Headlines in the Classroom: Media Narratives and the Selective Shifts in Teachers' AI Judgments

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Abstract

A 6-week online Learning-Theories course for 17 U.S. post-master's leadership candidates embedded critical analyses of AI's role in professional and student learning. Participants were educators seeking public school administrator certification. Grounded in Davis's Technology Acceptance Model (TAM), this study contends educator attitudes toward AI are shaped primarily by perceived usefulness (PU) and perceived ease of use (PEOU), which together predict their behavioral intention to integrate generative AI tools into instruction. A pre/post TAM-aligned survey (4-point Likert) tracked perceived usefulness (PU), ease-of-use (PEOU), and ethical-intent-to-use (EIU) measuring perceptions regarding educative tasks (e.g. AI supports differentiating lessons; AI is damaging to education; Students mostly use AI to cheat; AI supports learning). Paired t-tests revealed selective shifts: large PU gains for AI-driven lesson differentiation ($d = 0.68$, $p = .029$) and PD planning ($d = 0.47$, $p = .033$); no change in PU for time-saving ($d = 0.00$) or PEOU for implementation ($d = 0.12$). EIU declined solely on the "students will cheat" item ($d = -0.82$, $p < .001$). There was some positive, non-significant drift for several items (lesson-planning, assignment-planning, general "supports learning"). Candidates accepted utility claims that matched prior pedagogical goals and rejected those lacking concrete classroom examples. Results situate media cues as boundary conditions within TAM: headline ecological validity predicted attitude change better than technical affordances. Programs should couple AI headline critique with sustained, supported classroom practice before adoption. Classroom experiences must overcome prevailing narratives in the media to shift the ethical intention to use generative AI to support learning.

Keywords: generative artificial intelligence, AI, technology acceptance model, TAM, educator attitudes towards AI

Introduction

Between November 2024 and May 2025, national and Connecticut-based news coverage on generative artificial intelligence (AI) in education shifted rapidly from reactive concern to systemic recalibration (Table 1). Across outlets, reporting clustered around five dominant themes: (a) academic integrity and cheating, (b) erosion of reliable AI detection, (c) pedagogical adaptation and teacher practice, (d) student normalization of AI use, and (e) emerging concerns about learning quality and equity. Together, these themes illustrate a transition from viewing AI as a disruptive external force to recognizing it as an embedded feature of contemporary learning environments.

Table 1
Headlines Published in the Six Months Prior to the Class

Date	Headline	Publication	Source
Nov 2024	The rise of AI tools forces schools to reconsider what counts as cheating	Associated Press	https://apnews.com/article/4f89a552e9093ce2180471b4d4736675
Nov 2024	Why it's so hard to tell if a piece of text was written by AI	CT Insider	https://www.ctinsider.com/news/article/why-it-s-so-hard-to-tell-if-a-piece-of-text-was-21249821.php
Dec 2024	AI is taking hold in K-12 schools — here are some ways it can improve teaching	CT Insider (via The Conversation)	https://www.ctinsider.com/news/article/ai-is-taking-hold-in-k-12-schools-here-are-21230486.php
Dec 2024	Yale student sues over accusation of improper AI use	GovTech	https://www.govtech.com/education/higher-ed/yale-student-suing-over-accusation-of-improper-ai-use
Jan 2025	Here's how Connecticut schools tackle AI in the classroom as state develops guidelines	CT Insider	https://www.ctinsider.com/news/education/article/ct-schools-districts-ai-artificial-intelligence-21265976.php
Jan 2025	Yale SOM student suspended over alleged AI use sues	CT Insider	https://www.ctinsider.com/news/article/yale-som-student-suspended-alleged-ai-use-sues-20206927.php
Feb 2025	Majority of high school students use generative AI for schoolwork, new research finds	College Board Newsroom	https://newsroom.collegeboard.org/new-research-majority-high-school-students-use-generative-ai-schoolwork
Feb 2025	AI is widespread in higher education — helping and hurting student learning	NBC Boston	https://www.nbcboston.com/news/local/artificial-intelligence-education-college-learning/3850198/
Mar 2025	40% of American students use AI on assignments without permission	Times of India (U.S. education reporting)	https://timesofindia.indiatimes.com/education/news/40-of-american-students-use-ai-on-assignments-without-permission-whats-really-happening-in-us-classrooms/articleshow/123701891.cms
Mar 2025	See which seven CT school districts are piloting a state-approved AI program	CT Insider	https://www.ctinsider.com/news/education/article/ct-ai-program-pilot-20065504.php
Apr 2025	AI use in classrooms raises new concerns about fairness, bias, and assessment	Education Week	https://www.edweek.org/technology
May 2025	Rising use of AI in schools comes with big downsides for students	Education Week	https://www.edweek.org/technology/rising-use-of-ai-in-schools-comes-with-big-downsides-for-students

Early coverage framed generative AI primarily as an academic integrity crisis. For example, the Associated Press documented how schools were struggling to redefine misconduct as AI tools became widespread, noting that existing honor codes were ill-equipped to address AI-assisted work (Barrow, 2024). This concern was echoed locally in Connecticut through high-profile legal cases involving alleged AI misuse at Yale University. Coverage of lawsuits filed by students accused of improper AI use highlighted due process concerns and the fragility of disciplinary systems reliant on contested detection methods (Pappas, 2025; Zahn, 2025). These stories framed AI not only as a technological challenge, but as a legal and ethical one with significant implications for institutional governance. Connecticut-based reporting explicitly addressed the unreliability of AI-detection tools, emphasizing false positives and the lack of scientific consensus supporting their use (Haigh, 2024).

As concerns about academic integrity and detection failures intensified, reporting between December 2024 and February 2025 began to foreground teachers as active agents of pedagogical adaptation rather than passive recipients of technological disruption. This shift marked an important reframing: generative AI was increasingly discussed not solely as a threat to instructional control, but as a catalyst forcing educators to reconsider long-standing assumptions about task design, assessment, and instructional labor (Güner et al., 2024; Kulesa et al., 2025). Media narratives increasingly positioned teachers as instructional designers adapting pedagogy in response to AI, rather than as enforcers of prohibitive policies—signaling a shift toward professional agency and instructional experimentation.

Connecticut-based reporting provides a particularly clear illustration of this trend. Coverage emphasized that, in the absence of comprehensive state-level guidance, districts and individual educators were independently experimenting with how generative AI might support instructional goals such as lesson planning, differentiation, and feedback (Miller, 2024; Pappas, 2025). Rather than portraying teachers as overwhelmed or resistant, these articles framed them as navigating AI pragmatically—testing boundaries, setting classroom norms, and selectively integrating tools aligned with curricular objectives.

Importantly, this reporting highlighted pedagogical labor that often remains invisible in policy debates. Teachers described using AI to streamline administrative and preparatory tasks (e.g., drafting lesson outlines or generating multiple examples), thereby reallocating time toward student interaction and instructional decision-making (Miller, 2024). This narrative contrasts sharply with earlier media framings that positioned AI as either replacing teachers or undermining instructional authority.

By early 2025, reporting moved decisively beyond speculative debates about whether students might use generative AI to empirical documentation that AI use had become normalized within student learning practices. National research coverage confirmed that a majority of high school students were already using generative AI for schoolwork, including brainstorming, summarization, and drafting (College Board, 2025; Kulesa et al., 2025). This normalization reframed AI not as an external disruption, but as a routine component of students' cognitive and academic workflows.

Crucially, media narratives began to interrogate how students were using AI rather than simply whether they were using it. NBC Boston's reporting captured a growing tension between efficiency and learning depth, noting that while students often perceived AI as helpful for productivity, educators expressed concern that reliance on AI could bypass essential cognitive processes such as retrieval, synthesis, and self-monitoring (NBC Boston, 2025). These concerns echoed earlier academic integrity debates but were now reframed through the lens of learning quality rather than misconduct.

Across the November 2024 to May 2025 period, the six months before this class, media coverage of generative artificial intelligence in education traced a gradual shift from institutional disruption toward pedagogical recalibration. By early 2025, student use of generative AI was widely normalized in media narratives, redirecting attention from rule violations to questions of learning quality, cognitive engagement, and equity.

The MIT Media Lab Preprint Makes News, A Watershed Moment

This trajectory set the stage for a critical watershed moment in late spring 2025, largely during this summer class: the public dissemination of an MIT Media Lab study examining neural engagement during AI-assisted writing (Kosmyna et al., 2025). Whereas late 2024 and early 2025 coverage highlighted educators' adaptive use of AI to support planning, differentiation, and student access, June–July reporting (Table 2) foregrounded claims that AI use may actively diminish critical thinking and neural engagement.

Table 2
Headlines Published During the Six Weeks of the Class

Date	Headline	Publication	Source
Jun 17 2025	*ChatGPT May Be Eroding Critical Thinking Skills, According to a New MIT Study*	Time	https://time.com/7295195/ai-chatgpt-google-learning-school/ (TIME)
Jun 26 2025	*Brain Activity Is Lower for Writers Who Use AI. What That Means for Students*	Education Week	https://www.edweek.org/technology/brain-activity-is-lower-for-writers-who-use-ai-what-that-means-for-students/2025/06 (Education Week)
Jun 25 2025	*Educators warn that AI shortcuts are already making kids lazy: "Critical thinking and attention spans have been demolished"*	New York Post	https://nypost.com/2025/06/25/tech/educators-warn-that-ai-shortcuts-are-already-making-kids-lazy/ (New York Post)

This shift was catalyzed by widespread coverage of a Massachusetts Institute of Technology Media Lab preprint examining brain activity during AI-assisted writing tasks, which was rapidly framed in popular press as evidence that tools such as ChatGPT "erode" or "weaken" thinking (Chow, 2025; Schwartz, 2025). Unlike prior reporting, which largely inferred cognitive implications from classroom behavior, the MIT study introduced empirical claims about brain activity and learning processes, catalyzing a marked shift in national discourse. Education-focused outlets amplified these concerns by translating neuroimaging findings into classroom implications, often positioning AI as a shortcut that bypasses productive cognitive effort (Dobre, 2025; Gerlich, 2025; Schwartz, 2025).

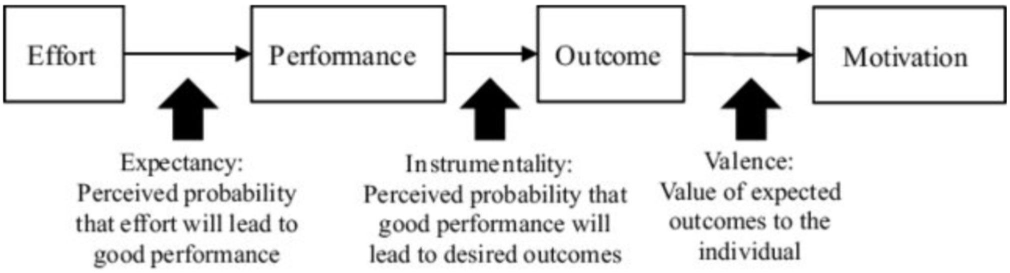
At the same time, the speed and scale of this coverage prompted backlash within academic and journalistic communities, with multiple commentators noting that the MIT study had not yet undergone peer review and cautioning against extrapolating short-term neural activation differences to claims about long-term learning or cognitive decline (D'Aurizio, 2025; Kosmyna et al., 2025). This tension—between compelling neuroscientific narratives and unresolved methodological questions—represents a significant discursive turn: media attention shifts from how teachers and students might use AI well to whether AI use itself is fundamentally incompatible with sustained learning. The June–July corpus thus reframes earlier pedagogical debates into a broader public concern about cognition and the brain, while simultaneously revealing the risks of allowing preprint research to function as de facto evidence in high-stakes educational discourse.

The shifting media discourse surrounding generative artificial intelligence in education provides a critical contextual backdrop for examining educator attitudes toward classroom AI use. To systematically examine these attitudinal dynamics, the present study draws on established psychological and technology-adoption frameworks that conceptualize attitudes as multidimensional and expectancy-driven. Expectancy theory offers a lens for understanding how educators' anticipated outcomes—such as improved efficiency or potential harm to student learning—inform motivation and willingness to engage with AI tools. Complementing this perspective, the triadic model of attitudes articulated by Fishbein and Ajzen conceptualizes attitudes as comprising cognitive beliefs, affective evaluations, and behavioral intentions, a structure that closely mirrors educators' responses to emerging technologies under conditions of uncertainty. Building on these foundations, Davis's (1989) Technology Acceptance Model operationalizes these attitudinal components within technological contexts, positing perceived usefulness and perceived ease of use as primary determinants of adoption. Together, these frameworks provide a theoretically robust basis for interpreting how exposure to shifting media narratives may influence educators' pre- and post-intervention attitudes toward AI integration in the classroom.

Expectancy Theory Grounds Attitudinal Measures

Expectancy theory, first articulated by Vroom (1964), provides a foundational motivational framework for understanding how individuals' behavioral choices are shaped by expected outcomes and their evaluations of those outcomes. At its core, the theory posits that motivation is a function of three components: *expectancy* (the belief that effort will lead to a certain level of performance), *instrumentality* (the belief that performance will lead to specific outcomes), and *valence* (the value placed on those outcomes; Figure 1).

Figure 1
Vroom's (1964) Expectancy Theory



Source: Adapted from http://faculty.css.edu/dswenson/web/OB/VIEtheory.html

This cognitive–evaluative structure foregrounds how individuals weigh anticipated rewards and costs when deciding whether to engage in particular behaviors—a conceptual lens that has been widely applied across organizational psychology, education, and technology adoption research. For example, expectancy-based models have been used to explain teachers' engagement with professional development technologies (Holden & Rada, 2011) and students' motivation to use educational software (Sánchez & Hueros, 2010). Studies exploring generative AI adoption in educational and workplace contexts also implicitly reflect expectancy logic, showing that users are more likely to embrace AI tools when they anticipate tangible performance benefits and positive learning outcomes.

By foregrounding individuals' expectations about performance outcomes and their subjective valuations of those outcomes, expectancy theory sets an important conceptual precedent for later attitudinal models—such as the triadic model of attitudes and the Technology Acceptance Model (TAM)—which formalize how beliefs, affective evaluations, and intention coalesce into technology use decisions. In this way, expectancy theory not only establishes a broad motivational foundation but also helps bridge classic motivational constructs and modern technology acceptance research.

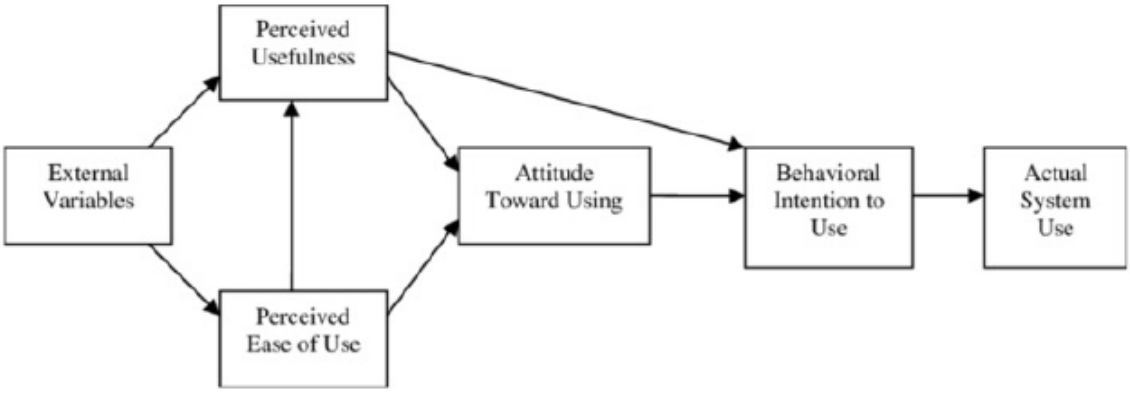
Building directly on the expectancy-based emphasis on anticipated outcomes and subjective valuation, the triadic model of attitudes articulated by Fishbein and Ajzen provides a complementary framework for understanding how such expectations are organized into stable evaluative orientations that guide behavior. Within this model, attitudes are conceptualized as comprising three interrelated components: cognitive beliefs about an object or behavior, affective evaluations of those beliefs, and behavioral intentions that reflect readiness to act (Fishbein & Ajzen, 1975). This structure mirrors the expectancy logic outlined by Vroom (1964), wherein individuals first form beliefs about likely performance outcomes (cognitive), assign value to those outcomes (affective/valence), and subsequently decide whether to engage in a behavior (intentional).

Importantly, the triadic model formalizes these processes into a coherent attitudinal system, making explicit how expectancy-driven beliefs are translated into intention. Ajzen's later extension of this framework through the Theory of Planned Behavior further situates attitudes within a broader decision-making context by incorporating perceived behavioral control and social norms, acknowledging that intentions are shaped not only by expected outcomes but also by perceived feasibility and contextual constraints (Ajzen, 1991). Together, these models clarify how expectancy-based evaluations become embedded within attitudinal structures that precede action. This conceptual progression provides a critical bridge to the Technology Acceptance Model, which operationalizes these attitudinal components in technology contexts by specifying how beliefs about usefulness and ease of use shape affective judgments and behavioral intention toward adoption (Davis, 1989). In this way, the triadic model functions as an essential intermediary between foundational motivational theory and contemporary models of technology acceptance.

Attitudes and Technology Acceptance

The Technology Acceptance Model (TAM; Figure 2) conceptualizes technology acceptance as a sequential process in which external variables influence users' beliefs, attitudes, intentions, and ultimately behavior (Davis, 1989). Perceived usefulness refers to the degree to which an individual believes that using a system will enhance performance, while perceived ease of use reflects the degree to which the system is perceived as free of effort. TAM posits a direct relationship between PEOU and PU, such that technologies perceived as easier to use are more likely to be judged as useful.

Figure 2
Technology Acceptance Model (TAM)



Source: Davis, 1989

These belief structures jointly inform an individual's attitude toward using the technology, which represents an affective evaluation of technology use. Attitude, in turn, predicts behavioral intention to use, which serves as the immediate antecedent of actual system use. This belief–attitude–intention pathway reflects TAM's grounding in expectancy theory and attitude–behavior models, translating expectancy-driven evaluations into measurable acceptance outcomes. Although later extensions of TAM have deemphasized the role of attitude under certain conditions, the original model remains particularly well suited for examining contexts—such as emerging educational technologies—where beliefs and affective evaluations are still forming and adoption norms are unsettled (Davis, 1989; Venkatesh & Davis, 2000).

Over subsequent decades, TAM has been subjected to extensive empirical validation across domains, including education and information systems research, where meta-analytic evidence affirms the centrality of PU and PEOU in explaining technology (Davis & Granić, 2024; King & He, 2006; Ma & Liu, 2004; Marangunić & Granić, 2015). More recent applications extend TAM to emergent technologies by incorporating external variables such as self-efficacy, subjective norms, and facilitating conditions, demonstrating that the core TAM constructs retain explanatory power even in complex adoption contexts (Kong et al., 2024; Venkatesh & Davis, 2000). In educational research specifically, TAM has been applied to examine teachers' intentions to integrate generative artificial intelligence tools, revealing that educators' beliefs about AI's instructional benefits and ease of integration predict their willingness to adopt these tools in practice (Kong et al., 2024). When interpreted through the lens of expectancy theory and the triadic model of attitudes, TAM operationalizes how expectancy-driven beliefs (about performance outcomes and effort) coalesce into affective judgments and intentions, making it an especially useful framework for examining pre/post changes in educator attitudes toward AI use.

The present investigation examines educator attitudes during a time of rapid narrative fluctuation, when beliefs about generative AI were actively forming and competing messages about instructional benefit and cognitive harm were simultaneously salient. Under such conditions, TAM's parsimonious focus on perceived usefulness, perceived ease of use, and attitude toward using offers a more precise analytic lens for isolating expectancy-driven belief change without conflating these shifts with social pressure, habit formation, or infrastructural constraints. Moreover, TAM's conceptual lineage from expectancy theory and the triadic model of attitudes aligns directly with the study's pre/post design, which seeks to capture changes in cognitive beliefs and affective evaluations rather than predict long-term adoption behavior. Accordingly, TAM provides the most theoretically coherent and methodologically appropriate framework for examining how evolving external narratives shape educators' attitudes and intentions toward AI use in the classroom.

Peer Pressure is Real

Although TAM emphasizes individual beliefs about usefulness and ease of use, its attitudinal foundations—derived from the triadic model of attitudes—also accommodate the socially situated nature of behavioral intention. Within this framework, the conative component of attitude reflects not merely a private readiness to act, but an intention formed in relation to anticipated social evaluation and normative judgment (Fishbein & Ajzen, 1975). In educational contexts, where professional identity and peer perception are salient, intentions to adopt instructional technologies are often shaped by how educators believe their actions will be interpreted by colleagues, administrators, students, and the broader public.

This dynamic is particularly relevant in the case of generative AI, where shifting media narratives have alternately framed AI use as innovative pedagogy, professional shortcut, or ethical risk. As a result, educators' intentions to use AI may reflect not only expectancy-driven beliefs about instructional benefit, but also concerns about reputational legitimacy and alignment with perceived professional norms. By situating behavioral intention within this conative–social space, the present study acknowledges that educators' acceptance of AI is shaped by how media discourse constructs the meaning of AI use, thereby linking individual attitude formation to broader cultural and informational environments.

Methods

To examine how educators' attitudes toward the use of generative artificial intelligence in the classroom evolved over time, this study employed a pre/post survey design grounded in expectancy theory, the triadic model of attitudes, and the Technology Acceptance Model (TAM). The design was intentionally selected to capture changes in participants' beliefs, affective evaluations, and behavioral intentions in response to a shifting informational environment surrounding AI in education. The survey instrument combined Likert-style rating scales and ten-point rating scales with open-ended items to allow for both quantitative measurement of key acceptance constructs and qualitative insight into participants' reasoning. Consistent with TAM, the instrument included items assessing perceived usefulness and perceived ease of use, alongside broader attitudinal statements addressing educators' perceptions of AI's instructional value, ethical implications, and impact on student learning and behavior.

Setting and Participants

This IRB-approved study (Southern Connecticut State University IRB Protocol #1324) was conducted during a six-week, fully online, synchronous summer session course on learning theory offered between May 27 and July 1, 2025. The course was situated within a graduate-level educational leadership program and was not designed as an artificial intelligence–focused course. Rather, AI-related content was incorporated as a supplementary enhancement to support discussion and application of core learning theory concepts. When addressed, generative AI was framed as a potential instructional and professional tool—for example, in lesson planning, classroom differentiation, and professional development—without serving as a central or organizing focus of the curriculum.

Participants were practicing educators who had all previously earned a master's degree and possessed a minimum of three years of experience working in public schools as certified teachers. At the time of the study, participants were enrolled in either a doctoral program in educational leadership or a sixth-year certificate program in educational leadership and were seeking administrative certification to serve as public school leaders in the state of Connecticut. This population was selected intentionally, as participants occupied dual roles as experienced practitioners and emerging instructional leaders, positioning them to evaluate both the pedagogical and organizational implications of AI use in educational settings.

Research Questions

Given the exploratory nature of this pre/post survey design and the rapidly evolving discourse surrounding generative artificial intelligence in education, the present study was guided by research questions that focus on patterns of change and stability in educators' perceptions rather than on causal claims. Grounded in the Technology Acceptance Model (TAM), the research questions center on educators' beliefs about the perceived usefulness and perceived ease of use of AI, as well as their broader attitudes toward AI use in educational contexts.

These constructs were selected to align with the study's analytic approach and to allow for the examination of directional shifts in perceptions across time, regardless of whether changes reached statistical significance. Accordingly, the following research questions were developed to examine pre- to post-survey differences using paired-samples analyses while remaining attentive to both meaningful trends and observed stability in participant responses.

Specifically, this research sought to answer the following questions:

1. To what extent do educators' perceptions of the perceived usefulness of generative artificial intelligence for instructional purposes change from pre- to post-survey?
2. To what extent do educators' perceptions of the perceived ease of use of generative artificial intelligence for instructional purposes change from pre- to post-survey?
3. How do educators' overall attitudes toward the use of generative artificial intelligence in educational contexts shift from pre- to post-survey?

Taken together, the study design, participant context, and analytic approach were intentionally aligned with the Technology Acceptance Model to examine how educators' beliefs about the perceived usefulness (PU) and perceived ease of use (PEOU) of generative artificial intelligence relate to their ethical intention to use (EIU) AI in educational settings. By employing a pre/post survey design with paired-samples analyses, the study was structured to capture shifts—or stability—in these expectancy-driven constructs over time, without presuming causal effects or normative adoption trajectories. Positioning ethical intention as an extension of behavioral intention allowed the study to account for the professional, pedagogical, and reputational considerations that may shape educators' willingness to engage with AI, particularly within a contested and evolving informational environment. With this methodological framework established, the following section presents the results of the pre- and post-survey analyses, reporting patterns across PU, PEOU, and attitudinal measures that inform subsequent discussion of educators' ethical intentions toward AI use.

Results and Discussion

Paired-samples *t*-tests revealed a pattern of selective change in educators' perceptions of generative artificial intelligence rather than uniform shifts across constructs. At the scale level, participants demonstrated a statistically significant increase in perceived usefulness (PU) from pre-survey ($M = 6.71$) to post-survey ($M = 7.71$), $t(16) = -2.38$, $p = .030$, indicating a more favorable evaluation of AI's instructional value over time. In contrast, although mean ratings of perceived ease of use (PEOU) increased modestly from pre-survey ($M = 6.59$) to post-survey ($M = 7.18$), this change did not reach statistical significance, $t(16) = -1.27$, $p = .221$, suggesting relative stability in perceptions of usability and implementation effort.

Item-level analyses further clarified this pattern, revealing that gains in perceived usefulness were concentrated in specific pedagogical domains. Significant increases were observed for items related to AI-supported lesson differentiation ($d = 0.68$, $p = .029$) and professional development planning ($d = 0.47$, $p = .033$), whereas no change was detected for perceived usefulness associated with time-saving ($d = 0.00$) or for PEOU related to implementation demands ($d = 0.12$). With respect to ethical intention to use (EIU), a significant decline emerged on a single item reflecting concern that students primarily use AI to cheat ($d = -0.82$, $p < .001$), while no other EIU-related items demonstrated statistically significant change. Several additional items—including those addressing lesson planning, assignment planning, and general support for learning—exhibited positive but nonsignificant directional drift, suggesting modest attitudinal movement that did not meet conventional thresholds for statistical significance. Given the relatively small sample size, these findings should be interpreted with caution; however, the consistency of directional trends across related items suggests meaningful differentiation in how educators evaluated AI's pedagogical value, usability, and ethical implications over time.

Timing Matters

The findings of this study must be interpreted in light of the specific temporal and informational context in which data were collected. The six-week study period (May 27–July 1, 2025) coincided with a marked shift in national and regional media discourse about generative artificial intelligence in education, most notably following the widespread circulation of a Massachusetts Institute of Technology Media Lab preprint that framed AI-assisted writing as associated with reduced neural engagement. As documented in the preceding media analysis, coverage during this period moved decisively away from earlier narratives emphasizing teacher agency, instructional efficiency, and pedagogical innovation, toward more cautionary and at times alarmist claims about cognitive harm, cheating, and the erosion of critical thinking. This discursive inflection provides a critical lens for understanding the selective and differentiated attitudinal patterns observed in the present study.

Within the Technology Acceptance Model (TAM), the observed increase in perceived usefulness (PU)—particularly for AI-supported lesson differentiation and professional development planning—suggests that educators continued to recognize the pedagogical value of AI even as public narratives grew more skeptical. Importantly, these PU gains were concentrated in domains aligned with educator-facing uses, rather than efficiency-oriented or time-saving functions. This pattern is consistent with earlier media framing, prevalent in late 2024 and early 2025, that positioned AI as a tool for enhancing instructional planning and professional learning when used judiciously by teachers. The persistence of these usefulness beliefs during a period of intensified critique suggests that educators were able to differentiate between AI's potential as a professional support tool and its more controversial applications, rather than adopting wholesale rejection in response to negative coverage.

In contrast, perceptions of perceived ease of use (PEOU) remained largely stable across the study period, despite modest, nonsignificant increases. This stability may reflect participants' existing familiarity with digital tools and leadership-oriented technologies, but it may also indicate that usability perceptions were less susceptible than usefulness beliefs to media influence. Notably, the dominant headlines during the study window focused on ethical and cognitive consequences rather than on technical complexity or accessibility, potentially limiting the salience of ease-of-use considerations. From a TAM perspective, this pattern reinforces the notion that PEOU stabilizes earlier in the acceptance process, while PU remains more responsive to evolving contextual narratives.

The most pronounced shift occurred within ethical intention to use (EIU), where concern that students primarily use AI to cheat increased significantly on a single item. This finding aligns closely with the dominant media framing during the latter half of the study period, which increasingly emphasized academic dishonesty, shortcutting, and the moral risks of student AI use. Headlines during this time frequently foregrounded cheating, cognitive offloading, and institutional loss of control, often invoking the MIT preprint as evidence despite its pre–peer review status. The specificity of this ethical shift—emerging for student-facing use but not for educator-facing applications—suggests that participants were responding not to AI in general, but to socially mediated concerns about legitimacy, accountability, and public scrutiny. Within TAM, this pattern illustrates how expectancy-driven beliefs about usefulness can coexist with heightened ethical hesitation, particularly when external narratives amplify reputational and professional risk.

Taken together, these findings suggest that educator attitudes toward AI during this six-week period were shaped by an ongoing negotiation between pedagogical opportunity and ethical constraint, rather than by a linear trajectory toward acceptance or rejection. Media discourse appears to have functioned as a powerful external variable, not by uniformly diminishing perceived usefulness, but by reframing the conditions under which AI use is viewed as professionally defensible. The timing of the study—embedded within a moment of heightened public attention and methodological controversy—underscores the importance of situating technology acceptance research within its broader informational environment. Future research should further examine how media-driven expectancy shifts interact with ethical intention to shape sustained and context-sensitive AI use in educational leadership and practice.

Recommendations for Practice

The findings of this study carry important implications for the preparation of educational leaders who must make instructional, ethical, and policy decisions in a professional landscape increasingly shaped by rapidly shifting media narratives about technology. The six-week study window—coinciding with heightened media attention to generative AI following the dissemination of a high-profile but non–peer-reviewed MIT preprint—illustrates the conditions under which school leaders are now expected to evaluate evidence, respond to public concern, and guide practice. Leadership preparation programs can no longer assume a stable informational environment in which policy decisions follow settled research consensus; instead, they must prepare leaders to operate amid discursive volatility, where headlines, preprints, and social media commentary often outpace formal scholarly review.

Within this context, the observed pattern of increased perceived usefulness alongside heightened ethical concern—particularly regarding student misuse—suggests that emerging leaders are capable of nuanced differentiation rather than binary acceptance or rejection of AI. Rather than positioning AI as either a threat to be controlled or an innovation to be universally embraced, preparation programs should foreground the role of leaders as translators between research, media discourse, and school practice, capable of contextualizing emerging findings and resisting reactionary policy shifts driven by headline cycles.

The findings also underscore the importance of preparing leaders to attend to the ethical and reputational dimensions of technology use, particularly in relation to student-facing applications. The selective decline in ethical intention around concerns of cheating highlights how media narratives can amplify professional risk perceptions, shaping leaders' willingness to endorse or constrain classroom practices. Leadership preparation should therefore integrate explicit opportunities to examine how ethical intention is formed not only through personal belief, but through anticipated public scrutiny and professional norms. Engaging candidates in structured analysis of media coverage, policy statements, and contested research can help future leaders develop the capacity to respond thoughtfully rather than defensively when new technologies become the focus of public concern.

Finally, these findings suggest that leadership preparation programs should model adaptive, evidence-informed decision-making by incorporating emerging technologies—such as generative AI—as contextual tools rather than curricular centers. Embedding AI discussions within courses on learning theory, assessment, or professional development, as was done in this study, mirrors the conditions leaders will encounter in practice: AI will rarely arrive as a discrete initiative, but rather as an overlay on existing pedagogical and organizational systems. Preparing leaders to evaluate AI's usefulness, usability, and ethical implications within these broader systems may better equip them to lead schools through future cycles of technological enthusiasm and skepticism alike. In a media-saturated educational environment, leadership preparation must therefore prioritize not only technical knowledge, but the cultivation of discernment, professional judgment, and resilience to narrative swings.

Conclusion

This study examined educators' evolving attitudes toward generative artificial intelligence within a uniquely dynamic informational context, leveraging the Technology Acceptance Model to interpret belief formation, attitudinal change, and ethical intention during a period of heightened media attention. The findings suggest that educators' responses to AI were neither uniform nor reactionary; instead, participants demonstrated selective recalibration, maintaining or increasing perceptions of AI's pedagogical usefulness while simultaneously expressing heightened ethical concern about student misuse. Importantly, these patterns unfolded during a six-week window marked by a pronounced shift in media narratives—particularly following the widespread dissemination of a non–peer-reviewed MIT Media Lab preprint—underscoring the role of public discourse as a salient external variable shaping technology acceptance.

Interpreted through TAM, the results highlight the differential sensitivity of core constructs to contextual influence. Perceived usefulness proved responsive to instructional framing and professional application, while perceived ease of use remained comparatively stable. Ethical intention, conceptualized as an extension of behavioral intention, emerged as especially vulnerable to media-amplified concerns around legitimacy, cheating, and professional risk. Together, these findings reinforce the value of TAM for examining attitudinal differentiation in contested adoption contexts, particularly when acceptance is negotiated at the intersection of expectancy-driven beliefs, professional identity, and public narrative.

For educational leadership preparation, the study underscores the necessity of preparing leaders not only to evaluate emerging technologies, but to do so amid discursive volatility. As AI and other innovations continue to enter schools through cycles of enthusiasm, skepticism, and moral panic, leaders must be equipped to interpret evolving evidence, contextualize media claims, and guide practice with discernment rather than reaction. Embedding AI as a contextual tool within foundational coursework—rather than as an isolated initiative—mirrors the realities leaders will face and supports the development of adaptive, ethically grounded decision-making. Ultimately, this study suggests that preparing educational leaders for a media-saturated future requires attention not only to what technologies can do, but to how beliefs about those technologies are formed, challenged, and reshaped in public view.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author declares that no generative AI or generative AI-assisted technologies have been used to generate, refine, or correct the content in the manuscript. The exceptions are AI supported embedded tools in Microsoft Word, such as the spelling check and grammar suggestions (red and blude underline) that are a native part of that word processing tool. References were managed using Mendeley and the Mendeley plug in in Microsoft Word. The ideas, design, procedures, findings, analyses, and discussion are originally written and derived from careful and systematic conduct of the research.

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