From Passive Learning to Active Learning: An AI–Digital Media Convergence Framework for Transforming Education

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ABSTRACT

Learning practice can be digitalised without altering its mode of transmission. Generative artificial intelligence (GenAI) has the potential to broaden the options for explanation, drafting, visualisation, dialogue and feedback, yet these capabilities do not necessarily lead to active learning. This conceptual paper proposes the AI–Digital Media Convergence Framework (AIDMCF) which outlines how AI capability and digital-media affordances can potentially facilitate the active construction of knowledge with purposeful pedagogy, learner agency, and teacher facilitation. Eight recursive processes are identified in the framework: knowledge discovery, creation of knowledge, visualisation, dissemination, engagement, assessment, feedback and enhancement. To enhance its scope of explanation, the paper combines SRL and metacognitive monitoring and discusses the expectancy–value perspectives to account for the possibility of meaningful or non-meaningful learning. It identifies the 8 processes based on the main didactic goal achieved and acknowledges that they can be present at the same time in the same activity. The working set of an operationalisation matrix provides observable indicators for future research, while a worked scenario describes how the processes interact in a media-literacy task. The paper also details qualitative, quantitative and mixed methods approaches to empirical validation as well as considers access, language, disability inclusion, privacy and institutional capacity. The AIDMCF is a conceptual model, not a model that has been tested empirically; the propositions and indicators are offered as guidelines for systematic testing and refinement.

Keywords: Generative AI; digital media; active learning; self-regulated learning; quality education

INTRODUCTION

Most formal education has been highly sophisticated and organized for the transmission of information from a knowledgeable speaker (teacher, book, talk) to a somewhat docile listener. The next steps in educational technology since the emergence of the print-based system of communication – film and radio, television, computers, and the early internet – have all been touted as solutions to replace it, but historical and contemporary research has converged to conclude that one after another technology development in education has arrived, passed, and gone, whilst remaining the same or a digital version of a pre-existing method. Since print, the next developments in the field of education technology have each had claims made for their capacity to replace the print-based system of communication, but each of these and the many that followed since then have come and gone, at least as far as replacing print is concerned, and often have been only the digitisation of existing practice (Facer & Selwyn, 2021).

Pedagogical transmission from experts and reception by students was mostly preserved, as were lectures, learning management systems, and the replacement of the chalkboard with video. The pedagogical relationship of the expert transmitting and the learner receiving was mostly intact, along with lecture notes, learning management systems and replacing chalkboard with video. Artificial Intelligence (AI), and in particular Generative (GenAI), has created a new technological circumstance. Aside from storing or delivering existing

content, modern AI models can create, transform, customize, visualize, simulate, converse and assess content in various modalities including text, image, audio and video (Kasneci et al., 2023). In theory, through this generative and multimodal ability, students can move from being mere recipients of information to their own construction, questioning and production of knowledge. The impact of GenAI on students' experience has been documented at large scale through extensive surveys, which indicate that many students have seen GenAI as a tool for personalised support, brainstorming, and research assistance (Chan & Hu, 2023); and systematic reviews suggest that evidence of this impact is gaining momentum rapidly but remains inconsistent (Wu et al., 2025).

The principal thesis of this paper is that ability in the field of AI is not synonymous with active learning. Technology of any type is pedagogically neutral until it is purposefully designed and creatively linked to a purpose in which the learner is given the "space" to build knowledge (as opposed to "information output"). Whether the use of AI is perceived as a replacement of a format (such as a worksheet) or a transformation of a learning task (such as a different way of inquiring, conversing, or creating a multimodal product), is determined by the interaction of four factors – AI capability, digital media affordances, pedagogical design, learner agency and teacher facilitation. This argument resonates with the studies of critique of technology in education, which have tended to focus on issues of technology determinism, and instead have pointed to the conditions that lead to educational outcomes in relation to the processes of appropriation of technologies (Facer and Selwyn, 2021).

From Digitalisation to Transformation

The past application of technology to education illustrates a consistent trend of technology being used in the context of what is already being done in education. This has been suggested in the Substitution–Augmentation–Modification–Redefinition (SAMR) model that differentiates between technology uses that simply replace an analogue technology and those that completely redefine tasks that could not have been done without the technology (Hamilton, Rosenberg, & Akcaoglu, 2016). Like many models, however, there are some concerns with SAMR that the hierarchical order can obscure context, the technology and learning outcomes relationship can be superficial, and the model can emphasize product or process (Hamilton et al., 2016). The SAMR model is thus used here as a helpful tool for viewing technology-mediated pedagogical change, not as an explanation in itself, which reflects the request for more contextually appropriate explanations of technology-mediated pedagogical change.

AI, Digital Media and the Active-Learning Problem

Decades of empirical research in undergraduate science, technology, engineering and mathematics (STEM) education has demonstrated that students who learn by doing the work who build their own knowledge, understanding and problem-solving skills have much better examination scores and lower failure rates than those who learn mainly through listening to lectures (Freeman et al., 2014). This evidence is used to draw pedagogical conclusions that learning is meaningful when the learner is involved in the learning process and not just exposed to it. But most of the research literature on the topic of AI in education has been produced outside of this tradition of active learning, and has focused on the technical capabilities, adaptive sequencing, or automated assessment (Zawacki-Richter et al., 2019). What ends up being produced is a copious amount of technical description, and surprisingly little theorising about the pedagogy of active knowledge construction and its structures or mechanisms, which lies at the core of the ability of AI.

Digital Media Technologies **are** practices that represent, produce and communicate information in the form of text, image, sound, video and interactive media. They create the contexts for examining and modifying AI generated and/or AI mediated content. Multimedia-learning research indicates that well-constructed combinations of words and pictures can aid understanding, as long as they are designed while taking into account cognitive-processing constraints (Mayer, 2021). Making a diagram or video is not a learning process itself; it is only educational if learners interpret, select, organize, and justify the diagram/video.

Research Gap

The domains of research related to AI-supported active learning are somewhat disjointed, including AI in higher education (Zawacki-Richter et al., 2019), GenAI and its educational implications (Kasneci et al., 2023; Wu et al., 2025), multimedia learning (Mayer, 2021), the frameworks of technology integration (Hamilton et al., 2016; Mishra & Koehler, 2006), and active and learner-centred pedagogy (Freeman et al., 2014; Laurillard, 2012). These works of art highlight the capacities of individual artists, as well as pedagogical challenges and dangers, but do not offer as much conceptual support for how AI and digital media might function throughout an inquiry-to-revision journey. The space for discussion addressed here is thus conceptual, in that the paper suggests a process-oriented account of this relationship. It does not say that each of the component processes is not studied, or that convergence necessarily enhances learning.

Research Problem and Questions

The central research problem is: How is the AI–digital media convergence to be conceptualised as a pedagogically meaningful process leading to a transformation of knowledge transmission into active, pedagogical knowledge construction? What can be thought of as a pedagogically meaningful process for transforming the transmission of knowledge to knowledge construction that is enabled by the convergence of AI and digital media? The paper addresses five questions: (1) How can the AI–digital media convergence be understood as a process that facilitates active knowledge construction? (2) What are the ways of analytically distinguishing its eight processes but acknowledging the overlap? (3) What role does self-regulation, metacognition and motivation play on learners' participation? (4) What are some of the factors that can be observed that might be used as an empirical test? (5) What conditions of pedagogy, institutions and equity can facilitate or impede the framework?

Purpose, Contribution and Structure

This conceptual paper introduces the AI–Digital Media Convergence Framework (AIDMCF), an eight-process model for the possible support of active knowledge construction by AI capabilities and digital-media affordances. It brings a process-oriented synthesis, a functional taxonomy of educational AI, as well as indicators and propositions for future testing. The paper presents a literature review of relevant theory, an explanation of the conceptual method, the framework and implications for implementation and concludes with theoretical propositions and an agenda for empirical validation.

Dimension	Passive / Traditional	Digitised (non-transformative)	AI–Digital Active Learning
Learner role	Recipient of transmitted content	Recipient of digitised content (e.g., slides, PDFs)	Producer and critical evaluator of knowledge artefacts
Teacher role	Sole authority and information source	Content distributor via digital channel	Designer, curator, and facilitator of AI-mediated tasks
Media function	Static delivery (chalkboard, textbook)	Digital replication of static delivery	Generative, multimodal, and interactive representation
Feedback	Infrequent, delayed, summative	Digitised but still largely summative	Frequent, iterative, formative, AI-assisted
Underlying logic	Transmission of fixed content	Digitisation of transmission logic	Convergence of AI capability and pedagogical design

Table 1. Conceptual comparison between passive, digitised, and AI–digital active learning.

LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

This section explores some of the literature on active learning, constructivist and conversational pedagogy, integration of technology, multimedia cognition, AI in education, GenAI, self-regulated learning and digital-

media practices. The review is thematic and not systematic because its aim is to explain the theoretical resources that were employed in building AIDMCF.

Active Learning and Learner Agency

Freeman et al. (2014) carried out a meta-analysis of 225 STEM studies and reported that active learning correlated to better performance on examinations and fewer failures, compared to traditional lecturing. This evidence suggests that a criterion for assessing technology mediated instruction should be based on the learner-action mode and the question should be asked whether the learners practise, question, apply, produce, explain, or not, irrespective of the tool that is used. AI can be used to aid in these, but it can be used as an active learning, too. Evidence of active-learning does not warrant active-learning evidence of the use of AI.

Constructivism and Knowledge Construction

Constructivist viewpoints view learning as one in which the learner constructs, elaborates and negotiates the meaning of the content they learn, rather than absorbing it without change. Conversational learning is also viewed as a process of constantly going back and forth between action, feedback, and revision, as outlined by Laurillard (2012). When tasks are not answer-related, but instead involve continuous, extended reasoning and revisiting of ideas, conversational AI may help such cycles, as it can follow up on student responses and prompt additional explanations.

Digitalisation and Pedagogical Transformation

A common distinction in research on educational-technology is that between digitalisation (the shift of the same learning activity from one medium to another, to digital) and transformation (the use of technology to make qualitatively different learning activity possible). Policies for new technologies should be grounded in understanding that these technologies do not necessarily threaten existing pedagogical practices, as noted by Facer and Selwyn (2021). The outcomes are not determined by the technology, but by the pedagogical design and institutional context, as well as equity of access.

Technological Pedagogical Content Knowledge and Teacher Judgement

The TPACK/TPCK model (Mishra & Koehler, 2006) sees effective technology integration as the situated interaction of content knowledge, pedagogical knowledge and technological knowledge. In the case of AI-based teaching, it involves assessing if the ability is relevant to the learning goal/purpose, subject matter/content, and learners' needs. It is, therefore, judgment of the teacher who acts as a mediating condition and not an optional add-on to tool selection.

Multimedia Learning and Multimodality

The cognitive theory of multimedia learning emphasizes that the simultaneous use of words and images has an advantage if it is designed well, but this advantage is negligible when the capacity for processing words and images is exceeded, and when the information presented need to be selected, organized and integrated by the learner (Mayer, 2021). AI-generated diagrams, narrated explanations and simulations can assist these processes when they explain relationships and manage cognitive load. The more modalities or complexity, the better the learning, is not always the case.

AI in Education

Zawacki-Richter et al. (2019) conducted a review of 146 studies on the use of AI in higher education from 2007-2018. They recognised three areas that needed to be explored: profiling and prediction; adaptive systems and personalisation; assessment and evaluation; and the fact that comparatively little attention has been given to educators and pedagogical theory. This review is useful background to this framework which emphasises the importance of learner activity, teacher judgement and technical function.

Generative AI and Pedagogical Transformation

Research on GenAI has identified the following capabilities: explanation, coding, feedback and content generation, and risks: inaccurate output, bias, academic-integrity concerns and over-reliance (Kasneci et al., 2023). Students share the positive aspects of personalised support and research, and the worries surrounding precision, ethics and free thinking (Chan & Hu, 2023). A recent review also notes both exciting uses and ongoing questions regarding the pedagogical impact (Wu et al., 2025). Academic-integrity issues must be evaluated and addressed within the institution and not simply detected, or given blanket permission (Cotton et al., 2024). Collectively, this body of literature not only raises the question of how best to organize AI-supported activity, but also does not confirm to anyone the effectiveness of this approach.

Self-Regulated Learning, Metacognition and Motivation

Self-regulated learning (SRL) is a learner's process of planning, monitoring, and adapting his/her learning. In Zimmerman's (2002) cyclical representation, forethought is represented by goal setting, planning; performance is represented by strategy use, self-observation; and self-reflection is represented by evaluation and decisions about future action. These stages can happen in any AIDMCF process, for instance, when planning the inquiry, learners can plan in discovery; during engagement, they monitor their reasoning; during assessment, they evaluate their work and select what to revise; and during enhancement, they decide what to revise. SRL is not a process but rather a cross cutting regulatory layer. AI might support and structure regulation by asking students to communicate goals and explain revisions, yet it could also limit regulation by providing students with answers without asking for monitoring.

Visible activity does not mean the same as learning because it is metacognition—the monitoring and regulation of thinking—helps explain this. Artifacts or AI claims may still have unpolished aspects or misinformation. Metacognitive evidence for candidates is thus displayed in the form of explanations for why a chosen source was used, why feedback was welcomed or resisted, and why there were changes in drafts. Reflection should be related to evidence of the task, not just to self-reported engagement. Motivation can affect learners' effort in these processes. According to SDT, autonomy, competence and relatedness are conditions that relate to self-motivated engagement (Deci & Ryan, 2000). For AI-assisted tasks, autonomy can be fostered through meaningful task choice and the ability to refuse to use AI; competence through scaffolding and making tasks appropriate; and relatedness through retaining teacher and peer conversation. According to the expectancy–value theory, engagement is influenced in part by expectations of success and value of the task (Eccles & Wigfield, 2020). Theories should look to mechanisms to be investigated, not motives.

Digital Engagement and Knowledge-Production Infrastructure

The design of media, learner activity and tasks influence learner's engagement other than the tasks. Digital tools can be used to aid inquiry where they can allow for testing of ideas, comparison of options and response. This further emphasizes AIDMCF's principle that the framework is not product or platform specific but is based on learner process. The use of digital media as knowledge-production infrastructure. The adoption of digital media as knowledge-production infrastructure.

In addition to being a means of transmitting information, digital media also give shape to the representation, testing and communication of knowledge. Making an explanatory diagram, video or data visualisation can be a learning activity in itself since learners need to choose and explain the representational decisions they make. Thus, AIDMCF sees knowledge creation and dissemination as separate but linked processes; knowledge creation focuses on creating an artefact or explanation, while dissemination focuses on communicating the artefact or explanation to an audience.

Synthesis of Theoretical Foundations

All these theories bring together complementary principles of AIDMCF: Learner participation, iterative feedback, situated teacher judgement, cognitive-aware multimodal design, and critical assessment of AI

capabilities and risks. The framework incorporates these concepts into a process model; the proposed links are conceptual and need to be empirically examined.

Theory	Core Idea	Contribution to the AIDMCF
Active learning (Freeman et al., 2014)	Learner participation, not exposure, drives measurable performance gains	Establishes learner activity as the evaluative criterion for every process
Constructivism / Conversational Framework (Laurillard, 2012)	Learning proceeds through iterative cycles of action, feedback, and revision	Provides the iterative, cyclical logic underlying Engagement, Feedback, and Enhancement
Multimedia learning (Mayer, 2021)	Well-designed combinations of words and images support cognitive processing within capacity limits	Grounds Visualisation and Dissemination in cognitive-load-aware design principles
TPCK (Mishra & Koehler, 2006)	Effective technology use requires situated integration of technology, pedagogy, and content	Frames teacher judgement as the mediating factor across all eight processes
SAMR (Hamilton et al., 2016)	Technology use ranges from substitution to redefinition of the learning task	Supplies a cautionary, critically-applied lens for evaluating depth of AI integration
Digital media and multimodality (Mayer, 2021)	Media are infrastructure for representing and communicating knowledge, not just delivering it	Reframes Knowledge Creation and Dissemination as epistemic, not merely presentational, activities

Table 2. Theoretical foundations and their contribution to the AI–Digital Media Convergence Framework.

METHODOLOGY

In this paper, a conceptual design that builds theories will be utilized, based on the integration of relevant scholarship and a preliminary framework. No original data was gathered and no participants, surveys, experiments or statistical analysis were performed. The aim is to combine the constructs, to state the proposed relationships between the constructs, and to propose propositions for further empirical testing. This study is not a systematic literature review nor does it achieve preregistered search, dual-reviewer screening or quantitative synthesis, as this would be PRISMA-level coverage. The literature was found by a targeted and purposeful search on foundational and recent peer-reviewed publications on active learning, constructivist pedagogy and conversational pedagogy, multimedia learning and frameworks for integrating technology in education and AI/GenAI in education. Where possible, bibliographic information and DOIs were verified against the records of the publisher or the indexer/repository. Studies that were relevant but not sought may not have been included as the search was not comprehensive.

The conceptual synthesis was done in four steps. Recurring constructs were identified: learner participation, iterative feedback, multimodal representation, pedagogical judgement and generative capability. Secondly, the relationship of these constructs has been investigated, such as the relationship of multimedia-learning principles to AI-generated visualisation, and conversational pedagogy to AI-mediated dialogue. Third, processes for candidates were mapped and evaluated for distinctiveness, overlap and theory. Fourth, the map was translated into the eight-process AIDMCF, the functional taxonomy of educational AI and a set of propositions for further testing. They are not empirically proven results, but rather conceptual results. Empirical results are referred to throughout the paper, with specific interpretations of existing theory, and original conceptual suggestions made in this paper, differentiated from cited empirical results. The mechanisms and propositions outlined in the framework are suggestions that should be considered as hypotheses rather than outcomes.

The AI–Digital Media Convergence Framework

Defining Convergence

AIDMCF's conception of convergence is the synergistic integration of AI capabilities and digital-media affordances for a targeted pedagogical objective. The learner activity (what the learner is expected to do) should match up with the technological function (what the system can do). If learners are asked to receive only, for example, an AI-generated summary on a lecture slide, this may be nothing more than a digitised version of the transmission. Convergence (here) is when task design places learners as active agents in one or more of eight mutually interconnected processes: discovery, creation, visualisation, dissemination, engagement, assessment, feedback, and enhancement. The processes are iterative and not linear – a learner can go back to discovery after feedback or change a visualisation in the process of explaining. The pedagogical purpose, the potential contribution of AI, the expected activity of the learners, and the role of the teacher and the pedagogical risks are identified for each process. These are categories to design and analyze learning tasks, and not an expectation that all use of AI will lead to the outcomes.

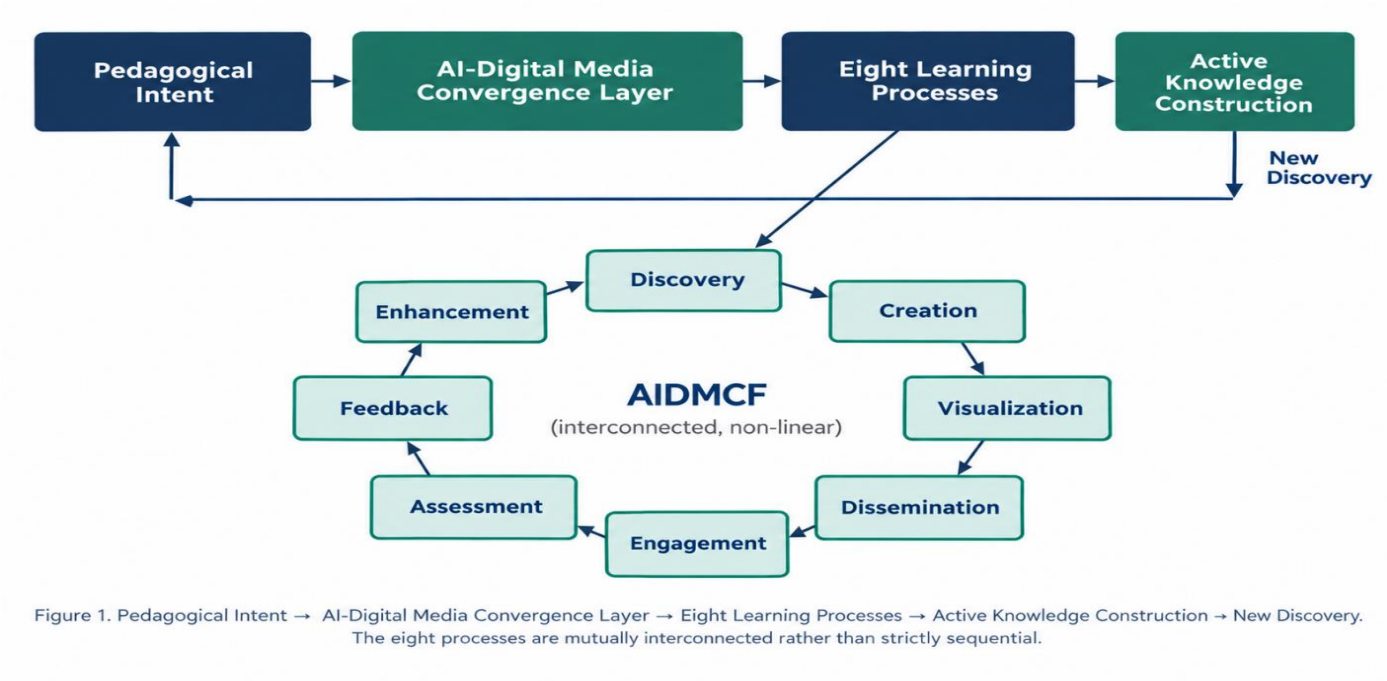

Figure 1. Conceptual representation of AIDMCF: pedagogical intent informs AI–digital media convergence across eight recursive processes, supporting active knowledge construction and further inquiry.

Process	Pedagogical Purpose	AI Contribution	Learner Activity	Potential Risk
Knowledge Discovery	Orient learner within a topic through inquiry	Retrieval, summarisation, question-answering	Investigate, question, compare sources	Uncritical acceptance of AI summaries
Knowledge Creation	Produce content learners take ownership of	Generative drafting (text, code, image)	Produce, then critique and revise	Over-reliance / cognitive offloading
Visualisation	Make abstract concepts perceptible	On-demand diagram/model generation	Interpret and design representations	Cognitive overload from poor design
Dissemination	Communicate knowledge to an audience	Drafting, formatting, translation support	Author with audience awareness	Polish masking shallow understanding
Engagement	Sustain iterative dialogue and	Conversational and simulation	Question, practise, iterate	Superficial, single-turn interaction

	practice	response		
Assessment	Evaluate understanding and performance	Pattern recognition, rapid scoring	Self-monitor using feedback	Bias or inaccuracy treated as authoritative
Feedback	Close the gap between performance and standard	Individualised, near-immediate feedback	Interpret and revise	Homogenisation of learner responses
Enhancement	Refine and extend prior work	Suggest revisions and extensions	Reflect and revise critically	Deference to AI-suggested changes

Table 3. The eight processes of the AI–Digital Media Convergence Framework (AIDMCF).

Knowledge Discovery

Knowledge discovery assists the learner to discover the topic rather than being told and to orient himself to it by asking questions. Digital media offers searchable, multimodal resources; AI can offer suggestions for search terms, candidate source summaries and questions. Learners should ask questions, check sources, check for uncertainty and record it. Creatively organized by teachers, reliable starting points and modeling of source evaluation are provided. This process can facilitate enquiry, but it can also be a limitation to investigation if people simply accept the AI-generated summary without questioning it carefully.

Knowledge Creation

Knowledge creation happens when pupils build or significantly modify an explanation, text, code, image or other artefact, utilizing AI-generated output as a possible starting point or catalyst for creation but not as a replacement for the learners' own creation. These artefacts can be created and edited within digital authoring environments. Teachers should be clear about authorship expectations and allow learners to use AI; learners should provide explanations for their decisions, and critically evaluate their outputs. While AI can help to decrease barriers to prototyping, over-dependence can diminish independent generative effort and hinder academic integrity (Cotton et al., 2024).

Visualisation

Visualisation is the use of diagrams, models, simulations or displays of data to represent abstract and/or complex relationships. AI can create or edit candidate representations, and digital media enable students to analyze and manipulate candidate representations. Learners need to explain (and, if relevant, evaluate or design) the representation. Teachers judge the effectivness and optimisation of the visual form for the learning objective and for avoiding unnecessary cognitive load (Mayer, 2021). Simply having a lot of visual information does not constitute conceptual understanding.

Dissemination

Dissemination includes presentation, video, blogs or other media to communicate constructed knowledge to a specific audience. AI can help with drafting, translation or formatting, and digital platforms will help with the publishing and distribution of the content. The accuracy, attribution, audience awareness and ethical communication requirements still apply to learners. A high quality finished product may mask lack of depth of understanding and questions about the evidence and decisions made in the creation of the artefact may be used to assess the work.

Engagement

Engagement in this context is defined as sustained dialogue, questioning, practice or simulation with content. Learner input can be answered by conversational AI and facilitate iterative exchanges that align with Laurillard's (2012) conversational framework. Pupils should pose questions to follow, experiment with options

and describe how answers impact on their argument. Teachers plan for multi-turn tasks and demonstrate effective questioning. One response is not enough to show ongoing engagement.

Assessment

Assessment is the process of making a judgement about what a learner knows or how well he or she performs against a specified set of criteria. Formative scoring and/or diagnosis could be done with AI and tasks can be given and responses recorded with digital media. Assessment can be used by learners to track their learning and teachers are responsible for the validity, fairness and appropriate use of judgements. While AI can provide automated scoring, it is essential to verify the results with careful human oversight to prevent potential inaccuracies or biases in the evaluation (Kasneci et al., 2023; Cotton et al., 2024).

Feedback

Feedback: Information about the difference between what one is doing and what one is trying to achieve or criterion. AI can offer personalised, quick responses, and digital media can facilitate and retain them. The learner has to understand the feedback and make decisions about what it means for their work; the teacher has to fix any inaccurate feedback and suggest when the feedback is useful. The feedback is not the same as revision, it is identifying a gap or a possible next step, the enhancement is a matter for the learner's next step.

Enhancement

Enhancement is intentional change of work as a result of assessment, feedback and reflection by the learner. Version histories and editing environments allow to see the changes, and AI may propose alternatives. Suggestions must be accepted, adapted or rejected with reasons, and for the teacher to evaluate the quality of the revision process and the revised product. If the process is designed to develop judgement, then uncritical acceptance of AI suggestions will remove the purposeful judgement.

A Functional Taxonomy of Educational AI

The paper proposes a functional taxonomy rather than a list of commercial products, which can change rapidly or combine functions. The six categories—AI Discoverers, AI Creators, AI Visualisers, AI Interactors, AI Assessors and AI Enhancers—describe dominant educational functions and map onto one or more AIDMCF processes. A single system can have more than one function (categories are not mutually exclusive). The taxonomy is designed to aid in the selection of pedagogical tools and not to assert the effectiveness or imply it.

Category	Function	Educational Role	Learner Activity	Primary AIDMCF Process
AI Discoverers	Information discovery and retrieval	Inquiry	Investigate	Knowledge Discovery
AI Creators	Content and idea generation	Knowledge creation	Produce	Knowledge Creation
AI Visualisers	Multimodal representation	Conceptualisation	Design	Visualisation
AI Interactors	Dialogue and simulation	Engagement / practice	Question	Engagement
AI Assessors	Evaluation and scoring	Assessment	Monitor	Assessment / Feedback
AI Enhancers	Revision and optimisation	Improvement	Reflect / revise	Enhancement

Table 4. Functional taxonomy of educational AI, classified by educational function rather than product.

Operational Definitions and Observable Indicators

There are eight processes that are differentiated by their key instructional question and by evidence that the learner has engaged in the corresponding activity. They are not mutually exclusive psychological states: one episode may involve several processes. Researchers to code the purpose of an action, and to provide several codes where evidence justifies several codes. The following indicators are proposed operationalizations, not scales that have been validated and are suitable for use in comparative or high-stakes research until they have been examined by experts, cognitive interviews, pilot coding and reliability analysis.

Table 5. Proposed operational definitions and indicators for empirical study of AIDMCF.

Process	Analytical boundary / primary question	Candidate observable indicators	Possible data source
Knowledge discovery	How does the learner locate, question and appraise information?	Learner-generated questions; source comparisons; verification; identification of uncertainty.	Search/source logs; annotated sources; think-aloud; inquiry notes
Knowledge creation	What knowledge artefact or explanation does the learner construct?	Original claim, draft, model or code; substantive transformation of AI output; reasons for choices.	Version history; draft comparison; artefact rubric; learner explanation
Visualisation	How does the learner represent relationships or make concepts perceptible?	Interpretation or critique of a diagram/model; justified visual choices; fit between representation and concept.	Annotated visual; design rationale; concept test; observation
Dissemination	How does the learner communicate constructed knowledge to an audience?	Audience adaptation; evidence-based explanation; attribution; response to audience questions.	Presentation; publication; audience rubric; oral defence
Engagement	How does the learner sustain inquiry or practice through interaction?	Follow-up questions; strategic prompting; testing alternatives; persistence; dialogue with peers/teacher.	Interaction transcript; observation; event log; stimulated recall
Assessment	What evidence is used to judge understanding against criteria?	Self/peer/teacher judgement; diagnosis of strengths and gaps; evidence cited for judgement.	Rubric scores; self-assessment; peer review; teacher records
Feedback	What information identifies a gap between current performance and a target?	Feedback received and interpreted; identification of a specific gap; explanation of next action.	Feedback annotations; interview; response record
Enhancement	What deliberate changes follow evaluation or feedback, and why?	Tracked revisions; acceptance/adaptation/rejection with reasons; reflection on strategy.	Version history; revision memo; before/after rubric; reflection

The principal analytical boundaries are: Assessment is a judgement against criteria; feedback is the communication of information related to the gap or next step; enhancement is the learner's next decision and action. Engagement is related to persistent interaction or practice while knowledge creation is about creating or significantly changing an artefact. The highlighting of relationships, interpreting relationships, is visualisation, while communicating knowledge is dissemination. Discovery is finding and valuing information, whilst creation is composing or amalgamating information. These are NOT chronological boundaries, but rather analytical, meaning that the processes may overlap in one episode.

Pedagogical Implementation

Procurement and tool novelty should not be used as the starting point for implementation; it should start with the intended learning outcomes and learner activity. The task of teachers is to determine what students need to know or to create, and then choose the AI and media functions that can help them achieve those goals. Tasks should include instructions on how the learner will check, compare, challenge, adapt, or reject the AI-generated output. Teachers should demonstrate how to check sources, how to exhibit uncertainty over the

knowledge, and how to disclose the use of AI tools, as well as how to differentiate between the teacher's support and what is the student's independent work. Process evidence (e.g. annotated drafts, decision logs, oral explanations) should be considered as well as the final artefact in the assessment. These are design recommendations based on the framework and not proven to have actual effects.

A sequence for the practical implementation can be (1) setting learning outcomes, (2) determining the learner activities required to fulfil the outcomes, (3) choosing an AI function and media format only when they meet the activities, (4) incorporating verification, critique and revision, and (5) evaluating the process and product. An activity for AI-critique requires learners to recognize any claims or omissions that are not supported by evidence, or bias in the product that has been created (Kasneci et al., 2023). Simulations can be used to practice activities that are expensive or otherwise difficult. Task design, accessibility, disclosure and academic integrity should be discussed as well as the operation of the tool in teacher development and institutional policies (Chan, 2023; Cotton et al., 2024).

Illustrative Learning Scenario

Imagine an undergraduate media-literacy course is given a task to critique a viral social media challenge regarding a social-health issue. The teacher has established an objective, made the source pack easy to access and created a rubric for evidence quality, uncertainty, ethical communication, and transparent use of AI. This is an illustrative scenario, not a report of an implemented intervention or evidence of effectiveness. In discovery, students ask questions, input their questions into AI to get search terms and potential answers, and check information with primary documents and trusted public health resources. In a multi-turn interaction, they engage in conversation with the AI that provides alternative theories and questions during engagement, engaging at least one of the AI's answers during the interaction and recording evidence to support their engagement. During creation, groups form an evidence-based explanation, considering AI-generated text as a draft or counter argument to assess. The key learning is the student's thinking and reworking of the material and not the presence of the prose generated.

Students then develop or critique an evidence map that depicts the claim, sources, support, opposing, and unknown evidence. They use a common rubric to evaluate the map and explanation for assessment purposes. Peer/Teacher/AI formative feedback identifies gaps in evidence, reasoning/audience clarity. Students make notes during enhancement procedures regarding their acceptance of suggestions, adaptation or rejection, and the reason(s). Lastly, they share their results in an understandable explainer to a specific group of people and respond to queries regarding their evidence and the application of AI. The scenario demonstrates how processes can overlap, without being indistinguishably. If the explanatory structure changes significantly, revising an evidence map following peer review might also require creating knowledge. If one interpretation of the feedback and/or improvement of the artefact will improve the explanatory structure, then revising the artefact will require the interpretation of feedback and the improvement of the artefact. Coding is based on the action studied. Goal setting, monitoring, and self-evaluation and strategic adjustment of SRL can be studied, and reports of autonomy, competence, task value, and persistence can be studied for motivation. The teacher maintains accountability for source quality, assessment, accessibility, and safeguarding, and maintains classroom dialogue.

Opportunities and Challenges

Opportunities

AI can also assist in customizing explanations, pacing, or feedback based on learner needs, though this may be helpful in some contexts and disciplines but not in others. Designed around cognitive principles, multimodal representations can facilitate understanding (Mayer, 2021). Generative tools can reduce the learning curve for drafting and prototyping, and dialogue and formative feedback can provide more opportunities for practice and revision. There are also potential for AI to help with accessibility and lifelong learning, but that will rely on the quality of the outputs, the accessibility of the interfaces, teacher preparation and equitable access. With regular preparation of materials, there may be increased efficiency, freeing up teachers to spend more time on higher value interaction, which must be tested, not assumed.

Challenges

There are several potential challenges with cognitive offloading, inaccurate or incomplete outputs, bias, privacy concerns and data-protection concerns, unclear authorship, and fewer opportunities for teacher–peer dialogue. Reliability of access to devices, connectivity and using approved tools are not even. The outputs presented may not be as reliable in languages, dialects or cultural contexts and interfaces or generated media may not be accessible to learners with disabilities. These risks are context dependent and need pedagogical and institutional protection.

Opportunity	Associated Risk	Primary Source in Literature
Personalised and adaptive learning	Widens digital and AI-access inequality if unevenly available	Zawacki-Richter et al. (2019)
Multimodal representation of concepts	Cognitive overload from poorly designed AI-generated visuals	Mayer (2021)
Increased frequency of formative feedback	Homogenisation of learner responses toward AI-preferred patterns	Kasneci et al. (2023)
Lower barriers to creative production	Cognitive offloading; reduced independent generative effort	Freeman et al. (2014); Kasneci et al. (2023)
Support for accessibility and lifelong learning	Reliability and quality vary; may not be universally accessible	Chan & Hu (2023)
Increased teacher capacity for higher-value interaction	Erosion of academic integrity without clear policy	Cotton, Cotton, & Shipway (2024)

Table 6. Opportunities and associated risks in AI–digital media convergence.

Equity, Accessibility and Contextual Conditions

Equity is about the access learners have to enter, stay in and gain from the eight processes. Access is determined by ownership, bandwidth, access to electricity, subscription fees, and platform limitations and institutional purchasing requirements. These conditions should be documented in studies and course designs should offer alternatives that either don't require AI or are low-bandwidth in order not to incentivize purchasing power in the assessment. Generative systems can be inconsistent in languages, dialects, registers and culturally relevant knowledge, translation can change nuance or obscure locally meaningful concepts. Students should be competent in using languages that are suitable and in criticizing outputs that misrepresent their communities. Captions, alternative text, keyboard navigation, colour contrast and cognitive accessibility are all important issues when dealing with disability inclusion and screen-readers. Not everything that is online is accessible. Other factors influencing implementation include privacy and institutional capacity. The entry of learner work and sensitive records into third party systems should not take place without relevant legal foundations, guidance and safeguards. Vet vendors, train teachers and keep infrastructure secure and monitor bias: different institutions have different capacities to do this. Thus, AIDMCF needs to be customized for the local policy, language, curriculum, class size and resources. Future research should be conducted by reporting on the involvement of whom, who is benefiting, who is risking, and whether there are differences in outcomes by learner groups.

DISCUSSION

AIDMCF's main contribution is to arrange learning that is supported by AI rather than focusing on products or technical functions, as part of eight interconnected pedagogical processes. This process perspective is a complementary perspective to the SAMR model for technology integration (Hamilton et al., 2016) and AI applications as discussed in functional categories (Zawacki-Richter et al., 2019), which makes the activity of the learners and the teacher's judgement visible. It also identifies risks, including a wrong finding of the output of discovery, cognitive offloading during the development of the discovery, or a biased evaluation, at the time in the learning process when they might occur. The process centred approach shifts the question of whether an AI tool is good or bad to what learners are asked to do with it, why, and how. This focus is aligned with active

learning studies, which emphasize the actions of the learner and conversational pedagogy, which emphasizes iterations of action, feedback and revision (Freeman et al., 2014; Laurillard, 2012).

The process-centred approach is important because it moves the evaluative question from is this AI tool good or bad for learning? to what does the learner need to do with this AI tool, in what process, and under what conditions? The reframing is also consistent with the active-learning evidence base that foregrounds that learning is dependent on what learners do, rather than the medium of instruction (Freeman et al., 2014), and with Laurillard's (2012) conversational framework, which emphasises a series of action, feedback and iteration cycles instead of content. Agency should not be considered a fixed effect of the use of AI. It can be influenced by the nature of the task and context: students can be asked questions and given the chance to make changes to the product, or be pushed to accept it as given. This is a plausible explanation to explore why experiences and outcomes reported in different GenAI studies are different, but it is a hypothesis that needs to be empirically tested (Chan & Hu, 2023; Wu et al., 2025). Media and Communication education puts a strong emphasis on critical multimodal literacy: learners must be aware of the ways in which the format, the evidence and the representation influence meaning. The production and evaluation of AI-mediated media can then be considered as an epistemic activity, as long as learners explain and defend their choices leading to the creation of the artefact.

Theoretical Contributions

The paper provides four related conceptual contributions. First, it focuses on pedagogical processes in which AI is applied rather than just the products. Second, it depicts AI as a mediating tool in the teachers–learners–AI interactions rather than as a fully independent substitute to teaching. Third, it views multimodal production/communication as a way to create and to test knowledge. Fourth, it connects these processes in a recursive model, and offers a functional taxonomy, candidate indicators and testable propositions. The "something new" in the contribution is the integration, the component theories and processes are from the previous research, and the suggested framework still needs to be proven.

Research Propositions

The following propositions are empirical statements that reflect the framework. These are speculations to be tested by future research, not proof or results that AIDMCF is effective.

P1. More alignment of AI assisted tasks to the active learning principle of learner participation with more learner engagement than AI assisted tasks where the learner is more passive consuming AI generated output.

P2. The increased potential of AI–digital media convergence for supporting active learning is more likely to occur when the learner is expected to produce and critically reflect on multimodal knowledge artefacts than when they are expected only to retrieve or reproduce AI-generated artefacts.

P3. The relationship between AI integration and active-learning outcomes (e.g., learning benefits) is mediated by teachers' technological pedagogical content knowledge, such that a higher level of situated technology–pedagogy–content judgement results in greater learning benefits from AI use.

P4. The pedagogical value of AI-generated multimodal products depends on the application of multimedia-design principles (e.g., cognitive load management), so that cognitive gains from AI-generated visualisations are weaker when they do not follow these principles, and stronger when they do.

P5. Tasks that involve an iterative revision process that include AI-assisted feedback result in more improvement in learner performance than those that provide AI-assisted feedback without a revision opportunity.

P6. Focusing on critically evaluating AI-generated content (an "AI critique cycle") is correlated with a lower rate of uncritical acceptance of inaccurate AI output compared to the instruction without the focus on critical evaluation.

P7. A clear policy on the appropriate use of AI in assessment is linked to a decrease in academic-integrity issues with generative AI compared to situations where policy guidance is limited or unclear.

P8. Equitable access to reliable connectivity and AI tools acts as a moderator between AI–digital media convergence and active learning, with convergence effects being lessened when access to digital or AI is highly unequal.

Empirical Validation Agenda

Since AIDMCF is conceptual, validation should be carried out in stages. First, the clarity, distinctiveness and coverage of process definitions and indicators can be evaluated by expert review. Learner reflection prompts may be tested against these cognitive interviews to determine if the prompts result in the intended reasoning; pilot coding can be used to determine whether trained observers can consistently apply the categories, even in cases where multiple codes are appropriate. Qualitative studies can integrate classroom observation, learner interviews, learner consented interaction records, histories of artefacts and versions to look at how learners move in and out of processes and how teacher facilitation affects learner moves. Process tracing and thematic analysis can be used to identify cases where the AI aspect adds to the active construction process, or cases in which it replaces and supports learner work, or cases that lead to paths that go beyond what the framework had foreseen. Quantitative studies can be used to design and validate process-specific coding schemes or measures as well as test the relationships between the task design, learner agency, SRL, motivation, artefact quality, conceptual understanding and transfer. Where possible, quasi-experimental and randomised designs could be used to compare the passive consumption of AI-generated content, structured critique and verification of AI-generated content, and similar non-AI scaffolding. Learning objectives and time-on-task should be as fixed as possible, outcomes should be defined beforehand, and should involve performance on independent tasks, not the quality of AI-assisted products.

Variation across learners and contexts can be explained through the use of mixed-methods studies that incorporate learning outcomes and process information. Researchers should record the version of the AI system, the prompts used, what other users may use it for, how the teacher was trained, institutional policy, prior knowledge, language, and accommodations and access conditions. Claims need to be replicated across educational levels, disciplines, language, and resource settings. The following is a provisional validation sequence: (1) expert review and construct mapping; (2) cognitive interviewing and pilot coding; (3) inter-rater reliability assessment and codebook revision; (4) testing against artefact quality, conceptual learning and transfer; (5) comparative intervention studies; and (6) replication and contextual adaptation. Threats include self-selection into AI use, novelty effects, unequal prior AI literacy, inconsistent outputs, teacher expectancy effects, contamination between conditions and measures that reward polish over understanding. Each step should incorporate ethical review, data minimisation, transparency in disclosure and open participation.

Implications

For teachers and educators, AIDMCF aims to give attention to pedagogical judgment and professional development beyond just using the tool. There must be room for students to challenge, check and use information created by AI. The curriculum designer can match learning outcomes, assessment to processes and assessment to curriculum. The design of assessment should prioritize documented reasoning and revision and final products. Clear policies, appropriate use, privacy and equitable access (Chan, 2023; Cotton et al., 2024) need to be established in institutions. Critical multimodal literacy is particularly pertinent in the context of media and communication education. The framework can also be applied to workplace learning and self-directed learning, which needs further empirical research.

CONCLUSION

This paper has presented the AI–Digital Media Convergence Framework as a conceptual description of the possibilities of the convergence of the AI capability and the digital media affordance for enabling active knowledge construction. It introduces eight recursive processes – knowledge discovery, creation, visualisation, dissemination, engagement, assessment, feedback and enhancement – to focus the viewer on the act of learners

and the context in which they act. Cross-cutting influences are covered by SRL, metacognition and motivation; teacher judgement, accessibility, privacy and institutional capacity influence implementation. The framework has not been empirically tested and its propositions and candidate indicators should not be viewed as evidence of the effects. Systematic construct refinement and empirical testing in various contexts, such as comparing with non-AI approaches, and evaluating outcomes of independent learning, then takes place.

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