Student Ambassadors for Sustainable AI EdTech Knowledge Sharing in Higher Education

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Abstract: This conceptual paper develops a framework for appraising institutional knowledge assets produced through AI EdTech dissemination. Knowledge mobilisation research emphasises dissemination, interpretation, usefulness, uptake and context, but does not typically isolate representational quality as a distinct asset-level appraisal dimension. This gap is especially consequential when verification asymmetry and promotional incentive co-occur: claims may exceed inspectable evidence, overstate attribution or omit material conditions and risks even when assets remain visible, accessible and reusable. The paper therefore conceptualises representational quality through four criteria: claim traceability, attribution restraint, condition disclosure and risk representation. It further specifies a student ambassador model in which case-linked direct-user knowledge is combined with evidence access, expert review and revision rights across a governed production-and-maintenance lifecycle. Production-stage verification constrains distortion before dissemination, while post-hoc fidelity audit supports correction after publication; engagement analytics substitute for neither. Five falsifiable propositions address construct distinctness, verification, direct-user informational advantage, conditional diagnostic value and maintenance after material change. The paper reports no empirical findings. Its contribution is to position representational quality as an explicit property of AI EdTech knowledge assets and to specify the conditions and governance mechanisms under which it should be appraised.

Keywords: Representational Quality; AI EdTech; Sustainable Knowledge Sharing; Student Ambassadors; Knowledge Mobilisation

1. Introduction

Higher education institutions are increasingly adopting AI-enabled educational technologies, including adaptive learning, automated feedback, learning analytics, AI assistants and intelligent tutoring systems. Reviews have mapped applications, outcomes, stakeholder perceptions, ethics and implementation challenges (Bond et al. 2024; Zawacki-Richter et al. 2019), but have paid less attention to how local implementation experience becomes durable institutional knowledge. Institutional value therefore depends not only on adoption but also on whether implementation knowledge can be examined, shared and reused. The transition from local experience to reusable knowledge constitutes a dissemination gap between AI-enabled innovation and sustainable institutional learning.

AI EdTech intensifies this gap because dissemination evidence is often difficult to interpret. AI systems may be difficult for users to inspect (Miao and Holmes 2023), while observed outcomes may be difficult to attribute to the technology rather than to novelty, selection, assessment design or concurrent teaching changes (Shadish, Cook and Campbell 2002). AI-enabled education also raises privacy, bias, transparency and learner-data concerns (Miao and Holmes 2023; Slade and Prinsloo 2013). Institutional communication may therefore produce claims that are stronger or clearer than the available evidence warrants.

Knowledge mobilisation (KMb), knowledge brokering and boundary-spanning research explain why evidence must be interpreted, adapted and connected to practice rather than merely transmitted (Akkerman and Bakker 2011; Carlile 2004; Davies, Nutley and Walter 2008; Levin 2013; Ward 2017). Recent KMb-product research emphasises user needs, relevance, usefulness, accessibility, stakeholder involvement and uptake (Elliott et al. 2024; Kastner et al. 2020; Sharp et al. 2022; Ziam et al. 2024). These concerns are important but do not by themselves establish whether circulating claims are proportionate to their evidential basis.

This paper develops a conceptual framework that distinguishes representational quality from visibility, accessibility and reusability, and specifies a student ambassador model for governing these asset-quality

dimensions. It further identifies verification asymmetry and promotional incentive as conditions under which explicit representational-quality appraisal is expected to add the greatest diagnostic value. Students are treated as trained, case-linked partners rather than as intrinsically more credible communicators. The model combines case-linked student participation with structural safeguards for evidence access, review and revision. The paper addresses three research questions:

RQ1. What asset-level criteria are required to appraise AI EdTech knowledge assets, and what does representational quality add to established criteria of visibility, accessibility and reusability?

RQ2. Which mechanisms create a need for representational-quality appraisal, and under what conditions does that dimension add the greatest diagnostic value?

RQ3. How should a student ambassador model be specified to strengthen representational quality during production and maintenance, and what evidence would count against its claims?

The paper addresses these questions analytically. It reports no empirical findings and does not present an effectiveness evaluation. Its claims are stated as propositions that subsequent empirical work could support, qualify or disconfirm.

2. Theoretical Framework

2.1 AI EdTech as Institutional Knowledge Assets

AI EdTech contributes to institutional learning when implementation experience is converted into knowledge that can be examined, interpreted and reused. KMb conceptualises this process as interpretation, adaptation, circulation and connection to local action rather than linear transfer (Davies, Nutley and Walter 2008; Levin 2013; Ward 2017). For the purposes of this framework, sustainable knowledge sharing is defined as the continued availability, interpretability, evidential warrant and revisability of knowledge assets as technologies and implementation conditions change. In this framework, institutional knowledge assets are digital outputs that preserve and organise implementation experience for subsequent interpretation and use beyond the setting in which it was produced.

Recent KMb research examines knowledge products in relation to their purpose, intended users, stakeholder involvement, adaptation and evaluation (Elliott et al. 2024; Kastner et al. 2020; Sharp et al. 2022; Ziam et al. 2024). Together, these strands provide a basis for treating AI EdTech dissemination outputs as knowledge assets rather than as transient communication products.

2.2 Student Ambassadors as Knowledge Mobilisers and Boundary Spanners

The students-as-partners (SaP) perspective provides a pedagogical and normative basis for student participation. SaP positions students as collaborators and emphasises reciprocity, shared responsibility and co-creation, thereby recognising experiential knowledge as a legitimate contribution (Bovill 2020; Healey, Flint and Harrington 2014). In AI EdTech initiatives, such experiential knowledge may capture aspects of use that formal implementation records overlook, including confusion, discontinuation, workarounds and support needs. Student participation is therefore relevant not because students are inherently more credible, but because direct experience may provide access to implementation conditions that are otherwise difficult to reconstruct.

Boundary-spanning theory explains how actors and artefacts connect communities that differ in vocabulary, evidence standards and priorities, while knowledge brokering emphasises the interpretation and adaptation of knowledge for use across settings (Akkerman and Bakker 2011; Carlile 2004; Rycroft-Smith 2022; Ward 2017). In the proposed framework, student ambassadors are conceptualised as performing these interpretive and connective functions, while digital knowledge assets serve as boundary objects through which implementation knowledge can circulate across learner, faculty, technical and institutional communities.

Building on these strands, the framework distinguishes direct-user status from the ambassador role. Direct-user status provides access to case-specific experiential evidence, whereas the ambassador role concerns translating, contextualising and mobilising that evidence across institutional boundaries. The proposed informational advantage is therefore bounded to case-linked direct users and should not be generalised to students as a category. Where ambassadors are not direct users, the framework does not assume equivalent access to case-specific experiential evidence or an equivalent informational advantage. This distinction locates the potential

contribution of student ambassadors in the combination of experiential access and boundary-spanning capacity rather than in student status itself.

2.3 Theoretical Synthesis and Design Assumptions

Drawing on the preceding literature, the framework adopts four design assumptions. First, knowledge assets require sufficient contextual information to support later interpretation and adaptation (Carlile 2004; Davies, Nutley and Walter 2008; Ward 2017). Second, stakeholder participation should be treated as substantive involvement in knowledge production rather than as a guarantee of asset quality; SaP scholarship emphasises reciprocity, shared responsibility and genuine partnership (Bovill 2020). Third, digital knowledge assets can function as boundary objects when they retain sufficient shared structure to connect communities with different vocabularies, evidence standards and priorities (Akkerman and Bakker 2011; Carlile 2004). Fourth, continued applicability requires maintenance because material changes in systems, policies or implementation conditions may alter the conditions under which a knowledge asset remains warranted for current use.

Together, these assumptions distinguish participation from the governance of knowledge assets. Experiential access can strengthen contextual reconstruction, but it does not by itself ensure the quality of the resulting knowledge asset. These assumptions nevertheless leave unresolved how the quality of circulating knowledge assets themselves should be assessed.

3. Asset Quality in AI EdTech Dissemination

3.1 Asset-Quality Dimensions from Knowledge Mobilisation

The KMb literature does not offer a single established taxonomy of knowledge-asset quality. Existing research spans diverse purposes, actors, processes and evaluation targets, including relevance, usefulness, stakeholder involvement, accessibility, uptake, effects and impacts (Elliott et al. 2024; Kastner et al. 2020; Sharp et al. 2022; Ward 2017; Ziam et al. 2024). These contributions inform KMb design and evaluation but do not establish a common set of properties for appraising the circulating asset itself.

For this framework, three baseline asset-level properties are distilled because they concern the asset's capacity for circulation, interpretation and reuse rather than its production process or downstream outcomes. Visibility concerns whether intended audiences can locate the asset (Davies, Nutley and Walter 2008; Levin 2013; Ward 2017). Accessibility concerns whether the asset can be understood by audiences with different knowledge and technical backgrounds (Akkerman and Bakker 2011; Carlile 2004; Elliott et al. 2024; Ward 2017). Reusability concerns whether sufficient contextual information is retained for later interpretation and adaptation (Carlile 2004; Davies, Nutley and Walter 2008; Ward 2017). These dimensions establish a baseline for whether an asset can be found, interpreted and reused, but do not establish whether its claims are proportionate to their evidential basis.

3.2 Verification Asymmetry and Promotional Incentive

Verification asymmetry arises when circulating claims exceed what producers or audiences can readily verify from the available evidence. In this framework, it has two distinct sources. Mechanism opacity concerns whether users can understand how an AI system generated an output (Miao and Holmes 2023), whereas attribution uncertainty concerns whether observed educational outcomes can reasonably be attributed to the technology rather than to plausible alternatives (Shadish, Cook and Campbell 2002; Weidlich, Hicks and Drachsler 2024). The two are analytically distinct: greater system transparency does not establish causal attribution, and stronger causal evidence does not make system operation transparent.

A separate condition is promotional incentive, which arises when institutions communicate their own outcomes in contexts shaped by reputational, recruitment or funding interests. AI education discourse is susceptible to hyperbole and value-laden claims (Selwyn 2022), although direct evidence of distortion in institutional AI EdTech communication remains limited. Evidence from university science communication nevertheless suggests that exaggerated institutional press releases can be associated with exaggerated subsequent coverage (Sumner et al. 2014), providing a relevant but bounded analogy. Within the framework, promotional incentive creates pressure toward favourable representation, while verification asymmetry makes resulting overstatement or omission more difficult to detect or challenge.

When verification asymmetry and promotional incentive are both substantial, an asset may therefore remain visible, accessible and reusable while overstating attribution, omitting material conditions or underrepresenting risks. Their conjunction defines a high-risk condition in which improved dissemination may amplify rather than correct distortion. These conditions do not define representational quality; rather, they identify when explicit appraisal of that dimension is expected to add the greatest diagnostic value. This limitation of the baseline dimensions motivates an additional asset-level appraisal dimension.

3.3 Representational Quality: Definition and Boundaries

Representational quality is defined here as the degree to which an asset's substantive claims are traceable to and proportionate to the available evidence, with sufficient context, limitations, uncertainty and ethical risks retained for responsible interpretation. This formulation aligns with broader concerns about transparency, uncertainty and ethical responsibility in educational AI and data use (Miao and Holmes 2023; Slade and Prinsloo 2013). Representational quality is therefore treated as a property of the circulating artefact rather than of the producer's intention or the audience's response.

Four criteria specify its appraisal. Claim traceability concerns whether substantive claims can be linked to specified sources or documented observations. Attribution restraint concerns whether outcomes are attributed to the technology only to the extent supported by the available design and evidence (Shadish, Cook and Campbell 2002). Condition disclosure concerns whether material features of the setting, cohort, duration, support arrangements and concurrent changes are reported. Risk representation concerns whether known limitations, uneven effects and ethical concerns are represented in the asset rather than omitted from the circulating account.

Representational quality is related to, but not reducible to, other forms of quality judgement. Factually accurate or persuasive statements may still misrepresent an outcome by omitting material conditions or implying unsupported causality, while ethical compliance concerns how evidence is obtained and used. Transparency concerns the visibility of processes or evidence, and credibility reflects audience judgement; representational quality instead concerns whether an asset's claims remain proportionate to the evidence and sufficiently contextualised. It may therefore correlate with visibility, accessibility or reusability without being reducible to any of them; empirical separability remains a proposition to be tested.

4. Student Ambassador Knowledge-Sharing Model

4.1 Integrated Framework

Figure 1 synthesises the preceding theoretical arguments into an integrated framework linking risk conditions, asset quality and the student ambassador lifecycle. Verification asymmetry and promotional incentive constitute the framework's principal risk conditions identified in Section 3. Student ambassadors contribute experiential interpretation and boundary-spanning functions grounded in the partnership and knowledge-mobilisation literature (Akkerman and Bakker 2011; Bovill 2020; Ward 2017). The framework pairs these functions with structural safeguards for evidence access, expert review and revision across production and maintenance.

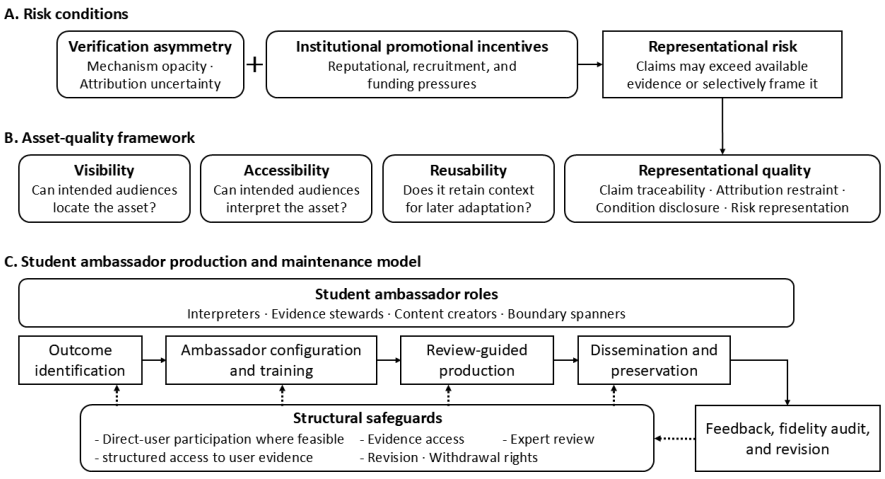


Figure 1: Student Ambassador AI EdTech Knowledge-Sharing Framework

4.2 Five-Stage Production-and-Maintenance Lifecycle

Drawing on the theoretical arguments developed in Sections 2 and 3, Table 1 specifies an author-derived five-stage production-and-maintenance lifecycle linking core activities, structural safeguards, outputs and asset-quality targets. Production-stage verification comprises claim–evidence mapping, expert review and revision before release, while post-publication fidelity audit reassesses whether an asset continues to represent its underlying evidence and implementation conditions faithfully. Together, these mechanisms distinguish pre-publication verification from post-publication maintenance and support evidential scrutiny and revision across the asset lifecycle.

Table 1: Five-Stage Student Ambassador Knowledge-Sharing Model

Stage	Core activity	Structural safeguards and outputs	Mechanism and asset-quality target
1 Outcome identification	Screen cases for relevance, evidence inspectability, ethical acceptability and reuse potential; map evidence before drafting.	Evidence access and case-eligibility screen; evidence map and review criteria.	Sets an evidential floor and excludes cases that cannot be responsibly qualified; targets representational quality.
2 Ambassador configuration and training	Prioritise case-linked direct users; otherwise provide structured access to user evidence. Train in AI literacy, interviewing, evidence stewardship and attribution restraint.	Direct-user participation or structured user-evidence access; role allocation, templates and revision/withdrawal rights.	Converts experiential access into interpretable evidence without presuming superior credibility; targets accessibility and representational quality.
3 Review guided production	Create assets using claim-evidence mapping, condition disclosure and risk prompts; revise through expert review before release.	Evidence access, expert review, claim-evidence matrix and pre-publication revision gate.	Tests evidential warrant before dissemination and retains material context; targets representational quality and accessibility.
4 Dissemination and preservation	Disseminate approved assets; preserve versions, provenance, metadata and retrieval information in durable repositories.	Version control and traceable provenance; published and archived assets.	Increases findability while preserving context for later adaptation; targets visibility and reusability.
5 Feedback, fidelity audit and revision	Use engagement analytics for uptake, fidelity audit for representational quality, and change monitoring to trigger revision or withdrawal.	Expert re-review, revision/withdrawal rights, audit record and archived versions.	Separates uptake from evidential warrant and supports quality maintenance; targets all four dimensions.

4.3 Ambassador Roles and Outputs

The model assigns student ambassadors four complementary roles: interpreters, content creators, evidence stewards and boundary spanners. They interpret user experience and context, translate knowledge into appropriate formats, steward claim–evidence links and connect learner perspectives with faculty, technical and institutional priorities, extending established interpretive and boundary-spanning functions (Akkerman and Bakker 2011; Carlile 2004). These roles position ambassadors across interpretation, production and revision rather than one-way dissemination.

The model yields reviewed digital artefacts and accumulated knowledge about their production, dissemination and revision. The former are appraised against the four asset-quality dimensions, while the latter informs subsequent production and revision.

5. Propositions and Boundary Conditions

5.1 Propositions

The framework's claims are stated as propositions rather than design intentions. Each is paired with evidence that would count against it.

5.1.1 Proposition 1

Representational quality is empirically distinguishable from visibility, accessibility and reusability.

Evidence against this proposition would be empirical inseparability from these dimensions or no incremental information beyond them.

5.1.2 Proposition 2

Production-stage verification will yield higher initial representational quality than comparable workflows without such verification.

Evidence against this proposition would be no difference in initial representational quality between the two workflows.

5.1.3 Proposition 3

Case-linked direct-user ambassadors will demonstrate greater condition disclosure than non-direct-user or institutional communication actors under comparable access to documentary evidence and review support.

Evidence against this proposition would be no such advantage, or a disadvantage, under matched production conditions.

5.1.4 Proposition 4

The incremental diagnostic value of representational-quality appraisal will be greatest when verification asymmetry and promotional incentive are both substantial.

Evidence against this proposition would be no greater diagnostic value under this joint high-risk condition than under other conditions.

5.1.5 Proposition 5

Post-publication maintenance will better preserve representational quality when material changes affect an asset's continued applicability.

Evidence against this proposition would be no advantage for maintained over unmaintained assets under such conditions.

5.2 Counter-Argument to Direct-User Advantage

Proposition 3 admits an important counter-argument. Direct experiential access does not eliminate institutional dependence, which may constrain students' willingness or capacity to represent unfavourable evidence. This concern is consistent with students-as-partners scholarship emphasising reciprocity, shared responsibility and genuine partnership as conditions of meaningful participation (Bovill 2020).

The framework therefore treats direct-user advantage as informational rather than motivational and limits it primarily to condition disclosure. Institutional dependence may therefore remain a constraint on attribution restraint and risk representation, reinforcing the framework's use of evidence access, expert review and revision rights as structural safeguards.

5.3 Boundary Conditions

The framework has two principal boundary conditions. First, the incremental diagnostic value of representational-quality appraisal is expected to be greatest when verification asymmetry and promotional incentive are both substantial; under lower-risk conditions, its added value may be more limited. Second, the proposed informational advantage applies specifically to case-linked direct users and should not be generalised to students as a category. For non-user ambassadors, structured access to direct-user evidence may mitigate this limitation but does not establish an equivalent informational advantage.

6. Discussion

6.1 Theoretical Contributions

The paper makes three theoretical contributions. First, it positions representational quality as an explicit asset-level property within institutional KMb. Existing KMb and product-oriented research addresses a broad range of concerns, including relevance, usefulness, stakeholder processes, uptake and impact (Elliott et al. 2024; Kastner et al. 2020; Sharp et al. 2022; Ziam et al. 2024). The framework adds an explicit appraisal of whether circulating claims remain proportionate to their evidential basis and sufficiently contextualised for responsible interpretation. Representational quality therefore complements, rather than replaces, visibility, accessibility and reusability.

Second, the framework differentiates mechanism opacity from attribution uncertainty as distinct sources of verification asymmetry. The former concerns whether system operations can be inspected, whereas the latter concerns whether observed educational outcomes can reasonably be attributed to the technology. This distinction separates technical transparency from causal warrant. Promotional incentive is theorised as a separate institutional risk condition, with the incremental value of representational-quality appraisal expected to be greatest when verification asymmetry and promotional incentive are both substantial.

Third, the framework provides a conditional account of student participation by separating direct-user informational access from the ambassador's boundary-spanning role. Its contribution lies in specifying the source of that advantage as case-linked experiential access combined with boundary-spanning capacity, rather than student status itself. The proposed advantage is bounded to case-linked direct users and primarily concerns condition disclosure rather than overall asset quality. The framework further formulates its central claims as falsifiable propositions, allowing the proposed construct distinctions, mechanisms and boundary conditions to be empirically supported, qualified or disconfirmed.

6.2 Practical Implications

For practice, universities should treat AI EdTech dissemination as a governed knowledge-management process rather than a sequence of publicity outputs. Knowledge assets should preserve sufficient evidence, context and provenance to support later interpretation and review. Visibility and engagement remain useful indicators of circulation and uptake, but they do not establish that claims remain evidentially warranted or current.

Governance should extend across the asset lifecycle. Before publication, verification should test whether claims are adequately supported and contextualised. After publication, engagement analytics should assess circulation and use, while fidelity audit should reassess representational quality. Material changes in system features, policies or implementation conditions should trigger review, revision or archival replacement where continued applicability would otherwise be misleading.

Student ambassador programmes should also differentiate roles according to evidential access. Case-linked direct users can contribute first-hand knowledge of implementation conditions, whereas non-user ambassadors may contribute interviewing, interpretation and production capabilities but should be supported by structured access to direct-user evidence. Evidence access, expert review and meaningful revision or withdrawal rights should therefore function as cross-cutting safeguards rather than as optional additions to student participation.

6.3 Limitations and Future Research

This study is limited by its conceptual design. The proposed construct, appraisal criteria, mechanisms and student ambassador model have not yet been empirically validated, including whether representational quality can be reliably distinguished from the other asset-quality dimensions and improved through the proposed governance mechanisms.

Future research should therefore begin by developing and testing a structured appraisal protocol for the four representational-quality criteria—claim traceability, attribution restraint, condition disclosure and risk representation—and applying it to AI EdTech knowledge assets produced in actual student ambassador programmes. Initial studies could compare condition disclosure between case-linked direct-user and non-user ambassadors, test whether structured evidence access improves representational quality among non-user ambassadors, and examine changes in representational quality before and after expert review. These designs would allow the framework's core mechanisms to be assessed under feasible implementation conditions while

examining which safeguards are associated with improvements in particular dimensions of representational quality. Subsequent matched comparisons with institutional communication staff could further test whether the proposed informational advantage of direct-user ambassadors is specific to condition disclosure rather than indicative of superior overall asset quality.

7. Conclusion

This paper reframes AI EdTech dissemination as a problem of knowledge-asset governance rather than circulation alone. Its central argument is that visibility, accessibility and reusability alone do not establish whether circulating accounts are proportionate to their evidential basis or sufficiently contextualised for responsible interpretation. Representational quality addresses this gap through claim traceability, attribution restraint, condition disclosure and risk representation, with its diagnostic value expected to be greatest when verification asymmetry and promotional incentive are both substantial.

The student ambassador framework translates this argument into a governed production-and-maintenance lifecycle. The framework does not assume that students are inherently more credible communicators; its rationale rests on the combination of case-linked experiential access, boundary-spanning capacity and governance safeguards. The broader implication is that sustainable institutional learning depends not simply on disseminating AI EdTech experience more widely, but on preserving the evidential and contextual conditions under which shared knowledge remains interpretable, warranted and revisable. Without such governance, wider dissemination may amplify poorly warranted claims rather than strengthen institutional learning.

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Ethics Declaration

Ethical approval was not required for this conceptual paper because the study did not involve the recruitment of human participants or the collection, analysis or reporting of personal or participant-derived data.

AI Declaration

Generative AI tools were used to support language editing and consistency checking. All arguments, citations and final wording were independently reviewed and verified by the authors, who take full responsibility for the manuscript. AI-generated material was not used as empirical evidence or research data.

References

Akkerman, S.F. and Bakker, A. (2011) “Boundary crossing and boundary objects”, *Review of Educational Research*, Vol 81, No. 2, pp 132–169, doi: 10.3102/0034654311404435.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S.W. and Siemens, G. (2024) “A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour”, *International Journal of Educational Technology in Higher Education*, Vol 21, Article 4, doi: 10.1186/s41239-023-00436-z.

Bovill, C. (2020) “Co-creation in learning and teaching: The case for a whole-class approach in higher education”, *Higher Education*, Vol 79, No. 6, pp 1023–1037, doi: 10.1007/s10734-019-00453-w.

Carlile, P.R. (2004) “Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries”, *Organization Science*, Vol 15, No. 5, pp 555–568, doi: 10.1287/orsc.1040.0094.

Davies, H., Nutley, S. and Walter, I. (2008) “Why ‘knowledge transfer’ is misconceived for applied social research”, *Journal of Health Services Research & Policy*, Vol 13, No. 3, pp 188–190, doi: 10.1258/jhsrp.2008.008055.

Elliott, S.A., Bialy, L., Scott, S.D. and Hartling, L. (2024) “Exploring methods for creating or adapting knowledge mobilization products for culturally and linguistically diverse audiences: A scoping review”, *Archives of Public Health*, Vol 82, Article 111, doi: 10.1186/s13690-024-01334-0.

Healey, M., Flint, A. and Harrington, K. (2014) *Engagement Through Partnership: Students as Partners in Learning and Teaching in Higher Education*, Higher Education Academy, York, [online], available at: https://www.advance-he.ac.uk/knowledge-hub/engagement-through-partnership-students-partners-learning-and-teaching-higher (accessed 1 September 2026).

Kastner, M., Makarski, J., Hayden, L., Lai, Y., Chan, J.Y.T., Treister, V., Harris, K., Munce, S.E.P., Holroyd-Leduc, J., Graham, I.D. and Straus, S.E. (2020) "Improving KT tools and products: Development and evaluation of a framework for creating optimized, Knowledge-activated Tools (KaT)", *Implementation Science Communications*, Vol 1, Article 47, doi: 10.1186/s43058-020-00031-7.

Levin, B. (2013) "To know is not enough: Research knowledge and its use", *Review of Education*, Vol 1, No. 1, pp 2–31, doi: 10.1002/rev3.3001.

Miao, F. and Holmes, W. (2023) *Guidance for Generative AI in Education and Research*, UNESCO, Paris, doi: 10.54675/EWZM9535.

Rycroft-Smith, L. (2022) "Knowledge brokering to bridge the research-practice gap in education: Where are we now?", *Review of Education*, Vol 10, No. 1, Article e3341, doi: 10.1002/rev3.3341.

Selwyn, N. (2022) "The future of AI and education: Some cautionary notes", *European Journal of Education*, Vol 57, No. 4, pp 620–631, doi: 10.1111/ejed.12532.

Shadish, W.R., Cook, T.D. and Campbell, D.T. (2002) *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*, Houghton Mifflin, Boston.

Sharp, C.A., Boaden, R.J., Dixon, W.G. and Sanders, C. (2022) "Does the process of developing products for knowledge mobilisation from healthcare research influence their uptake? A comparative case study", *Implementation Science Communications*, Vol 3, Article 132, doi: 10.1186/s43058-022-00360-9.

Slade, S. and Prinsloo, P. (2013) "Learning analytics: Ethical issues and dilemmas", *American Behavioral Scientist*, Vol 57, No. 10, pp 1510–1529, doi: 10.1177/0002764213479366.

Sumner, P., Vivian-Griffiths, S., Boivin, J., Williams, A., Venetis, C.A., Davies, A., Ogden, J., Whelan, L., Hughes, B., Dalton, B., Boy, F. and Chambers, C.D. (2014) "The association between exaggeration in health related science news and academic press releases: Retrospective observational study", *BMJ*, Vol 349, Article g7015, doi: 10.1136/bmj.g7015.

Ward, V. (2017) "Why, whose, what and how? A framework for knowledge mobilisers", *Evidence & Policy*, Vol 13, No. 3, pp 477–497, doi: 10.1332/174426416X14634763278725.

Weidlich, J., Hicks, B. and Drachsler, H. (2024) "Causal reasoning with causal graphs in educational technology research", *Educational Technology Research and Development*, Vol 72, No. 5, pp 2499–2517, doi: 10.1007/s11423-023-10241-0.

Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019) "Systematic review of research on artificial intelligence applications in higher education—where are the educators?", *International Journal of Educational Technology in Higher Education*, Vol 16, Article 39, doi: 10.1186/s41239-019-0171-0.

Ziam, S., Lanoue, S., McSween-Cadieux, E., Gervais, M.-J., Lane, J., Gaid, D., Chouinard, L.J., Dagenais, C., Ridde, V., Jean, E., Fleury, F.C., Hong, Q.N. and Prigent, O. (2024) "A scoping review of theories, models and frameworks used or proposed to evaluate knowledge mobilization strategies", *Health Research Policy and Systems*, Vol 22, Article 8, doi: 10.1186/s12961-023-01090-7.