Department of Digital Business
Journal of Artificial Intelligence and Digital Business (RIGGS)
Homepage: https://journal.ilmudata.co.id/index.php/RIGGS
Vol. 5 No. 2 (2026) pp: 10072-10080
P-ISSN: 2963-9298, e-ISSN: 2963-914X

Artificial Intelligence and Education Business-Model Viability: A Systematic Literature Review

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Abstrak

Generative artificial intelligence (AI) is now part of the education process. It can explain material, give practice, and answer questions at almost no cost. This raises a question: can providers survive as businesses? The study asks how AI changes their business models, what it disrupts for learners, and what strategies help them adapt. Using a systematic literature review based on PRISMA 2020, the study searched the Springer Nature Link database with nine keyword sets for 2019 to 2026 and analysed 36 of 1,258 records. The review finds four ways AI changes business models: turning data and content into income-earning assets, automating cost and labour, uneven change across institutions, and new market structures. Disruption is real but only partial. Services that mainly transfer knowledge are hit first, while formal providers face a crisis over the trust placed in their assessment and a loss of control over data and content to technology vendors. Based on the dynamic capabilities view, survival comes from how fast providers sense change, seize new value, and reshape their model, not from owning assets. For managers, the main task is to close the speed gap with vendors and rethink what they offer, instead of leaning on defensive rules. In short, survival depends on how fast a provider can move its value to things AI cannot copy.

Keywords: *Artificial Intelligence, Education Business Model, Dynamic Capabilities, Disruption, Systematic Literature Review*

1. Introduction

Education is basically a process in which learners take in knowledge, practise it, and then use it, rather than simply receive it. Models of learning describe this as a series of steps, from remembering and understanding, to applying and analysing, and finally evaluating and creating. This is the well-known hierarchy of thinking skills set out by Bloom and later updated by Anderson and Krathwohl [1], [2]. Real learning therefore depends on practice and use, not only on being told facts. Seen this way, an education provider is not just a source of information but a guide. It arranges learning experiences, supports understanding, and helps learners build knowledge actively through social and mental interaction [3]. The value an institution gives lies in this guiding work, which turns information into real understanding and skill.

To protect this learning process, education providers are expected to follow accepted teaching principles that move learners through the stages of learning, not around them. However, the fast rise of generative AI is shaking this expectation. Since ChatGPT was released to the public in late 2022, information and answers can be obtained instantly, and this speed is changing every knowledge-based industry, including education [4], [5]. When the results of learning seem available with one click, the slower, guided process that the institution provides can look unnecessary. This raises a basic question about whether, and why, the education provider is still needed [6].

Generative AI is a type of model that produces human-like text, explanations, and solutions on demand. In education, a learner can use it to find information, work through and solve problems, and finish assignments, often well enough to get good marks without really going through the learning process [5], [4]. Signs of this shortcut are already clear. Web traffic to essay-writing and homework-help sites has shifted as easy-to-use AI has spread [7], and studies of paid ‘homework-helper’ platforms show they are used to complete graded work [8]. This ability threatens the main signal that formal providers rely on, namely proof of real learning, and it supports the criticism that presenting AI as easy, ‘democratised’ access can weaken the learning process itself [9].

This debate is usually about teaching, yet education is also an industry with large economic value, and its business logic is changing. Automation and the turning of learner data and academic content into income-earning assets

have become business strategies in their own right, not only teaching choices [10], [11], and platform models are changing the cost structure of established providers, including in tutoring [12], [13]. The stakes are real. Zenius, a 20-year pioneer of national edtech in Indonesia, closed in early 2024, before the competitive pressure of generative AI was even fully felt [14]. Research on this business side, however, is still scattered across separate topics, such as online program management partnerships [15], the strategy of edtech firms [10], and the tutoring industry [12], without bringing them together.

Importantly, this pressure is not likely to ease. AI keeps advancing with no sign of slowing down, and its abilities grow faster than institutions can adapt. This widens the gap between what learners can get instantly and what providers can offer through their slower, guided work [6], [5]. As this substitution spreads, with free platforms taking the place of paid tutoring and AI shortcuts reducing demand for formal teaching [12], [7], the business base of the education sector is likely to shrink, a direction the closure of established providers already shows [14]. If nothing is done, this trend risks emptying out the sector until no financially stable, trusted body is left to protect the quality of learning and to improve it further. It is exactly this risk, the possible loss of the institutions that keep and raise the quality of education, that makes the business survival of education providers, and not only the teaching side of AI, an urgent topic to study.

This scattered evidence is made worse by a gap in theory. Common studies of education's survival assume a fairly stable set of resources, but the situation here is one of rapid change, where the technology keeps weakening and reshaping what providers offer. The dynamic capabilities view, which builds on the resource-based view, was made for exactly these conditions. It holds that, in fast-changing environments, advantage comes not from owning resources but from the ability to sense opportunities and threats, seize them, and reshape the resource base and business model accordingly [16], [17], [18]. So far, this view has not been used in a systematic way to study how AI reshapes the business models and survival of education providers.

For this reason, the aim of this study is to map and bring together the 2019 to 2026 literature on how AI affects the business and industry side of education, and to read it through the dynamic capabilities view. The study answers three research questions: (RQ1) how does AI change the business models of education organisations; (RQ2) what kinds of disruption does easy, AI-based access to knowledge create for their value to learners; and (RQ3) what adaptation strategies are found to keep provision going. In answering them, the study argues that AI moves the basis of survival away from owning resources and toward how fast and how well a provider can move its value to things that AI cannot copy.

2. Research Methods

2.1. Review approach

This study uses a systematic literature review (SLR). Unlike a simple narrative review, an SLR follows a clear, fixed procedure to find, select, and judge relevant studies. It follows the PRISMA 2020 guideline to reduce bias and to make the review transparent and repeatable [19].

2.2. Search strategy and data sources

The search was carried out on the Springer Nature Link database in June 2026, chosen for its coverage of major higher-education and management journals. It was limited to English-language journal articles published between January 2019 and June 2026. Nine keyword sets (S1 to S9) were used to cover three parts of the industry at once: higher education, educational technology firms, and tutoring. S1“artificial intelligence” AND “higher education” AND “business model”; S2 “generative AI” AND “higher education” AND disruption; S3 ChatGPT AND university AND “business model”; S4 edtech AND “artificial intelligence”; S5 “educational technology” AND “business model”; S6 MOOC AND “business model” AND sustainability; S7 “education industry” AND “artificial intelligence”; S8 “shadow education” OR “private tutoring” AND “artificial intelligence”; and S9 “private education” AND (AI OR “artificial intelligence”) AND market.

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2.3. Inclusion and exclusion criteria

To keep the review focused and of good quality, the criteria in Table 1 were applied to the search results.

Table 1. Inclusion and exclusion criteria for article selection

Criterion	Inclusion	Exclusion
Time period	2019 to 2026	Published before 2019
Document type	Peer-reviewed journal articles	Editorials, opinion pieces, book reviews
Language	English	Non-English
Focus	Business, industry, market, institutional or strategic dimension of education in relation to AI/digital technology	Purely pedagogical studies (learning outcomes, learner acceptance, teaching methods); outside education
Availability	Full text available	Abstract-only or restricted access

2.4. Article selection process (PRISMA)

The selection followed the four stages of PRISMA. Identification produced 1,258 records. After screening, 132 duplicates were removed; 1,126 titles were screened (947 excluded) and 179 abstracts were checked (100 excluded). At the eligibility stage, of 79 full texts sought, 27 could not be obtained because of paywalls, leaving 52 assessed. Of these, 16 were excluded for stated reasons, mostly because AI was only a minor background topic. In the end, 36 articles formed the final set (Figure 1).

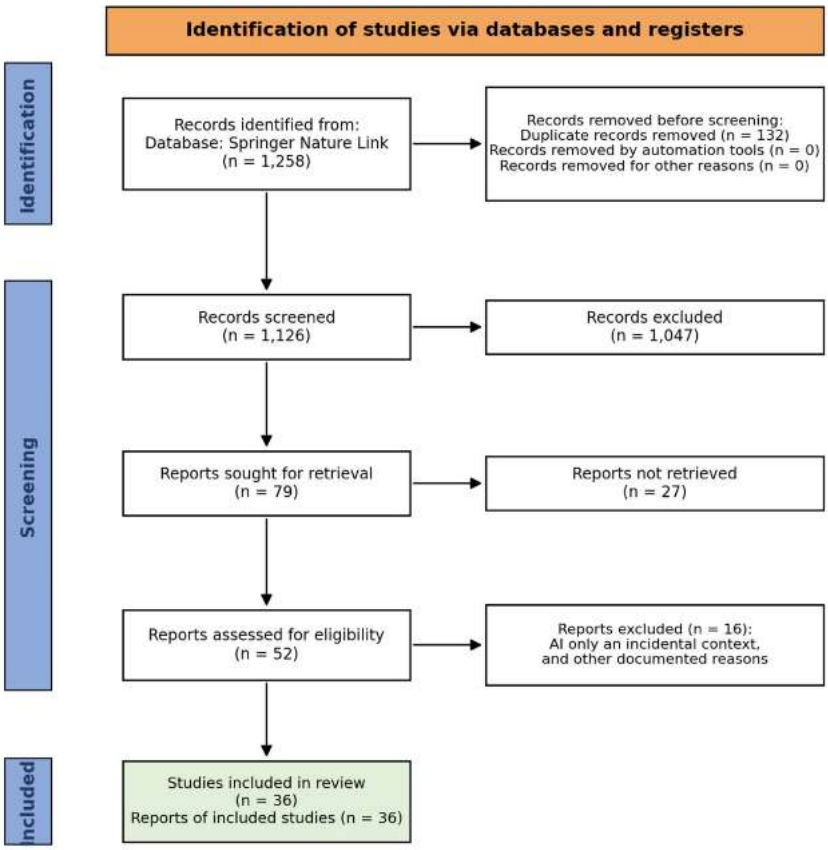


Figure 1. PRISMA 2020 flow diagram of study selection.

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2.5. Summary of the included literature

Most of the 36 included studies come from the period after generative AI appeared: 26 (72%) were published in 2025 to 2026, and only five before 2023 (two in 2023 and three in 2024). By segment, 18 deal with higher education, six with educational-technology firms, six with K-12 schooling, four with several segments, and two with tutoring. By region, 14 are global or conceptual, 11 are set in Europe, four in Australia, three in Asia, three in Africa, and one compares six countries; none is set in Indonesia. In terms of method, most studies are qualitative or conceptual, supported by survey-based quantitative work (several using structural equation modelling), bibliometric reviews, one discrete-choice experiment, and web-traffic analyses. Table 2 summarises each study by main focus, method, and key findings.

Table 2. Summary of the included literature (n = 36)

Author(s) & Year [ref]	Core focus	Methodology	Key findings
Fernández et al. (2023) [20]	HE digital transformation	Multivocal review (184 initiatives)	Only 23% of universities hold a digital strategy; initiatives remain isolated
Komljenovic, Williamson et al. (2026) [11]	Content assetisation	Critical-conceptual (3 cases)	Academic content enclosed as an income-generating asset (publisher/AI licensing)
Comas Forgas et al. (2026) [7]	Contract-cheating market	Longitudinal web analytics (44 sites)	Cheating-site traffic shifts with GenAI; survival via SEO and paid search
Hughes et al. (2025) [5]	GenAI adoption in HE	Mixed (29 interviews, ISM)	GenAI threatens the existing academic model; maps interdependent factors
Jensen et al. (2025) [4]	Disruption discourse	Systematic grey-literature review	Contested ‘disruptor vs hype’; ten institutional response claims
Crompton et al. (2026) [21]	GenAI governance	Global Delphi	Eight-area governance framework with update mechanisms
Watermeyer et al. (2024) [22]	Automation of academic labour	Survey (n=284)	GenAI automates academic work; extends an industrialisation logic
Watermeyer et al. (2025) [23]	Resistance to GenAI	Survey follow-up (n=284)	Deskilling; dual academic labour market; embedded without opt-out
Arviansyah et al. (2024) [24]	Tech innovation in HEIs	Bibliometric (662 Scopus)	Intellectual capital as a competitive asset; innovation agenda
Galal & El Morsy (2026) [25]	Dynamic capabilities & climate	Survey (n=300), SEM	Productivity paradox: IT/AI spend needs a supportive digital culture
Jacobs-Basadien & Pather (2026) [26]	GenAI policy progress	Document analysis	Maturity of institutional GenAI policy and guidelines
Korseberg & Elken (2025) [6]	Institutional response	Qualitative (17 interviews)	‘Wait-and-see’ paralysis; existential questions of institutional value
Quttainah et al. (2025) [27]	AI-savvy leadership (EdTech)	Survey (n=281), SEM	AI-savvy leadership drives AI utilisation and engagement
Hansen & Komljenovic (2023) [10]	Assetisation in EdTech	Conceptual-empirical (20 interviews)	Revenue shifts from selling products to controlling assets and data
Southgate et al. (2025) [28]	School datafication	Document analysis	Data brokering in schools; proposes a governance roadmap
Kucirkova et al. (2026) [29]	National EdTech policy	Comparative case (6 countries)	National policy shapes procurement; calls for shared standards
Sposato (2025) [30]	AI in educational leadership	SLR (314 publications)	Administrative automation; a ten-domain AI taxonomy for leaders
Gao & Hassan (2025) [31]	Online knowledge payment	Bibliometric (226) + BM analysis	Five online knowledge-payment business models
Brehm et al. (2026) [12]	Shadow education / tutoring	Qualitative, exploratory	Free-platform ‘DIY tutoring’ erodes fee-for-service tutoring
Degen et al. (2025) [32]	National digital ecosystem	Mixed methods	Public- vs private-value tension in a national ecosystem
İçen (2022) [33]	National AI in education	Qualitative + experiment	AI within a ‘learning marketplace’; national AI strategy
Bhardwaj & Kumar (2025) [34]	RPA in HE administration	PRISMA review (54 studies)	Time savings of 96.97 to 99.9% on specific admin tasks via RPA (not GenAI)
Ellis (2025) [35]	Postdigital leadership	Conceptual	Explicit ‘academic business model’ refinement; ecosystem leadership
Wieczorek (2025) [9]	Democratisation critique	Philosophical (Dewey)	Critiques commercial ‘democratisation’ claims as narrowing education
Pickering & Schuller (2025) [8]	Paid homework-helper (Chegg)	Empirical audit (50 units)	Paid-helper revenue growth and assessment-integrity threat
Komljenovic, Sellar & Birch (2025) [36]	Data-driven universities	Qualitative (14 interviews)	LMS vendors become platforms; data-return demanded via API

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Pietsch & Mah (2025) [37]	AI leadership in schools	Survey (n=179), SEM	Digital mindset and ambidextrous leadership enable transformation
Dai et al. (2025) [38]	AI–leader decision-making	Conceptual (Simon; Mintzberg)	AI–leader 'symbiotic collaboration' framework
Bower et al. (2025) [39]	Policymaker priorities	Qualitative two-phase (22 leaders)	Free, powerful GenAI forces system-level response; risk management
Teräs et al. (2020) [13]	EdTech solutionism	Critical conceptual essay	Pandemic 'seller's market'; solutionism and datafication
Matthews (2022) [40]	Unbundling the lecturer	Postdigital essay	'Unbundling' discourse pressures the lecturer's core value
Ullrich et al. (2022) [41]	AI in teaching vs administration	Bibliometric (796 WoS)	Maps AI research across teaching and administration
Lu et al. (2026) [42]	AI skills governance (TVET)	Discourse analysis (30 docs)	AI relocates assessment authority; learner data as strategic asset
Mbithi & Maina (2026) [43]	Parental AI-tool preferences	Discrete choice experiment (451)	Tiered pricing and willingness-to-pay; demand for data governance
Renz & Hilbig (2020) [44]	EdTech business models	Qualitative (25 firms)	Business-model typology; make-or-buy; entry of 'techlords'
Pischetola et al. (2024) [45]	University futures	Scenario survey (755 + 53)	Commodification/modularisation scenarios; reaffirming the mission

3. Results and Discussions

3.1. Theoretical implications: from asset ownership to dynamic capability

The main theoretical point of this review is to see the survival of education providers as a question of dynamic capability, rather than of market position or owning assets [16], [17]. Taken together, the 36 studies suggest that, in the AI era, what matters most is not what a provider owns but how quickly it can sense change, seize new sources of value, and reshape its business model.

1. From owning to coordinating. Across the studies, owning content or technology no longer guarantees an advantage, and in several cases that ownership is being worn away. Komljenovic and colleagues show how universities' own learning content and data are taken over and sold back to them as platform products [36], [11], while the services whose value stops at passing on knowledge, such as essay-writing sites, paid homework help, and fee-based tutoring, are the first to be replaced by free AI [7], [8], [12]. Value stays instead in things AI cannot easily copy, such as trusted certificates, human mentoring, and proven learning results [4]. The source of advantage therefore moves from the assets a provider holds to its ability to rearrange value, which is a problem of coordination rather than ownership.
2. Buying AI is not the same as building capability. The evidence is very consistent that getting AI without changing the organisation achieves little. Fernández et al. found that only 23% of the universities they studied had a digital strategy and 56% had started separate, uncoordinated projects [20], while Galal and El Morsy, in a survey of 300 academic staff, found a productivity paradox: spending on technology improves innovation only when it goes together with a supportive digital culture [25]. This is the dynamic-capabilities idea in practice: advantage comes from sensing, seizing, and transforming, not from the resources by themselves [17], [18].
3. A gap in the speed of response. The review shows a mismatch in speed. Technology vendors have already moved to earning ongoing income from data and turning it into assets [10], [11], [36], while institutions have been much slower. In Korseberg and Elken's study of three Norwegian universities, using Scott's three pillars of institutions, ChatGPT was at first seen mainly as a rule problem to be controlled, so the organisation's response lagged behind the technology [6]. It is this difference in speed of response, more than the technology itself, that best explains why some providers change while others stand still.

3.2. Managerial implications: from defensive response to value reformulation

For practitioners, the studies point beyond simply defending the old model toward redesigning it, and they help explain why the most common responses fail.

1. Defence is the weakest option. The responses reported most often, such as exam rules, going back to in-person exams, and AI-detection tools, are also the least lasting. Pickering and Schuller's audit of an Australian engineering school found cheating content for more than half of the course units checked, and about 50% of questions on Chegg were answered within roughly 1.5 hours, which shows how easily detect-and-ban strategies are beaten [8]. The studies suggest that rethinking what the provider offers lasts longer.

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Pischetola et al.'s Danish teachers restate the university's mission of preparing students to solve real problems [45], and Jensen et al. list genuine assessment and a human teaching role among the responses most likely to hold [4].

2. Managing data becomes a strategy. As control over data and content moves to platforms, managing vendors is now a core capability, not just a purchasing detail. Komljenovic, Sellar and Birch describe how UK universities struggle to make their data valuable and try to get it back, asking for data to be returned through APIs as their learning-management suppliers turn into platforms that build products from university data [36]. School systems face similar pressure from data brokers [28], and in China's vocational reform even the power to assess skills moves into platforms controlled by vendors and the state [42]. Providers that do not treat data as a strategic issue risk being locked in to their vendors.
3. Move the value, and set prices with care. Staying viable means moving value toward certificates, mentoring, and proven results, and using AI to support teachers rather than replace them [9], while pricing access carefully. Mbithi and Maina's choice experiment with 451 Kenyan parents is a useful example: a price rise of about USD 7 per month lowered take-up by up to 32 percentage points among low-income families, who were both the most willing to pay for the features and the most sensitive to price. This points to a two-tier market in which a single price for everyone would widen inequality [43].

3.3. Conceptual deepening: how AI reconfigures education business models

Below these points, the studies show AI reshaping the education business model along five connected dimensions.

1. Turning data and content into assets. The clearest business change is turning learner data and academic content into things that earn income. Komljenovic, Williamson and colleagues describe three paths: universities locking up their online learning content, EdTech platforms collecting large databases of student assignments and manuscripts, and academic publishers licensing publications to generative-AI firms to train large language models. In each case, licensing of intellectual-property rights is the legal tool that gives one party ownership and power [11]. From interviews with business-to-business EdTech firms, Hansen and Komljenovic show that automating learning is itself a way to control digital assets and user data [10], and learning-management suppliers increasingly turn university data into platform products and sell them back to the universities [36]. The same pattern appears in the trading of school data [28], in tutoring platforms [12], and in treating learner data as a key asset in platform-based vocational reform [42].
2. Automating cost and labour. AI reshapes the cost base, starting with administration. Bhardwaj and Kumar's review of robotic process automation reports time savings of up to about 99.9%, and cost cuts of about 43 to 67%, on specific administrative tasks such as checking attendance and processing internship reports [34]. As automation moves into core academic work, however, Watermeyer et al.'s survey of 284 academics warns of lost skills and less secure jobs, with generative AI built into work platforms with no real way to opt out, and its benefits shared unevenly within the status-driven world of academia [22], [23]. In line with this, most current uses are still in administration, such as admissions, student retention, and service chatbots, as shown by Sposato's ten-area classification and Ullrich et al.'s bibliometric mapping [30], [41].
3. Disruption of the value to learners, which is real but only partial and uneven. On the demand side, Comas Forgas et al.'s long-term study of 44 contract-cheating sites finds their traffic changing as easy-to-use AI spreads, although it does not prove cause and effect [7], and Brehm et al. show how free platforms such as YouTube and Telegram allow 'do-it-yourself' tutoring that eats into fee-based providers in Cambodia [12]. Yet paid platforms can still survive in their own niche, as Chegg's continued use alongside ChatGPT shows [8]. The more serious, slower threat to formal providers is not lost market share but a loss of trust in their assessment and certificates, that is, the very qualification they exist to guarantee [4], [5], [39].
4. A shift of control toward technology vendors. Beyond cost and demand, AI also moves power around. Generative tools come built into work platforms with no way to opt out [23], and in China's Smart Vocational Education programme Lu et al. show how moving services onto platforms and joining up data shift the power to define skills and judge performance into systems controlled by vendors and the state, which is about governing skills, not just a technical upgrade [42]. At the same time, vendors' claims to 'democratise' education are criticised for narrowing what education means and for hiding whose interests the technology really serves [9], [35].
5. New market structures and ways of earning revenue. The studies record several new business models rather than one single path. Renz and Hilbig's study of 25 EdTech firms found only one offering fully adaptive, AI-based learning in 2020, framed the providers' choice as 'make or buy', and warned that large technology companies such as Google and Amazon were entering the market [44]. Gao and Hassan identify five different ways of charging for knowledge online, from live question-and-answer to streaming courses and short audio,

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which attract users in different ways [31]. Together with different prices for different groups [43], national learning marketplaces [33], and public-private digital ecosystems led by the state [32], these complete a picture of new ways to earn revenue.

3.4. A dynamic-capabilities reading of educational viability

Read through the dynamic capabilities view, these findings fit closely with Teece's three abilities: sensing, seizing, and transforming [17], [18]. Sensing means reading the disruption to the provider's value (RQ2), that is, seeing which services are being replaced and where trust in assessment is weakening [4], [5]. Seizing means choosing new value and new ways to earn revenue (RQ1), such as genuine assessment, human mentoring, content licensing, and prices set for different groups [31], [43]. Transforming means reshaping the business model, its governance, and its handling of data so these choices last (RQ3), through a joined-up digital strategy, careful data and vendor governance, and building capability, of the kind set out in Crompton et al.'s eight-area governance framework for generative AI [36], [21], [25]. On this reading, survival depends mostly on the speed of transforming. A provider whose value rests on passing on knowledge must move its value faster than vendors can turn that value into their own assets, while a provider built on certificates and human contact faces a slower but real challenge to its credibility. The view also highlights two risks that usual survival studies tend to miss: heavy dependence on vendors and the data they hold, and a splitting effect in which market-based AI can widen inequality rather than reduce it [43], [39]. Finally, because no included study is set in Indonesia, the national tutoring and private higher-education segments, whose value rests heavily on passing on knowledge, stand out as a case to test in future [14].

The studies do not all agree, and the disagreements are useful in themselves. Even the idea of 'disruption' is debated. Some see it as an unavoidable break, while others see it as overstated hype, much like earlier predictions about MOOCs that never came true [4]. The evidence on substitution is mixed too, since free tools replace some providers while paid platforms continue alongside them [12], [8]. Claims that AI 'democratises' learning sit directly against evidence that market-based access splits it by income [9], [43]. Through the dynamic capabilities view, these differences are not noise but conditions that shape outcomes: results vary by segment, by context, and by how fast institutions respond, not by the technology alone.

3.5. Limitations and future research

Several limits apply to these conclusions. First, the dynamic capabilities view is a lens used to interpret the findings, not a category that came out of the coding. The extraction matrix recorded business-model areas, not capabilities, so the account is offered as one way to interpret the evidence, not as a tested model. Second, the search used only one database (Springer Nature Link). This tilts the coverage toward that publisher's journals and leaves out leading journals indexed elsewhere. Related to this, the 27 eligible reports that could not be obtained because of paywalls create an availability bias that may especially affect the evidence on pricing and market structure, where paywalled management journals are common. Third, one reviewer did the screening and extraction without a second coder, and the review covered only English-language articles, which limits both reliability and coverage. Finally, the set leans toward conceptual and qualitative work published in 2025 to 2026, so the findings are best seen as an early, theory-based map rather than a final account.

These limits point to an agenda for future research. The central claim, that survival depends on how fast a provider can move its value to things AI cannot copy, should be tested with real data rather than assumed, for example through long-term or comparative case studies of providers that adapt and those that do not. The review should also be repeated across more databases, especially Scopus and Web of Science, and extended to non-English studies to widen coverage. Studies focused on specific segments and countries are especially needed in contexts missing from this review. Indonesia, with its large private tutoring sector and its private universities that depend on tuition fees, fits the profile most exposed to substitution and is a priority case for studying how providers sense, seize, and transform under pressure from AI.

4. Conclusion

This review of 36 articles published between 2019 and 2026 reframes the effect of AI on education as a question of dynamic capability rather than of owning assets. AI changes business models by turning data and content into assets, by automating cost and labour, through uneven change across institutions, and through new market structures. Its disruption of the value providers offer is real but only partial: services that mainly pass on knowledge are hit first, and formal providers face a loss of trust in their assessment along with a shift of control over data and content to vendors. Responses range from common but weak defensive rules to the rarer, more decisive step of rethinking what the provider offers. Read through the dynamic capabilities view, survival comes down to sensing,

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seizing, and transforming rather than owning assets, and it depends on how fast a provider can move its value to things AI cannot copy. For practitioners and policymakers, this means that protecting the quality of education in the AI era depends less on resisting the technology and more on building the ability to move value faster than it can be automated away.

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DOI: https://doi.org/10.31004/riggs.v5i2.10412
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