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Physical Learning Environments and AI-Powered Personalized Learning in Higher Education: A Systematic Literature Review

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Abstract

In tightly managed tests, AI that gives each student a learning path tailored to them shows improvements of 0.42 to 0.76 standard deviations. However, this review of 22 studies (1984-2026) examines an overlooked aspect: the quality of the actual learning space. Barrett et al. (2015) found that classroom design explains 16% of the variation in student performance, about the same as the impact of the AI itself. We believe that temperature, noise, and lighting all make it harder for students to manage their own learning, and AI that adapts to students' needs requires self-direction to work.

Keywords: Adaptive learning; Environment-behaviour; Higher education; Physical learning environment;

DOI:

1.0 Introduction

Bloom, back in 1984, described the 'two-sigma problem': students getting one-to-one tuition, where they had to really master each thing before moving on, did about 2 standard deviations better than students in normal classes. You cannot have a tutor for every student, and nothing schools have ever done has ever gotten close to this level of improvement. The most serious effort to get this kind of improvement on a larger scale comes from AI-powered learning, which adjusts to each student.

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From this broader improvement goal, three types of research have emerged. Adaptive learning programs guide students through material in a specific order based on their performance. Intelligent tutoring systems determine what a student knows at each step of a task and provide specific advice. Furthermore, AI-based assessments automatically mark work and provide feedback. Moreover, as shown by careful testing, all three yield worthwhile results. VanLehn (2011) found that intelligent tutoring systems, across 62 studies, averaged 0.76 standard deviations of improvement over standard teaching. Wang et al. (2024) reported a mean effect size of 0.70 in a review of 45 adaptive learning studies. Ma et al. (2014) reported 0.42 when compared to computer-based lessons.

However, these numbers deteriorate when used in actual schools. Pane et al. (2014) found almost no impact in the first year in 147 schools in the U.S., and even in the second year, only a small 0.20 standard deviation increase, with the amount of change varying widely between schools. This difference between research and the real world is not a small detail. It is the main problem that has not been solved in educational AI.

The usual explanations for this focus on the technical side of things, teachers being ready to use the systems, and biases in the data used to train the AI. These explanations are not incorrect, but they do not tell the whole story. Something very basic has been consistently left out of how AI in education is being tested: the actual rooms and buildings students are learning in.

This paper says that how good the physical learning space is - things like how comfortable the temperature is, the sound, natural light, and how good the chairs and desks are - is not just a side issue when using AI. It is essential. Adaptive AI requires students to control themselves, concentrate, and reflect on their own thinking. Being physically uncomfortable makes all of those things harder. If the surroundings reduce a student's ability to think, the AI gets poor information from how they use it, and thus does not personalize the learning effectively.

Three questions guide this review:

Firstly, what aspects of the physical environment affect how well university students concentrate?

Secondly, how do these aspects combine with what adaptive AI asks students to do?

Moreover, thirdly, could the quality of the physical environment explain why adaptive learning works in research but not in schools?

2.0 Literature Review

2.1 AI personalized learning and the lab-to-field gap

AI systems for learning built around each student's needs actually do what Bloom wanted to do by arranging topics in an order determined by an algorithm, giving each student their own feedback, and continually assessing what they do and do not understand (Aleven et al., 2017). Piech et al. (2015) went a step further with something called Deep Knowledge Tracing, which uses neural networks to create a picture of how a student is learning and, importantly, does not require you to have already many thoughts about how learning works.

When these systems are tested in a highly controlled environment, the results are good. Wang et al. (2024) examined 45 studies from 2010 to 2022 and found that AI systems that adapt to students yielded a Hedges' g of 0.70 compared to traditional teaching. du Plooy et al. (2024) checked 69 studies and found that in 59% of them, student performance improved. VanLehn (2011) found a difference of 0.76 standard deviations from 62 Intelligent Tutoring Systems (ITS) studies, and Ma et al. (2014) reported an improvement of 0.42 standard deviations when using these programs instead of learning on a computer. However, when you use them in actual classrooms, it is not the same. Pane et al. (2014) randomly assigned Cognitive Tutor Algebra I to 147 schools and did not see much difference in the first year, and by the second year, the improvement was only 0.20 standard deviations, and even less in schools where students were already doing poorly. Jamali et al. (2025) found that students finished work most quickly on adaptive platforms, but they actually preferred platforms that showed them the "steps" or provided support. Burns (2026) pointed to the basic issue: most of these platforms change how quickly you move through material that has not changed, rather than how you learn.

So, the very same kind of technology will show a 0.76 standard deviation improvement in a research setting, yet only 0.20 in schools. This difference is the main issue this paper is about.

Table 1. AI personalization effect sizes across study conditions

Study	AI system type	Setting	Effect size
VanLehn (2011)	Intelligent tutoring	Controlled — 62 studies	0.76 SD
Wang et al. (2024)	Adaptive learning	Mixed — 45 studies (2010–2022)	0.70 (Hedges' g)
Ma et al. (2014)	Intelligent tutoring	Controlled vs. computer-based instruction	0.42 SD
Pane et al. (2014)	Cognitive tutor	Real-world — 147 U.S. schools	0.20 SD (year 2)

Note. SD = standard deviation from the control group. Effect sizes reflect post-intervention academic performance.

2.2 The physical learning environment as a missing variable

Barrett et al. (2015) conducted the largest study to date on the effects of classroom layout on learning. They used a complex statistical approach across 153 classrooms, 27 schools, and 3766 students to determine the extent to which building decisions matter, independent of students' characteristics or teachers' effectiveness. Light, temperature, air quality, a sense of being able to personalize the space, how easily a room can be changed, how visually interesting it is, and color were all considered, and together they accounted for 16% of the difference in how well students did in their work. This HEAD project was in primary and secondary schools, but the effects would likely be at least as strong in colleges and universities, as students there have fewer school rules.

Brink et al. (2021) examined this specifically in universities. Their thorough examination of 21 studies on the Internal Environmental Quality of university classrooms showed that being at a comfortable temperature, with good sound, good lighting, and clean air, all help with doing well and the quality of learning in the short term.

Paschoalin Filho et al. (2022) conducted a study with 47 university students and carefully controlled heating, air conditioning, airflow, and noise levels. Their results clearly changed depending on the particular conditions.

Choi et al. (2014) explain why this happens. Using cognitive load theory as a basis, they suggest that environmental irritants, such as noise, temperature, and poor lighting, make your brain work harder on unnecessary tasks. This uses up the part of your brain you need for learning and managing your own study.

Brooks (2011) found the same thing in a study: students in a classroom with technology to support active learning did better than students in a regular classroom when everything else was kept the same.

Table 2. Physical environment factors and their effects on cognitive performance

Environmental factor	Cognitive effect	Mechanism	Key source(s)
Thermal discomfort	Impairs performance	Increases extraneous cognitive load; depletes working memory	Choi et al. (2014); Paschoalin Filho et al. (2022)
Acoustic interference	Reduces sustained attention	Disrupts working memory; impairs comprehension of audio content	Brink et al. (2021)
Poor/inadequate lighting	Degrades working memory	Reduces visual processing capacity; increases visual fatigue	Brink et al. (2021)
High CO_2 / poor ventilation	Impairs decision-making	Reduces cognitive arousal; degrades executive function	Paschoalin Filho et al. (2022)
Overall classroom design	16% variance in outcomes	Combined IEQ effect isolated by multi-level modeling across 153 classrooms	Barrett et al. (2015)

Note. IEQ = indoor environmental quality. Mechanisms are as described in the cited sources.

2.3 Self-regulated learning as the connecting mechanism

Adaptive AI in education relies on students actually doing something with the advice it gives, rather than on a teacher understanding what is happening in the classroom (Shute, 2008).

Zimmerman (2002) described this ability to learn on your own as self-regulated learning (SRL), which consists of three stages: planning, doing the work, and reflecting on how you did. Panadero (2017) examined six SRL ideas and found one commonality: SRL is not a fixed part of a person. It changes depending on how much thinking power you have and what is going on around you.

Moreover, the place you are in is directly related. Each of those SRL phases needs your executive function and your short-term memory. Choi et al. (2014) explained that if your surroundings bother you, they make you think about things that are not important and use up the short-term memory you need for self-regulation. A student who is too cold to focus, or bothered by the heating or air conditioning, is not doing badly with the AI. They are not able to do what the AI is expecting them to be able to do in the first place.

Shute (2008) showed that receiving feedback intended to help you learn will only change how you think if you can actually think about it. So if stress from the environment has used up your short-term memory, even AI advice that is exactly what you need will not be helpful, because you will not be able to use it.

3.0 Methodology

For this study, we conducted a thorough, systematic review of the published literature and followed PRISMA guidelines. The research we reviewed (from journals) spanned 1984 to 2026, and we found it through searches of IEEE Xplore, Springer, Elsevier, Frontiers, MDPI, and Wiley. Searches returned approximately 850 records, which, after removing duplicates, were screened to 670; 88 were assessed for full eligibility, and 22 met the inclusion criteria.

To be included in the review, sources had to be about one of these three things: research (either based on experiments or ideas) about AI and learning that is adjusted for each student in universities; research based on experiments about actual university buildings and how well students do; or research (again, experiments or ideas) about students managing their own learning when they are being taught with technology. We did include some research from before university, as long as it provided important information used in universities – Barrett et al.'s 2015 study with younger students is a good example.

We found things to read by combining words. We used "AI", "adaptive learning", or "intelligent tutoring" with "higher education", "personalized learning", and "self-regulation". Moreover, we used "indoor environmental quality", "classroom design", "cognitive load", and "thermal comfort" in relation to "higher education" and "academic performance". We also identified additional sources by reviewing the references in key studies (a process called snowballing), which was particularly helpful in the building/environment area, as it has fewer links between studies.

In the end, twenty-two sources fit what we were looking for. Ten were about AI and education; four were about university buildings; two were about self-regulated learning; one was about foundational learning theory; one was about cognitive load; and two were about ethics and governance of AI.

The review is about bringing things together and interpreting them, not listing everything that has been written about a particular topic. Wang et al. and du Plooy et al., both published in 2024, have already conducted comprehensive reviews of papers on adaptive learning. Instead, we wanted to establish a reasonable link between two areas of research that rarely interact.

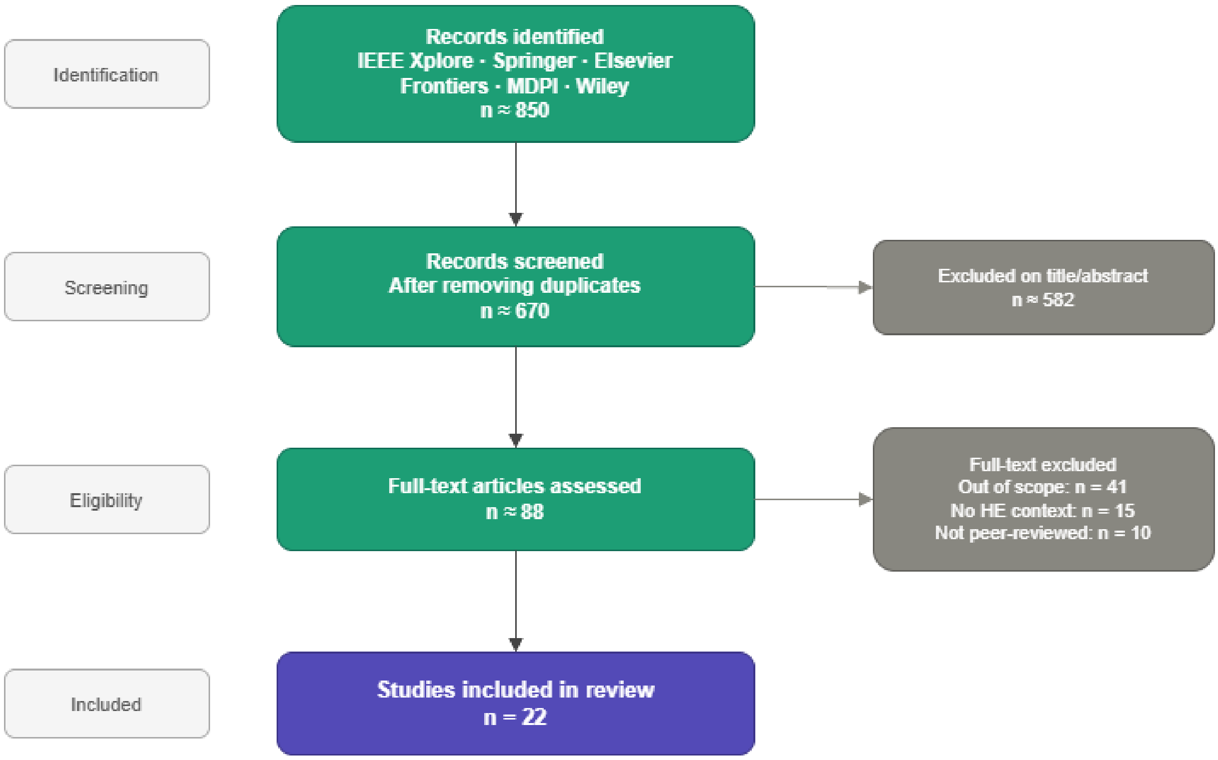

Figure 1. PRISMA flow diagram for the systematic literature review

Table 3. Summary of reviewed literature (n = 22)

Author(s) & year	Domain	Method	Key finding
Bloom (1984)	Foundational	Experimental	Two-sigma problem: one-to-one tutoring = 2 SD advantage
VanLehn (2011)	AI / EdTech	Meta-analysis (62 studies)	ITS produces 0.76 SD over conventional instruction
Ma et al. (2014)	AI / EdTech	Meta-analysis	ITS produces 0.42 SD over computer-based instruction
Pane et al. (2014)	AI / EdTech	RCT (147 schools)	Cognitive tutor: near-zero year-one, 0.20 SD year-two
Shute (2008)	AI / EdTech	Theoretical review	Effective feedback must be specific, timely, and goal-directed
Piech et al. (2015)	AI / EdTech	Technical	Deep Knowledge Tracing models student learning via neural networks
Aleven et al. (2017)	AI / EdTech	Review	Adaptive systems rely on learner-generated interaction data
Barrett et al. (2015)	Physical env.	Multi-level analysis (153 classrooms)	Classroom design explains 16% of the variance in learning outcomes
Brooks (2011)	Physical env.	Quasi-experimental	Technology-enhanced space outperforms traditional classroom
Choi et al. (2014)	Cognitive load	Theoretical	Physical discomfort increases extraneous cognitive load
Zimmerman (2002)	SRL	Theoretical	Three-phase cyclical SRL model: forethought, performance, reflection
Panadero (2017)	SRL	Theoretical review (6 models)	SRL is state-sensitive, not a fixed trait
Brink et al. (2021)	Physical env.	Systematic review (21 studies)	IEQ conditions affect short-term performance in higher education
Paschoalin Filho et al. (2022)	Physical env.	Experimental (47 students)	Indoor conditions produce measurable undergraduate performance differences
Alam (2021)	AI / EdTech	Conference paper	Co-agent framework: AI handles data, teachers handle socio-emotional support
du Plooy et al. (2024)	AI / EdTech	Scoping review (69 studies)	AI improves performance in 59%, engagement in 36% of cases
Wang et al. (2024)	AI / EdTech	Meta-analysis (45 studies)	AI adaptive systems: Hedges' g = 0.70 over non-adaptive instruction
Merino-Campos (2025)	AI / EdTech	PRISMA review (17,899 articles)	AI enables real-time adaptation; access equity remains unresolved
Jamali et al. (2025)	AI / EdTech	UX study	Adaptive platforms are faster but less satisfying than visible scaffolding
Burns (2026)	AI / EdTech	Brookings report	True personalization requires strategy adaptation, not just pacing
Zawacki-Richter et al. (2019)	AI / EdTech	Systematic review	AI research lacks educator perspectives; a governance gap has been identified.
García-López & Trujillo-Liñán (2025)	AI / EdTech	Systematic review	Ethical and regulatory challenges of generative AI in education

4.0 Findings

4.1 Physical environment factors and cognitive engagement (RQ1)

Lots of research on how our surroundings affect us all comes to the same three conclusions. Being too hot or too cold makes it harder for people of all ages to think, and this effect is even bigger when people cannot control the temperature themselves. Background noise and echoes can interfere with concentration and make it harder to understand, even when the audio comes from an AI. Poor lighting and excessive carbon dioxide from a lack of fresh air demonstrably worsen your working memory and decision-making (Brink et al., 2021; Paschoalin Filho et al., 2022).

Barrett and colleagues' (2015) finding that 16% of the difference in how well students do is down to classroom design is not a maximum. Instead, it is a calculation of how much of a student's academic improvement is explained by the classroom itself, when you're already accounting for the student and the teacher. This 16% is comparable to the effect reported for AI systems that adapt to the learner.

A substantial amount of the learning AI aims to influence is already being shaped by the learning environment. Furthermore, Brink et al. (2021) and Paschoalin Filho et al. (2022) show that this pattern holds for university students as well, based on 21 studies and one carefully controlled experiment with undergrads.

4.2 The self-regulated learning bridge (RQ2)

AI that adjusts to how you learn gets its personalization from your activity. It cannot figure out what you are thinking or doing unless you actually do something. So if a student does not really participate in the give and take of feedback, ignoring questions asking them to think about their work, rushing through a lesson to finish it, or giving up on a tough problem, the AI records all of that and changes its understanding of the student's abilities as a result; the AI's thinking gets less accurate.

This is not the AI program being at fault, but a problem with what happened before the AI even gets going. Zimmerman (2002) breaks learning down into planning, doing, and reflecting on what you have done, and all three steps require good self-control. Moreover, as Panadero (2017) showed in a review of six self-regulated learning models, those stages are easily affected by mental fatigue. Choi et al. (2014) explained how this happens: being in a distracting or unpleasant environment uses up your short-term memory, a depleted short-term memory makes self-regulated learning harder, hampered self-regulated learning leads to poor quality interactions, and that poor quality input is what the AI uses to build a problematic system for tailoring things to you.

4.3 The lab-to-field gap revisited (RQ3)

AI is tested in labs that are surprisingly carefully set up. University labs for AI assessment usually have lighting that's adjusted, temperatures that are precisely set, and rooms that have been treated to deal with sound. Students in these tests sit in chairs designed to help them focus for long periods. Furthermore, the issues that research often points to as why AI does not seem to help much – problems with how things are set up, professors not being prepared, and the AI not fitting in – are actually avoided by the way the experiments are conducted.

However, when AI is used in a typical university setting, those problems persist. They are part of what is happening. Old heating and cooling systems, classrooms that were designed before teachers were encouraged to get students actively involved, and big rooms for lectures with bad views and terrible sound…these are the standard conditions in many universities (Brink et al., 2021). So when AI in these places only shows an improvement of 0.20 of a standard deviation (and the controlled lab tests show 0.70), the difference is not simply about how the AI is being used.

In fact, Pane et al. found in 2014 that AI had less effect at schools with students who were not doing as well. Furthermore, schools with more disadvantaged students usually have worse buildings. We often confuse a student's financial situation with the quality of their school building, but the building itself matters. A student struggling to concentrate in a 31°C classroom in summer is not failing because of a lack of trying. They are struggling because their brains are using their energy to deal with the heat.

5.0 Discussion

5.1 Statistical equivalence of two effect magnitudes

The core of what this paper asks is straightforward. Controlled testing shows adaptive AI systems change results by 0.42 to 0.76 standard deviations. Moreover, the physical classroom design accounts for 16% of the differences in how well people learn. While you cannot swap these figures directly (one is how much a treatment does, the other is how much of the difference in results is due to the design), their sizes are roughly the same. So, a significant amount of the variation in learning that AI is trying to affect is already being shaped by the classroom itself.

This is something educational technology has not really considered. The idea behind spending money on AI to tailor learning to each student assumes a certain basic mental state, which the building students are in might not provide. If this basic state is poor, the additional benefit from the AI decreases, falling to the lowest point within its range of demonstrated performance, or even lower.

5.2 The co-agent reframe

Alam (2021) suggested we think of AI and human teachers working together, with the AI handling large amounts of data for personalization and teachers providing emotional and social support. That is a good idea, but it does not account for the physical surroundings. We propose, instead, to think of AI, the teacher, and the physical environment working together, each with a measurable effect on learning. You cannot improve any of them in isolation.

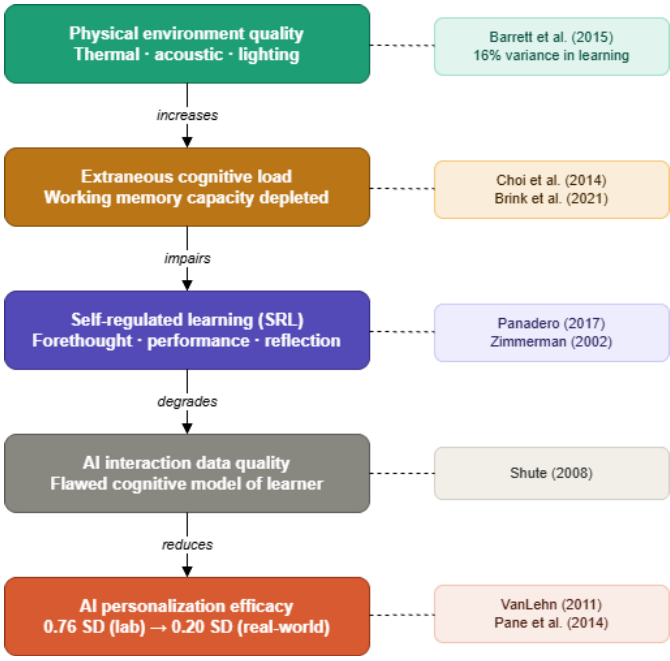

Figure 2. Proposed causal framework: physical environment quality to AI personalization efficacy

This different way of looking at things has a very real effect on how institutions are run. Currently, universities have different departments, different budgeting timelines, and different ways to measure success for AI and for the buildings they use. Research on AI treats classrooms as mere background. Moreover, research on school buildings treats AI as a computer program, which is not their concern. No one is bridging the gap between these two areas.

5.3 What this account does not claim

We are not saying the physical environment is the most important factor. How ready teachers are, the technology available, biases in the data used to train the AI, and how the learning activities are designed all impact how well AI works (Zawacki-Richter et al., 2019; García-López & Trujillo-Liñán, 2025) - and we know this. We are only saying that the physical environment has been consistently left out of the discussion, and that, by doing so, we do not get a full explanation for why AI that works in the lab does not produce the same results in real schools.

Also, we have not proven this with an experiment. None of the studies we reviewed measured both the quality of the physical environment and how well the AI performed in the same place. This argument is based on three separate discoveries coming together: classroom design impacts learning (Barrett et al., 2015; Brink et al., 2021), being uncomfortable in your surroundings uses up your working memory (Choi et al., 2014), and self-regulated learning (which AI needs to work on) depends on working memory (Panadero, 2017; Zimmerman, 2002). The logical next step is to measure all of these things directly.

6.0 Conclusion & Recommendations

The problem of making AI-based, individualized learning work in the real world is not just about how you do it. Looking at the research, something important is consistently left out: the quality of the actual learning space. Barrett et al. (2015) found that classroom design alone explains 16% of the variation in how well students learn. That is about as much effect as people are saying AI personalization has! Moreover, the ideas of how our brains are taxed (Choi et al., 2014) and how much learning relies on managing your own learning (Panadero, 2017; Zimmerman, 2002) provide a logical path from the physical room to the usefulness of AI. However, nobody has tested this whole path all at once, and they really should.

For universities and colleges, this means something very practical. They should not decide which AI to buy and how to improve buildings separately. If a university installs a program that adapts to how you learn in a room that's too hot or cold, too noisy, or not well-lit, they are spending money on a program that is not working as well as it could. The building itself causes the problem, and the university has control over it, but is not looking at it.

This overview of the research is not totally complete in any one specific area; it is more of a bringing-together. It also uses evidence from primary and secondary schools (K-12) to suggest what is happening in higher education. Brink et al. (2021) have started to address this, but we do not yet have a university equivalent of the big HEAD study. Plus, the overview does not clearly show how the idea of the physical space works, because no research has examined both the building and AI simultaneously.

From this, we can see three areas for future research. First, studies that deliberately change the quality of the learning space and the AI used in a carefully controlled way would test the idea of this path directly. Second, looking at data from where AI is already being used and dividing it by the quality of the building could reveal patterns that have been missed. Finally, creating a way to plan spaces and buy educational technology simultaneously, ensuring they work together, would turn this finding into something institutions do. All of these are possible, and yet none have been done.

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Paper Contribution to the Related Field of Study

This paper contributes to environment-behavior research and educational technology literature by identifying physical learning environment quality as an unmeasured variable in the evaluation of AI-powered personalized learning systems. By connecting classroom design effects (Barrett et al., 2015), cognitive load theory (Choi et al., 2014), and self-regulated learning models (Panadero, 2017; Zimmerman, 2002) to the documented lab-to-field gap in adaptive learning research, the paper proposes a tri-agent framework for institutional decision-making in higher education that integrates AI procurement with physical plant planning.

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