source inflation.
P5	Ethical and professional compliance (D5) conditions the associations among D1, D2, D3 and D4: where compliance is weak, those associations are attenuated.	Moderating (governance)	Interaction terms between compliance and each conditioned path, with simple slopes reported at high and low compliance.
P6	Goal-oriented dependency moderates the association between dimension quality and outcomes in both directions: under high dependency, strong dimensions yield larger benefits and weak dimensions yield larger harms.	Moderating, dual-valenced	Interaction between dependency and dimension scores, tested for asymmetry across the range rather than for a single positive interaction; multigroup comparison across resource-rich and resource-constrained institutions.
P7	The evaluative frame, comprising the institutional resource environment and the national repository policy regime,	Moderating, contextual	Multilevel or multigroup model with institutions nested within policy systems; the frame is measured and reported but not scored as a dimension.

	moderates the dimension-outcome associations.		

Three of the propositions carry more weight than the others in the sense that their failure would require the framework to be rebuilt rather than adjusted. If P1 fails, and performance is better modelled as an outcome distinct from the dimensions, then the architecture of the framework is wrong. If P3b fails, and acceptance does not mediate the path from technological capability to instructional use, then TAM has no warranted place in the framework and should be removed rather than relocated. If P6 fails in its asymmetric form, and dependency amplifies benefit without amplifying harm, then the critical function claimed here for MSD is unfounded and the equity argument built on it would need to be withdrawn. Stating which failures would be fatal is part of what makes a conceptual framework a scientific rather than a rhetorical object.

Boundary Conditions and Scope

The framework is scoped to discipline-specific, AI-driven teaching resource repositories in vocational journalism and communication education, and its propositions should be read within that scope. Four boundary conditions merit emphasis.

The first is geographical and systemic. As stated in the introduction, the framework is developed primarily for the discipline-specific national repository systems that constitute an established policy instrument in the Chinese vocational college sector, and secondarily for the Malaysian technical and vocational education system, whose repository provision is more institutionally dispersed.

This is not an incidental detail: the two systems differ precisely on the variable that P7 makes a moderator, and applying the framework in either without measuring the evaluative frame would discard information the framework treats as essential. Application beyond these two reference systems is possible but is an empirical question, and the multigroup comparison specified in the validation pathway is the means of answering it rather than a formality.

The second is the institutional resource environment. Following MSD, the framework anticipates stronger repository effects, of both signs, where alternative resources are scarce, so cross-regional applications should model dependency explicitly rather than assume homogeneous effects.

The third is AI maturity and function mix. The technological dimension presupposes platforms with operative AI functions; for conventional digital libraries the framework reduces to a CIPP-derived structure with diminished D2 content. Where generative capability is absent, the criteria in Table 6 are not scored, and the framework should be reported as having been applied in its non-generative form so that scores from generative and non-generative deployments are not compared as if equivalent.

The fourth is disciplinary transfer. While the CIPP-derived structure and the acceptance mechanism are portable to other vocational disciplines, the dependency layer and the professional-ethics loading of D5 are calibrated to media-related fields. Transfer to other disciplines would require substituting an appropriate discipline-specific theoretical lens and rebuilding Table 7, and would not be a matter of relabelling.

DISCUSSION

Theoretical Contributions

The framework makes three theoretical contributions, stated here once rather than restated from earlier sections. The first is a discipline of role assignment. Multi-theory frameworks are common and are often criticised as eclectic; the defence offered here is that each theory has been given a jurisdiction and denied the others, that the jurisdictions are recorded in a derivation matrix, and that the framework specifies for each theory what evidence would show it to have been misapplied. This is a transferable strategy for the evaluation of other complex educational technologies, and it is a stronger claim than the assertion that a framework is theoretically grounded.

The second is the respecification of two constructs whose treatment in comparable models is often loose. Acceptance is confined to a mediating role on a single path, rather than functioning as a general conditioner that no evidence could disconfirm. Overall performance is specified as a second-order construct rather than as an outcome distinct from its own constituents, which removes a tautology that would otherwise have been carried into measurement (Jarvis et al., 2003).

The third is an extension of MSD theory itself. Conceptualising an educational repository as a media system on which teachers and students are goal-dependent revives a classical communication theory for the platform era, and the dual-valence formulation developed here adds something the original formulation left implicit: dependency is not a benign amplifier but a condition that magnifies harm as readily as benefit, and that removes the corrective which alternatives would otherwise supply. That reformulation gives the theory a critical function within evaluation and connects repository quality to structural questions of educational equity that individual-level acceptance theories cannot reach.

Practical and Policy Implications

For repository managers, the framework functions as a diagnostic map rather than as a prescription. The five dimensions organise self-assessment, the derivation matrix indicates what each dimension is meant to capture, and the evaluative frame prompts managers to record the conditions of deployment alongside the scores. What the framework does not yet supply is a priority ordering. An earlier version advised that content renewal and pedagogical integration should be addressed before technical embellishment; that advice presupposed a weight hierarchy which has not been established, and it is withdrawn here.

Any ordering of remediation priorities should follow the weighting exercise described below, and until then recommendations derived from the framework should be treated as provisional. What can be said without weights is narrower and more defensible: that a dimension left unmeasured cannot be managed, and that ethical and professional compliance operates as a condition on the others rather than as a component that can be traded against them.

For vocational educators, the framework legitimises demands that AI functions serve curriculum and workflow rather than the reverse, and it supplies vocabulary for articulating discipline-specific requirements to platform developers; realising this in practice also requires sustained investment in educator readiness for AI-mediated teaching (Luckin et al., 2022). For institutional leaders and policymakers, the dependency layer carries a distributive message that is more demanding than the familiar one.

Because dependency amplifies in both directions, investment in shared repositories yields its largest educational returns in under-resourced institutions and also concentrates its largest risks there; the policy implication is not simply to invest but to hold high-dependency deployments to a higher evidentiary standard on currency, diversity and data governance (UNESCO, 2023; OECD, 2023; Ifenthaler et al., 2024). Institution-level AI policy frameworks provide a natural home for the compliance criteria set out in Tables 6 and 7 (Chan, 2023).

Alignment with the United Nations Sustainable Development Goals

The framework aligns primarily with Sustainable Development Goal 4 (SDG 4): ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. Target 4.3 concerns equal access to affordable technical and vocational education, and Target 4.4 concerns increasing the number of youth and adults with relevant skills for employment; high-quality, well-governed AI-driven repositories in vocational journalism and communication education advance both, by widening access to current, industry-aligned learning resources and by supporting the digital and AI-related competencies that media employment now requires (Miao et al., 2021; UNESCO, 2023).

The lifelong-learning emphasis of SDG 4 is reinforced by regional scholarship demonstrating how technology-mediated, self-determined learning can sustain education beyond formal schooling (Kamrozzaman et al., 2020). Through its dependency-sensitive treatment of regional resource disparities, the framework also contributes to SDG 10 (Reduced Inequalities): evaluation criteria that reward cross-institutional sharing and equity of benefit direct repository development toward narrowing, rather than reproducing, digital divides. Embedding SDG-relevant criteria within the ethical compliance and teaching effectiveness dimensions ensures that sustainability commitments are audited rather than merely asserted (Kamalov et al., 2023).

Limitations and Future Research Directions

As a conceptual contribution, this paper carries the limitations of its genre, and four should be stated without softening. First, the framework is derived from theory and literature rather than from data: its seven propositions are warranted but untested, and Table 8 states what would count against each of them precisely because none has yet been examined. Second, the review underlying it is integrative rather than systematic.

The protocol is reported in Table 2, but screening was conducted without independent duplication, no appraisal of study quality was applied, and saturation was judged against the emerging framework rather than against an external criterion; the derivation matrix is published so that readers can test the mapping, but publication is not the same as independent verification. Third, the framework supplies no indicator weights, and the relative importance of the five dimensions is deliberately left open; practical recommendations drawn from it are therefore provisional until the weighting stage is complete. Fourth, the scope conditions confine confident application to vocational journalism and communication education within the two reference systems described in the boundary conditions, and transfer beyond them is an empirical question rather than an extension.

These limitations define a concrete research agenda, set out as a staged pathway in Table 9. The sequence matters: weighting before indicator validation would weight items that may not survive, and structural modelling before construct-validity testing would confound measurement failure with structural failure. The pathway also extends the earlier three-step operationalisation plan in two respects that the framework now requires, namely explicit construct-validity testing of the second-order specification, and multigroup comparison of dependency effects rather than a single pooled estimate.

Table 9. Staged pathway for the empirical validation of the framework

Stage	Design	Principal output	What it tests
Stage 1. Delphi indicator development	Two or three rounds with panels combining vocational journalism educators, repository managers, and AI governance specialists across the reference systems.	A validated indicator hierarchy for D1 to D5, including the generative and discipline-specific criteria in Tables 6 and 7.	Tests whether the indicators assigned to instructional integration and to outcomes are judged to belong to separate constructs, as the framework claims.
Stage 2. AHP weighting	Expert pairwise comparison with standard consistency verification (Saaty, 1980), conducted separately within resource-rich and resource-constrained strata.	An empirically derived weight structure, and a first indication of whether weights differ by deployment context.	Supplies the priority ordering that the framework deliberately declines to assert in advance.
Stage 3. Construct-validity testing	Survey administration to instructors and students, with confirmatory factor analysis, composite reliability, average variance extracted, and discriminant validity assessment.	A measurement model, and a decision on whether performance is better specified as a formative second-order construct or as a distinct outcome.	This is the direct test of Proposition 1, and it is the stage at which the architecture of the framework is most exposed.

Stage 4. Structural modelling	Structural equation modelling of Propositions 2 to 5, with bias-corrected bootstrapping for the mediated path and interaction terms for the compliance condition.	Estimates of the dimension relationships and of the acceptance mediation.	Tests whether TAM earns its place in the framework; a null indirect effect would require its removal rather than its relocation.
Stage 5. Multigroup and contextual comparison	Multigroup analysis across resource-rich and resource-constrained institutions, and across the Chinese and Malaysian reference systems, with measurement invariance established before structural comparison.	Estimates of the dependency and evaluative-frame moderations, including asymmetry across the range of dimension quality.	Tests Propositions 6 and 7, and with them the equity argument that the framework rests on MSD.
Stage 6. Outcome and use-data validation	Linkage of framework scores to actual repository log data and to independently assessed learning and competence outcomes, ideally longitudinally.	Evidence on whether the framework predicts educational value rather than merely describing platform properties.	Fuzzy comprehensive evaluation (Zadeh, 1965) may be used at this stage to aggregate multi-stakeholder judgements into composite grades.

Two further studies would strengthen the framework beyond validation. A comparative application across repositories with and without generative capability would establish whether the criteria in Table 6 discriminate as intended, and a longitudinal design tracking repository improvement against subsequent competence attainment would test the claim, currently only asserted, that framework-guided improvement translates into educational value.

CONCLUSION

AI has transformed teaching resource repositories from digital warehouses into intelligent educational platforms, and evaluation practice has not kept pace. This paper has developed an evaluation framework for AI-driven teaching resource repositories in vocational journalism and communication education by assigning the CIPP evaluation model, the Technology Acceptance Model, and Media System Dependency theory distinct and non-overlapping roles within a single architecture. The framework specifies five evaluation dimensions within a second-order performance construct, retains the context component of CIPP as an evaluative frame rather than as a scored dimension, confines acceptance to a mediating role on one designated path, and treats dependency as a moderator whose valence is dual. It brings generative capability explicitly within scope and extends the compliance dimension with the professional-ethical criteria the discipline itself supplies.

The framework is offered as a hypothesis about how repository quality should be conceived, not as a finding. Its derivation is published in a matrix so that it can be contested, its propositions are stated with the tests that would refute them, its weight structure is left open rather than asserted, and its validation is planned in six stages beginning with the construct-validity test on which its architecture depends. Its intended contribution is to ensure that when the measuring begins, the instrument knows why it measures what it measures, and can be shown to be wrong if it does not.

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