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AI in education and the future of teachers' meaningful work

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This article examines how different configurations of artificial intelligence (AI) in education may reshape teachers' opportunities to experience teaching as meaningful work. Using a scenario methodology, we develop three plausible scenarios grounded in existing educational AI: Labor-Replacing Classrooms, where AI tutors displace core instructional tasks and teachers are redeployed into surveillance and exception-handling; AI-Managed Teaching, where teachers remain central but are guided and evaluated through dashboards, nudges, and performance indicators; and Human–AI Teaming, where AI is implemented as a teacher-governed, co-designed support intended to augment professional judgment. Drawing on work-design theory and scholarship on meaningful work, we assess each scenario against five dimensions: task integrity, skill cultivation and use, task significance, autonomy, and belongingness. The analysis indicates that labor substitution and the pervasive use of algorithmic surveillance threaten the integrity of pedagogical processes, potentially constraining professional autonomy and shifting the focus of teaching toward metrics and outputs that are easily processed by machines. While human–AI collaboration has the potential to enhance agency and foster collegial inquiry, it remains fragile and could lead to overdependence on AI systems if governance structures and workflows are not kept under scrutiny. Overall, the trajectory of AI in education depends on policy, on which technologies are adopted, and on broader institutional choices that can either erode or safeguard meaningful teaching.

KEYWORDS
algorithmic management, artificial intelligence in education (AIED), datafication, future of teaching, human–AI collaboration, meaningful work, scenario methodology

1 Introduction

Debates about AI in education move quickly between optimism and alarm. Policy and tech industry narratives highlight automation, personalization, and efficiency, envisioning AI tutors, automated grading systems, and exam proctoring tools that can operate at superhuman scale (Agrawal et al., 2018; Selwyn, 2024; World Economic Forum, 2025). Critical accounts argue that such systems can intensify surveillance, narrow pedagogical practice, and reorient institutions around data proxies, that is, measurable indicators that stand in for more complex educational processes, at the expense of professional judgment and autonomy (Kellogg et al., 2020; Zuboff, 2019). Economists further warn that many recent AI innovations represent the "wrong kind of AI" oriented toward labor-replacing automation and contributing to stagnating job growth and inequality (Acemoglu and Restrepo, 2020).

Underlying these dynamics is a powerful economic driver: cost reduction. Education, like other labor-intensive service sectors, is often discussed in relation to Baumol's (2012)

"cost disease": because productivity gains are difficult to achieve, costs tend to rise as wages increase in step with more productive sectors of the economy. This leaves education persistently vulnerable to pressures for efficiency and cost containment. As Acemoglu and Restrepo (2020) argue, many automation technologies are designed to replace human labor with cheaper capital. Their concern is that some forms of "so-so" automation are just productive enough to be adopted, but not productive enough to generate gains large enough to offset labor displacement. In this context, AI is framed not only as a pedagogical innovation but also as a possible response to structural cost pressures in education.

Selwyn (2024, p. 4) urges moving beyond hype and doom by calling for "*more reasoned responses to the educational possibilities of AI*" and for "*paying closer attention to the experiences and standpoints of those groups likely to gain least (and likely to lose most) from the unfettered implementation of AI technology in education*," in particular teachers and students. This article responds to that call by presenting three plausible futures for AI in education, each evaluated based on how it affects teachers' ability to do meaningful work: (1) *Labor-Replacing Classrooms*, (2) *AI-Managed Teaching*, and (3) *Human–AI Teaming*.

Across these futures, our guiding question is constant: How do different configurations of AI reshape teachers' opportunities to experience teaching as meaningful work? Building on work design theory (Hackman and Oldham, 1976) and scholarship on meaningful work (Bailey et al., 2019; Lips-Wiersma and Morris, 2009; Veltman, 2016), and drawing in particular on Bankins and Formosa's (2023) synthesis, we conceptualize meaningful work through five interrelated conditions: task integrity, skill cultivation and use, task significance, autonomy, and belongingness. Together, these conditions shape teachers' everyday experience of teaching while also grounding the broader quality and civic mission of education.

This perspective can be further sharpened by recognizing that teaching is also cognitively intensive professional work. Teachers continuously interpret incomplete information and generate feedback under conditions of uncertainty and time pressure. From this perspective, AI reshapes teachers' work not only by redistributing tasks, but by redistributing cognitive labor. While some systems may reduce routine burdens, they may also shift aspects of diagnosing student understanding, sequencing instruction, and providing feedback away from teachers, thereby weakening opportunities to exercise and further develop professional expertise (Rind, 2026; Rind and Qureshi, 2026).

In this sense, the risk is not simply automation as such, but pedagogical deskilling through disuse: when teachers are less involved in core instructional decisions, the knowledge and judgment those practices sustain may gradually erode (Rind and Qureshi, 2026). At the same time, teacher agency does not simply disappear in AI-mediated environments. Rather, it becomes more conditional and effortful, depending on teachers' capacity to interpret, question, override, and contextualize algorithmic outputs in relation to students' needs and broader educational purposes (Rind, 2026; Rind and Qureshi, 2026).

In pursuing our inquiry, we focus on actually existing AI in education, such as automated grading, dashboards, tutoring systems, and proctoring, rather than speculative notions of artificial general intelligence (AGI), that is, AI systems with human-like general problem-solving capacities, which remain distant and uncertain (Holmes and Tuomi, 2022; Mitchell, 2019; Selwyn, 2024). Holmes and Tuomi's (2022) taxonomy is instructive here, as it groups AI applications into three domains: student-facing systems (e.g., tutoring, feedback, proctoring), teacher-facing systems (e.g., grading assistants, analytics dashboards), and institution-facing systems (e.g., enrollment management, predictive analytics). Our scenarios build directly on these categories and envision how their large-scale adoption might reconfigure the meaningfulness of teachers' work.

Following Farrell et al. (2025), we treat AI not as an intelligent agent but as a cultural and social technology. In this view, its importance lies less in intelligence as such than in its capacity to make human-generated information accessible, reorganizable, and usable at scale. This shifts attention away from debates about AGI and toward the more immediate political and institutional questions raised by the AI systems: who gains and who loses from their adoption, how power and influence are redistributed, and what kinds of regulatory or normative institutions are needed to shape their effects. Harari (2024) sharpens the critical implications of this view by reminding us that such information systems are not neutral truth-seeking infrastructures. As these systems are mostly commercialized, truthfulness may be subordinated to business imperatives, especially the imperative to maximize user engagement. In this context, platforms may privilege content that captures attention and spreads widely, even when it is less truthful or socially damaging.

The AI entering classrooms today consists of narrow, data-driven systems optimized for specific tasks, such as predicting student failure risk, flagging plagiarism, generating text or feedback, curating content, proctoring exams, or recommending next learning steps. Such systems often rely on machine-readable proxies, for example screen time as a stand-in for engagement, keystroke dynamics as a proxy for authentic authorship, or gaze fixation as a proxy for attention (Holmes and Tuomi, 2022; Selwyn, 2024). As Wajcman (2019, p. 1274) notes, "the increasing use of metrics and indicators as proxies for performance is changing the way work is experienced and valued," raising concerns about what is reduced or overlooked when educational processes are translated into data. In complex social settings, such proxies are often brittle, reducing rich educational practices to narrow indicators in ways that make their effects difficult to foresee (Selwyn, 2024; Wajcman, 2019). Farrell et al. (2025) help frame this process by showing how AI systems turn complex human activity into simplified but usable representations. Rather than merely storing or retrieving information, such systems reorganize and restructure it in ways that make large-scale coordination possible. In educational settings, this means that teaching and learning must be translated into simplified, categorized, and machine-readable forms before AI systems can process them, rendering some aspects more visible while obscuring others.

Shelby et al. (2023) distinguish several forms of sociotechnical harm arising from algorithmic systems, including those labeled as AI: allocative harms, where algorithmic decisions distribute resources and opportunities unevenly; quality-of-service harms, where systems systematically underperform for particular groups; and representational harms, where stereotypes and

misleading classifications are reproduced. Selwyn (2024) shows that these harms are highly relevant in education, pointing to cases such as automated grading that advantages already privileged students, voice-recognition systems that wrongly flag students with accented speech, facial-recognition tools that misidentify students of color, and systems that marginalize disabled or neurodiverse learners. As McQuillan (2022) argues, socially applied AI has a structural tendency to harm the less privileged. This is often rooted in design: the people shaping algorithmic systems are likely to represent a privileged standpoint, and automated decision systems can be tuned in many ways by adjusting decision boundaries and thresholds. These choices affect who is misclassified through false positives and false negatives and are shaped both by engineers' outlook and by the priorities of the institutions that employ them. Such choices are often opaque and appear neutral, making them difficult to detect and contest.

Winner (1978, p. 229) argues that once a technological system is in place, society (and individuals) often reshape their goals, values, and expectations to fit the possibilities and demands of the technology rather than the other way around. He calls this process reverse adaptation, "*the adjustment of human ends to match the character of the available means*." Instead of technologies simply serving pre-set human purposes, their very presence reshapes what we consider worthwhile to pursue. Høvsgaard Maguire's (2019) study of algorithmic testing (testing shaped by an algorithm that actively selects and sequences questions) offers a clear example: students are taught to "adapt to the test," and teachers are tasked with managing testing situations so that algorithms can generate valid, "pure" results. Rather than adjusting the system to human variability, schools standardize instructions and routines to fit the technical logic of the test. Selwyn (2024) maintains that AI technologies require teachers and students to reorganize their behavior to be machine-readable. Students are compelled to write, speak, and act in ways that can be easily translated into machine-readable data, while teachers are nudged toward pedagogies that produce codified outputs suitable for system input. In both cases, the complexity and nuance of teaching and learning are subordinated to what the system can register.

The same pattern is even more evident beyond education. Algorithmic management in workplaces reorganizes labor by standardizing tasks, tightening control, and treating professional judgment as variance to be minimized. In Amazon's warehouses, for example, scan tracking and automated discipline have been used to raise throughput at the expense of autonomy, task integrity, and well-being (Delfanti, 2019; Delfanti and Frey, 2021). Similar dynamics are visible in other AI-mediated settings. Christl (2023, 2024), for example, shows how corporate surveillance systems track keystrokes, communications, and even workers' emotional tone, compelling employees to adjust their behavior in order to remain machine-legible and avoid being flagged as anomalous. In this way, these cases illustrate reverse adaptation in action: algorithmic monitoring encourages conformity to predefined metrics, thereby narrowing the space for open-ended judgment and undermining the conditions of meaningful work.

In research on automation, a central distinction is between substitution, where automation displaces human work by transferring tasks wholesale to machines, and augmentation, where technology complements and extends human capabilities (Acemoglu and Restrepo, 2018, 2020; Autor, 2015; Willcocks, 2020). AI-driven automation is often designed to replace human labor, removing workers from tasks they previously performed and relegating them to supervision or exception-handling roles, gradually eroding room for professional judgment and opportunities to use and develop skills. By contrast, AI augmentation involves creating new tasks or redesigning roles so that AI systems amplify uniquely human strengths, such as judgment, empathy, or creativity, while offloading routine, codifiable work (Acemoglu and Restrepo, 2018). Autor (2015) argues that automation replaces some tasks while complementing others, so its effects on work cannot be reduced to simple job replacement. Willcocks (2020) similarly argues that most implementations involve partial automation and role redesign rather than wholesale job elimination.

Organizational research highlights that the benefits of AI are realized when it is used to complement rather than replace human expertise. Effective human–AI collaboration depends on redesigning roles, building trust in systems, and creating opportunities for human judgment to interact with algorithmic recommendations (Bankins et al., 2024; Jarrahi, 2018). Just as importantly, outcomes hinge on governance: the metrics, incentives, and accountability structures that organize practice determine whether AI empowers or constrains workers. Algorithmic control mechanisms, such as restricting workers' options, recommending courses of action, recording activity, rating performance, automating tasks, and rewarding compliance, may improve coordination, but they can also intensify manipulation, disempowerment, surveillance, discrimination, precarity, and stress (Kellogg et al., 2020). Notably, even technologies intended to enable or augment workers can play out in divergent ways. Furendal and Jebari (2023) caution that higher productivity through AI can be achieved in two modes: one that promotes the "goods of work" (opportunities for excellence, community, and purpose), and another that diminishes those goods and amplifies the "bads of work" (injury, coercion, loss of autonomy). In other words, a purportedly labor-enabling scenario can still end up stunting human capabilities if implemented without regard for human dignity and development.

Education now stands at a crossroads along these axes. The same technical capabilities can be configured to replace core teaching tasks, tightly supervise teachers, or support them as designers of learning experiences. The three scenarios developed below make these alternatives explicit and link them directly to teachers' opportunities for meaningful work.

2 Materials and methods

This section describes the construction of the three foresight scenarios and the analytical framework used to assess their implications for teachers' meaningful work.

2.1 Scenario construction

To explore the future of AI in education and teachers' meaningful work, we adopted a foresight scenario methodology. We drew on the stepwise approach to strategic scenario development outlined by Duus (2016), particularly its emphasis on identifying a central problem, specifying relevant drivers of change, considering their relative importance and uncertainty, and constructing internally consistent and distinct scenario narratives. The aim was not prediction, but the construction of plausible alternative futures that clarify underlying trade-offs, hidden assumptions, and institutional choices. Rather than applying Duus's model as a fixed template, we adapted this approach to our own research purpose by developing three scenarios structured around distinct institutional logics for AI in education: labor substitution, algorithmic supervision, and human–AI teaming. Each scenario is illustrated with a short narrative vignette to make its implications for classroom life more tangible.

The study does not draw on new empirical classroom data. Rather, it is based on existing scholarship and documented applications of AI in education, supplemented by analogies from AI-intensive workplaces where algorithmic management and labor reorganization are already more developed. From this material, we identified recurring trends, tensions, and drivers relevant to the future organization of teachers' work, especially around automation, datafication, and forms of algorithmic management. Schools and universities are increasingly adopting AI systems that automate, structure, and monitor teachers' work. Examples include analytics dashboards, predictive and early-warning systems, automated grading and feedback, adaptive platforms promoted as personalized learning, and tools for proctoring, plagiarism detection, and classroom monitoring. Together, these developments push education toward practices that can be measured and tracked in digital systems, while emerging forms of human–AI collaboration frame AI as a means of augmenting rather than replacing teachers' expertise.

These developments are propelled by a mix of technological, economic, and institutional drivers. Advances in machine learning and natural language processing broaden what is technically feasible, while cost pressures make automation attractive to educational systems operating under resource constraints. Tech industry actors and policy agendas emphasize efficiency, personalization, and accountability, reinforcing data-driven solutions aligned with standardized outcomes. Broader cultural expectations for individualized digital services also shape demand for "personalized" education. Competing drivers include professional advocacy and ethical debate, which stress transparency and autonomy.

The three scenarios were selected because they represent analytically distinct and normatively significant trajectories already visible in existing technologies, policy discourses, and organizational debates about AI in education. More specifically, the scenarios were constructed to vary along three dimensions central to the future organization of teachers' work: the degree of task substitution, the extent to which algorithms control work processes, and the extent to which professional judgment remains central in pedagogical decision-making. This produced three contrasting but plausible configurations. In line with Duus's (2016) consistency criteria, we sought to ensure that the scenarios were distinct from one another, plausible in relation to current developments, internally consistent in their technological, organizational, and pedagogical elements, and grounded in influential drivers already visible in the field. These contrasting configurations provide the analytical basis for examining how different pathways of AI adoption may reshape the meaningfulness of teachers' work.

2.2 Analysis of teachers' work

Our analysis examines how teachers' meaningful work is shaped and affected across the three scenarios. It is guided by classic work design theory (Hackman and Oldham, 1976) and by ethical and philosophical accounts of meaningful work (Bailey et al., 2019; Lips-Wiersma and Morris, 2009; Veltman, 2016), synthesized in the recent framework developed by Bankins and Formosa (2023). This framework conceptualizes meaningful work through five interrelated conditions: task integrity (the opportunity to carry out work as a coherent whole rather than as fragmented micro-tasks), skill cultivation and use (the extent to which work enables the development and exercise of knowledge, skills, and expertise), task significance (the sense that work contributes to a broader purpose or to the well-being of others), autonomy (discretion and control over how work is performed), and belongingness (the experience of social connection, recognition, and shared values in work).

In the analysis that follows, each scenario is examined through these five dimensions of meaningful work. In the educational context, task integrity concerns whether teachers are able to carry out the full cycle of planning, instruction, assessment, and feedback rather than fragmented or system-defined activities. Skill cultivation and use relates to the opportunities teachers have to develop and apply their pedagogical, relational, and subject-specific expertise. Task significance reflects the extent to which teaching continues to contribute to students' learning, well-being, and the civic mission of education. Autonomy captures teachers' individual and collective discretion in interpreting and enacting their work, while belongingness refers to their participation in collegial communities of practice and the recognition they receive for their professional contributions.

3 Results

The results are organized around three plausible scenarios for AI in education. Each scenario is introduced through a short vignette, discussed in broader terms, and then analyzed more specifically through five dimensions of teachers' meaningful work: task integrity, skill cultivation and use, task significance, autonomy, and belongingness.

3.1 Scenario 1: labor-replacing classrooms

> The classroom is quiet in a new way, no chatter, only the steady whisper of headsets. Ms. K's "cohort" watches their AI tutors bloom and contract like jellyfish on their tablets,

> pulsing hints and micro-explanations. Ms. K paces, a shepherd without a flock, handling escalations: misplaced logins, a frozen audio driver, a tearful fourth-grader who keeps failing "attention checks." At 10:37, a wall panel reports 86 percent of learners in the green zone; by 10:42 it drops to 79 percent. She swipes her badge at a kiosk to register an intervention. The kiosk spits out a receipt. At lunch, a boy shows her a sketch of a kite with a question about lift. Ms. K begins to talk about angles, wind, and the feel of a taut string between fingers. The boy glances at his tablet. "Can I ask Tutor for that?" he says, already scanning the QR code. The string goes slack, their connection loosening until it can no longer be felt.

In this scenario, education authorities, which are pressured by budget constraints and the political demand to do more with less, turn to AI tutor systems as a seemingly rational solution. The economic rationale is clear: automation promises cost-efficiency (by reducing reliance on salaried teachers), standardizing instruction, and scaling delivery with minimal human input. Corporate actors in the tech industry, motivated by profit, position themselves as indispensable partners in this transformation. They promote end-to-end platforms that bundle content pipelines, behavioral analytics, automated assessment, and "next-step" recommendation engines optimized for narrow performance metrics.

The economic logic is veiled behind an ideological façade. Policymakers and corporate representatives frame AI tutoring as an emancipatory project of personalized learning and innovation, invoking the language of inclusion, choice, and evidence-based practice. The system may also be marketed as teacher-supportive, for example by claiming to free teachers from routine instruction and allow them to focus on students who need human attention most. In this rhetoric, automation is not openly presented as a way of reducing teacher numbers, but as a means of democratizing access and improving quality.

Once implemented, however, fewer teachers are needed. Learning is reorganized around what can be efficiently captured and optimized as data. The pedagogical relationship is displaced by a data infrastructure that privileges measurable transactions (clicks, responses, and completion rates) over the interpretive, dialogical, and affective dimensions of education. In effect, what counts as learning is re-coded into streams of machine-tractable interaction data, while the economic and political interests driving this transformation recede into the background.

3.1.1 Task integrity

Coherent pedagogical cycles of diagnosing, designing, instructing, and giving and receiving feedback are fragmented and transferred to the system. The teacher's role contracts to episodic surveillance; monitoring compliance, logging interventions, and fixing technical failures. Assessment is automated and detached from classroom life, breaking the feedback loop that once linked teaching and evaluation. The craft of teaching loses its wholeness. Remaining is a sequence of isolated reactions to algorithmic processes.

3.1.2 Skill cultivation and use

Opportunities to develop and exercise pedagogical or relational expertise decline sharply. Professional learning revolves around dashboard literacy and platform maintenance rather than experimentation with methods or reflection on learning. Over time, this risks a gradual pedagogical deskilling through disuse. When teachers are less involved in core teaching practices, the knowledge and judgment those practices sustain may erode. Teachers' skills are increasingly defined by their ability to operate within the system rather than to design learning beyond it.

3.1.3 Task significance

The meaning once derived from shaping students' understanding gives way to the management of throughput and completion targets. Teachers are no longer engaged as intellectual contributors but as supervisors of machine-mediated instruction. Occasional moments of care remain, yet they feel peripheral to the system's core logic of efficiency.

3.1.4 Autonomy

Pacing, content, and assessment criteria are pre-set by the platform. Deviation from the AI-generated script is logged and discouraged, narrowing the scope for discretion or critical judgment. Teachers become implementers of automated routines rather than interpreters of educational aims.

3.1.5 Belongingness

With fewer colleagues and minimal collaborative planning, collegial inquiry and shared reflection wane. Interaction is mediated through dashboards and performance indicators that measure individual compliance rather than collective purpose. Professional identity is maintained symbolically but drained of communal substance.

3.2 Scenario 2: AI-managed teaching

> The dashboard wakes before Mr. R does. Overnight it has drafted a lesson spine, ranked three questioning strategies, and flagged two students for probable "quiet disengagement." In second period, Mr. R deviates. A student's half-right answer is too intriguing; he follows the teachable moment. A yellow banner unfurls on his tablet: Pacing deviation (+7 min). "Noted," he mutters, and continues. The discussion is messy and alive. After class, the analytics coach calls: the model recommends a re-teach. Mr. R explains why he didn't re-teach: the student's analogy connected the text to a local protest. "Understood," says the coach, "but the indicator dipped." At 16:00 the dashboard prompts: Please record rationale for deviation. Mr. R types, "We were learning." The text box glows red: insufficient detail. He sighs and translates the moment into bureaucratic form: citing a curriculum standard, describing evidence of learning, and attaching a student work file as proof. The

> banner turns green. Tomorrow's algorithmic lesson plan adjusts, but very slightly.

In this scenario, human teachers remain in the classroom, but their work is increasingly structured and surveilled through AI-driven dashboards, nudging systems, and automated evaluations. Lesson planning, pacing, and assessment are mediated by digital interfaces that continuously capture, analyze, and compare data on student performance. The economic rationale mirrors that of automation: algorithmic coordination promises higher productivity, data-driven accountability, and reduced costs. From the perspective of corporate actors in the tech industry, this model opens a profitable middle ground: schools retain most teachers, but must subscribe to platforms and analytics services that become integral to everyday instruction.

These arrangements are presented under an ideological banner of precision and support. Policymakers and tech providers describe algorithmic dashboards as tools that empower teachers to "see" their students more clearly, intervene earlier, and base decisions on objective evidence rather than intuition. Yet the same systems subtly redefine what counts as good teaching. The constant flow of indicators and alerts does not simply add information. It reorganizes teachers' attention and redirects cognitive effort toward interpreting metrics, documenting deviations, and maintaining alignment with system expectations. Professional judgment thus becomes something to justify rather than exercise. Over time, teachers may be drawn away from the diagnostic and reflective work through which pedagogical expertise is sustained, as classroom decisions are increasingly translated into forms acceptable to the system.

Thus, the promise of timely intervention gives way to the reality of algorithmic management, a mode of control that organizes teaching around measurable compliance rather than pedagogical reflection. Instructional priorities are recalibrated to what the system can track and reward, while the slower and dialogical aspects of education are marginalized. Teachers remain visible at the front of the classroom, but their autonomy is mediated through layers of datafication that both enable and constrain what they can meaningfully do.

3.2.1 Task integrity

Core teaching practices still take place, but they are refracted through the lens of the dashboard. The pedagogical sequence remains recognizable, yet its coherence is compromised by the constant mediation of indicators and alerts. Teachers adjust classroom practice to satisfy performance metrics rather than pedagogical flow. Integrity holds only when algorithmic measures coincide with professional judgment. The lesson becomes a hybrid of teaching and reporting, with reflection increasingly replaced by data entry and justification.

3.2.2 Skill cultivation and use

Opportunities for professional growth exist, but they are directed by the logic of the platform rather than teachers' own inquiry. Analytics can illuminate misconceptions and free time for targeted support, but the same systems may confine teachers to a narrow repertoire of responses. Professional development focuses on tool mastery and indicator interpretation rather than inquiry into learning itself. Over time, the skills most rewarded are knowing how to navigate, justify, and document within the platform.

3.2.3 Task significance

Teachers still witness learning and may care for students, but the sense that their own judgment and presence make a difference is undermined. The satisfaction of contributing to a student's growth gives way to the imperative of satisfying the dashboard's performance logic. In this environment, teachers may increasingly struggle to experience themselves as genuine contributors to learning. Instead, they feel reduced to intermediaries of the machine, executing prompts and rationales written elsewhere.

3.2.4 Autonomy

AI-generated recommendations define the expected course of action, and deviation requires justification. Each pedagogical improvisation must be logged, explained, and aligned to system criteria, transforming autonomy into a burden of proof. What remains is a more conditional and effortful form of agency. Teachers can still depart from system recommendations, but doing so requires cognitive work: interpreting algorithmic outputs, judging their relevance, and translating one's own reasoning into forms the system recognizes. The need to rationalize decisions in platform-compatible terms may foster self-censorship, as teachers begin to anticipate what the system will approve rather than what students need.

3.2.5 Belongingness

The data infrastructure reshapes collegial life. When dashboards are used for collective reflection, they might support peer inquiry and strengthen professional community. More often, data are individualized, comparative, and hierarchical. Teachers' performance becomes a private metric or a public ranking, eroding trust and mutual support. Dialogue about pedagogy gives way to talk about indicators, and belongingness weakens as teachers' relationships become mediated through screens and scores rather than shared judgment.

3.3 Scenario 3: human–AI teaming

> There is no bell on Ms. T's wall, just a corkboard of student work and a small tablet she docks when she chooses. Last night, an AI co-writer drafted student feedback using her assessment guide; she quickly refined a few of its comments. During seminar, a suggestion blooms in the margin: "Possible follow-up question (based on last week's exit ticket)." Ms. T taps it, tweaks the phrasing, and poses the question. A student connects the text to a family story; the class pivots. After school, the grade-level team meets around a shared analytics workspace with work samples, snippets from classroom conversations, and a visual map of the

> questions students asked. They debate what progress means in this unit and adjust the system settings so next week's prompts better reflect this. On her way out, Ms. T notices that her tablet has already generated tomorrow's lesson outline and predicted gaps in students' understanding. She smiles with relief, it already knows what she'll need. She closes her notebook without adding anything.

In this scenario, AI technologies are introduced not as substitutes for teachers but as collaborative instruments designed to extend and support their professional judgment. The prevailing logic is augmentative, with AI positioned as a co-worker that handles routine administration, synthesizes information, and generates feedback, allowing teachers to focus on the creative and relational aspects of education. The economic rationale is framed around the idea that improving working conditions, enhancing teachers' expertise, and reducing burnout will ultimately make education more effective and sustainable. For corporate actors in the tech industry, this scenario also offers a profitable model, with platforms and analytics tools marketed as teacher-enabling services rather than as substitutes for teachers.

The ideological rhetoric surrounding this model emphasizes collaboration, ethics, and professionalism. Policymakers present human–AI teaming as the balanced alternative, a third way between technological displacement and nostalgic resistance. Teachers are positioned as empowered decision-makers who can interpret algorithmic insights, challenge automated suggestions, and adapt technology to their pedagogical goals. Implementation strategies stress co-design, transparency, and teacher agency, with AI framed as an assistant that learns together with the educator.

In order to realize this, schools invest in time for teacher participation, ongoing professional learning, and mechanisms for collective governance of AI systems. Decision-making structures shift from top-down adoption to participatory design processes where educators help determine what data are collected, how they are interpreted, and what pedagogical purposes they serve.

Without adequate resources, democratic governance, and genuine teacher involvement, human–AI teaming can easily regress into the other two scenarios. The rhetoric of empowerment may conceal new dependencies. Teachers may become reliant on opaque systems for decision-support, while institutions may find themselves tied to privately controlled corporate platforms that dictate standards and updates. The promise of augmentation, therefore, may depend less on technical capability than on the economic and political infrastructures that determine who ultimately governs the machine and to what ends.

3.3.1 Task integrity

Human–AI teaming aims to maintain coherence in the teaching cycle. The phases of diagnosis, design, instruction, and feedback remain under teacher direction, but the ease of automation can tempt teachers to defer parts of their own reflection. Feedback generators and analytics tools support continuity between teaching and assessment, but they also begin to define what coherence means according to the system's parameters. Teachers integrate the process of learning more smoothly but the craft risks quiet dependence on automated routines that think ahead for them.

3.3.2 Skill cultivation and use

AI-assisted tools can enhance professional growth by surfacing patterns and sharing insight across teaching teams. New teachers can climb learning curves faster, and experienced teachers may redirect effort toward complex interpretation and mentorship. Yet, convenience can erode inquiry: when the system anticipates next steps, teachers may reflect less deeply or feel less ownership of pedagogical problem-solving. Professional learning is more likely to thrive when AI helps teachers reflect on practice rather than displacing the work through which expertise is sustained.

3.3.3 Task significance

The sense that teaching contributes to a broader purpose can be strengthened when AI relieves teachers of repetitive chores, freeing time for mentoring and reflection. Yet significance also depends on teachers experiencing themselves as the source of insight and initiative. When systems anticipate their next move, relief at not having to work begins to hinder the fulfillment of purposeful labor. Meaning still endures, but it thins out if the machine quietly shifts from being an assistant to becoming the author of thought.

3.3.4 Autonomy

Autonomy is preserved in principle through opt-in recommendations and teacher override, but it requires vigilance and institutional support. Each convenience feature carries an incentive to comply. The more seamlessly the system integrates into daily routines, the easier it becomes for teachers to confuse its recommendations with their own decisions. Teachers retain the option to decide differently, but substantive independence depends on the cognitive work of interpreting, questioning, and overriding algorithmic suggestions. Collective autonomy in professional networks remains essential to prevent a slow drift into dependency.

3.3.5 Belongingness

Collaboration is strengthened when teachers use shared analytics spaces to discuss and co-design improvements. These forums might foster trust and collective intelligence rather than competition. Still, collegial bonds rely on teachers, not algorithms, setting the agenda. If participation becomes routinized through platform workflows, community can harden into compliance. Belongingness blossoms when technology sustains conversation among professionals rather than replacing it with coordination around data points.

4 Discussion

This article set out to shift the AI-in-education debate away from abstract promises and fears, and toward a grounded question: what kinds of configurations of AI sustain, reshape, or erode the conditions under which teaching can be experienced as meaningful work? Using foresight scenario methodology, we developed three plausible futures: Labor-Replacing Classrooms, AI-Managed Teaching, and Human–AI Teaming. Read through the lens of the five conditions of meaningful work (task integrity, skill cultivation and use, task significance, autonomy, and belongingness), the scenarios make clear that AI in education is not one trajectory but a contested terrain of design, governance, politics, and economic pressures.

Across the scenarios, a central insight is that the danger is not only job loss, but the reconfiguration of teaching into work that is thinner in integrity, less professional in skill, and more peripheral in purpose. In Labor-Replacing Classrooms, task wholeness is broken as planning, instruction, and assessment are transferred to platforms, leaving teachers to supervise, troubleshoot, and register interventions. Meaningful moments of pedagogical connection become residual to the system's throughput logic. In AI-Managed Teaching, teaching remains human-staffed, yet autonomy becomes conditional and effortful: teachers can deviate, but only by expending cognitive effort to translate judgment into the bureaucratic language of indicators, rationales, and documentation. This gradually conditions teachers to anticipate what the system will approve rather than what the situation calls for, risking a slow normalization of what Winner (1978) termed reverse adaptation, in which educational ends are adjusted to fit machine-readable means rather than the other way around.

Read through Farrell et al. (2025), these scenarios also suggest that the significance of AI in education lies in its capacity to reorganize pedagogical work as information. AI systems do not simply support pre-existing educational practices. They depend on teaching and learning being translated into data, machine-readable representations that can be compared and acted upon at scale. In this sense, AI in education is best understood as a cultural and social technology for large-scale coordination rather than as an autonomous pedagogical actor. What is at stake is not only whether teachers are replaced, but whether pedagogical judgment is increasingly replaced by infrastructures that privilege what can be translated into data.

These trajectories are not driven by informational logics alone. They also need to be understood in relation to the structural cost pressures that shape educational systems (Baumol, 2012). As Acemoglu and Restrepo (2020) argue, some forms of automation are adopted not because they generate substantial qualitative improvements, but because they are just productive enough to justify replacing labor with cheaper and more controllable technical systems. From this perspective, AI in education is a potential response to pressure to reduce costs. This helps explain why labor-replacing and surveillance-oriented uses of AI may persist even when they weaken the conditions of meaningful teaching.

Human–AI Teaming is therefore not best understood as a happy ending but as a fragile possibility. When AI is introduced as an instrument under teacher direction, it might reduce administrative load, widen teachers' interpretive capacity, and strengthen collegial inquiry. Yet the scenario also highlights risks as convenience can drift into overreliance. If systems increasingly prefigure the next move, teachers may experience relief from routine burdens while gradually losing opportunities to exercise judgment, pedagogical problem-solving, and reflective inquiry for themselves. In that sense, even augmentative arrangements may contribute to deskilling through disuse if teachers are positioned primarily as approvers of algorithmic suggestions rather than as authors of pedagogical decisions. The implication is that augmentation is not so much a technical feature as an institutional achievement that depends on governance: who sets the metrics, who controls the workflows, who can refuse or redesign, and what kinds of professional deliberation are protected.

If the scenarios are read as warnings and invitations, they suggest three practical implications for policy and the institutional processes through which AI systems are selected and rolled out. First, meaningful teacher work should be treated as a non-negotiable design criterion rather than an accidental byproduct. Evaluations of AI should therefore extend beyond accuracy and efficiency to ask: does this system preserve coherent pedagogical cycles, deepen professional skill, and widen teachers' discretionary space, individually and collectively? Second, schools should be wary of systems that couple analytics with automated evaluation, ranking, or compliance nudging, since these mechanisms can convert support into algorithmic control and risk hollowing out belongingness and trust. Third, teacher participation must be institutionalized, not symbolic. Educators need time, resources, and formal authority to co-decide what data are collected, how proxies are interpreted, and which forms of pedagogical work should remain under human judgment. This also makes procurement crucial. Rather than adopting locked-in, one-size-fits-all platforms, schools should favor systems that can be locally adapted, professionally scrutinized, and meaningfully governed by teachers and school leaders.

These implications align with a broader call in critical scholarship to slow down and re-politicize AI adoption. The question is not simply how to "use AI," but how to decide, collectively, what parts of education we are willing to reorganize around data proxies, and what forms of human judgment we want to preserve. As Selwyn (2024) argues, the future of AI and education is not a foregone conclusion that educators must simply adapt to; it is something that can be resisted and reimagined, with power over who gets to set up AI as a central stake. Harari's (2024) analysis of contemporary information networks sharpens this point further. The issue is not only that AI systems simplify and reorganize information, but that in commercialized systems these processes may be aligned to business logics rather than to truth or human flourishing. In educational settings, this raises a critical governance question: if AI systems are procured and optimized primarily around market expansion, then the resulting infrastructure likely will not prioritize what is educationally meaningful.

The study has clear limitations. It does not offer empirical classroom evidence, nor does it predict which pathway will

dominate. Its contribution is primarily analytical. The scenarios are heuristic constructions rather than forecasts, and real educational settings may combine elements of more than one pathway. The study's value lies in providing a vocabulary and set of contrasts that help educators, unions and policymakers see the trade-offs otherwise hidden behind the rhetoric of personalization, efficiency, and innovation. Future research should therefore combine scenario thinking with empirical work in schools, including ethnographies of AI-mediated teaching, comparative studies of governance models, and research examining what teacher-led teaming with AI looks like in day-to-day routines. Just as importantly, future research should examine distributional effects, including which teachers and students bear the burdens of experimentation, surveillance, and error, and which groups are positioned to benefit from AI-enabled support.

In closing, the key message of the scenarios is simple: while technical capabilities matter, the educational significance of AI will likely be shaped more by what institutions choose to do with these systems. If cost-reduction and auditability remain dominant, AI will likely accelerate the fragmentation, surveillance, and deprofessionalization of teaching, even when packaged as support. If, however, educators are granted real authority over design and governance, AI could be shaped into a limited but valuable collaborator that strengthens the conditions of meaningful work: coherent craft, developing expertise, experienced purpose, protected autonomy, and durable professional community. The task ahead is therefore not to embrace or reject AI in the abstract, but to build the political, organizational, and ethical infrastructures that keep teaching worth doing.

Data availability statement

The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Author contributions

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