Test Anxiety in the Age of AI: Revisiting Mulvenon's Multi-Stakeholder Framework Under Algorithmic Accountability

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Abstract

This article revisits Mulvenon et al.'s (2005) multi-stakeholder framework of test anxiety in light of AI-mediated assessment systems. It argues that while the original framework remains relevant, the nature of assessment-related pressure has fundamentally shifted from episodic, high-stakes testing to continuous, data-driven evaluation. Drawing on recent research in learning analytics and AI in education, the article examines how adaptive systems, real-time feedback, and predictive analytics reshape experiences of anxiety across students, teachers, parents, and administrators (Gašević et al., 2023; Holmes et al., 2023). It introduces the concept of algorithmic accountability as a new pressure system and proposes an AI-mediated multi-stakeholder anxiety model. The central claim is that AI does not eliminate test anxiety but redistributes and reconfigures it into more diffuse, persistent, and system-driven forms, with implications for instructional design, policy, and future research.

Keywords: AI-mediated assessment, test anxiety, algorithmic accountability, learning analytics, continuous evaluation, educational stakeholders

Introduction

The integration of artificial intelligence (AI) into educational assessment is increasingly reshaping how learning is measured, monitored, and acted upon. Generative AI tools, adaptive learning systems, and predictive analytics enable forms of continuous, real-time feedback that were previously difficult to achieve at scale (Holmes et al., 2022; Kasneci et al., 2023). These developments are shifting assessment from discrete, high-stakes events toward more ongoing, data-informed processes embedded within everyday learning environments. AI-powered platforms can analyze student performance rapidly, adjust instructional content dynamically, and generate personalized feedback, thereby influencing both the purpose and experience of assessment (Zawacki-Richter et al., 2019). While these advancements offer potential gains in efficiency, personalization, and responsiveness, they also introduce new complexities related to evaluation, accountability, and psychological impact. In particular, the increasing use of continuous monitoring raises important questions about how assessment-related pressure and anxiety are experienced across educational stakeholders.

A foundational perspective on test anxiety is provided by Mulvenon et al. (2005), who examined perceptions of standardized testing among students, parents, teachers, principals, and counselors. Their findings challenged dominant assumptions by suggesting that student anxiety was often overstated, while teachers reported higher levels of stress and concern. Moreover, they found that external pressure—particularly from parents and teachers—was negatively associated with student performance, whereas anxiety itself was not a significant predictor of achievement.

Importantly, their work demonstrated that perceptions of testing vary across stakeholder groups, highlighting the need for a system-level understanding of assessment-related experiences. However, this framework was developed within a pre-AI context characterized by periodic, standardized testing rather than continuous, technology-mediated evaluation.

The emergence of AI-mediated assessment environments calls into question whether traditional assumptions about test anxiety remain fully applicable. In contrast to the episodic nature of earlier assessment models, many contemporary systems incorporate more continuous data collection and feedback processes that inform instructional decisions in near real time (Luckin et al., 2022). This shift may redistribute the locus of pressure from isolated testing events to more persistent forms of performance monitoring. Students may experience reduced anxiety associated with single high-stakes tests, yet also encounter new forms of cognitive and evaluative pressure linked to ongoing feedback and performance tracking. Similarly, teachers are increasingly subject to data-driven evaluation systems that quantify aspects of instructional effectiveness, potentially influencing perceptions of accountability and professional autonomy (Williamson, 2017). These developments suggest that test anxiety is not eliminated but may be reconfigured in ways that are less visible yet potentially more pervasive.

The purpose of this article is to revisit multi-stakeholder test anxiety within the context of AI-mediated assessment environments. Building on the framework established by Mulvenon et al. (2005), this study examines how the integration of AI technologies may reshape the distribution, intensity, and nature of assessment-related pressure across students, teachers, parents, and administrators. Rather than focusing solely on individual psychological responses, the analysis adopts a system-level perspective that considers how technological infrastructures influence perceptions, behaviors, and decision-making processes. By synthesizing insights from educational technology, assessment research, and learning analytics, the study offers a contemporary reinterpretation of test anxiety that reflects the evolving conditions of digitally mediated education.

This article contributes to the literature by extending Mulvenon's multi-stakeholder framework through the lens of algorithmic accountability. Algorithmic accountability refers to the increasing reliance on automated systems to evaluate performance, inform decisions, and enforce standards within educational institutions (Selwyn, 2019). In AI-influenced environments, assessment is not solely human-centered but is increasingly co-mediated by algorithmic processes that shape how performance is measured and interpreted. This shift has important implications for how pressure is experienced, as stakeholders must navigate both institutional expectations and the logic of AI systems. By integrating the concept of algorithmic accountability with established theories of test anxiety, this study proposes a forward-looking framework for understanding assessment in the age of AI.

Ultimately, this article argues that AI does not eliminate test anxiety but may redistribute and transform it across stakeholders and contexts. Understanding these shifts is essential for designing assessment systems that balance technological innovation with psychological well-being, equity, and ethical responsibility.

Original Framework: Mulvenon et al. (2005) Revisited in Contemporary Context

Mulvenon et al. (2005) introduced a foundational multi-stakeholder framework for understanding test anxiety, emphasizing that assessment-related experiences extend beyond students to include parents, teachers, principals, and counselors. This systems-oriented perspective remains highly relevant, particularly as educational environments become more complex and increasingly mediated by digital technologies. However, key assumptions and findings of this framework warrant reconsideration in light of developments in AI-integrated and data-rich assessment environments.

At the core of Mulvenon et al.'s model is the recognition that test anxiety is not a singular, student-centered phenomenon but a distributed experience shaped by interactions among multiple stakeholders. Their findings challenged dominant narratives by suggesting that student anxiety was often overstated, while teachers reported the highest levels of stress. More importantly, the study showed that external pressure—especially from educators and parents—was more strongly associated with negative student performance than anxiety itself. This distinction between pressure and anxiety marked a significant shift in interpreting assessment-related outcomes.

Recent research continues to support the importance of distinguishing between internal emotional states and externally imposed pressures, while also suggesting that these dynamics may be evolving in digitally mediated environments. For example, some studies indicate that students in AI-supported learning systems may experience lower levels of traditional test anxiety due to reduced emphasis on high-stakes, one-time examinations (Heilweil, 2024). Instead, assessment is increasingly embedded within ongoing feedback processes, which may normalize evaluation and reduce acute stress episodes. However, this does not necessarily imply a reduction in overall psychological burden. Rather, anxiety may become more diffuse, manifesting as sustained cognitive load or ongoing performance vigilance (Kovanović et al., 2021).

In contrast to Mulvenon et al.'s finding that teacher anxiety was highest among stakeholders, more recent work suggests that educator stress may be intensifying under conditions of data-driven and algorithmically informed accountability. Teachers are increasingly evaluated through dashboards, predictive analytics, and performance metrics generated by digital systems. While these tools can support instructional improvement, they may also create conditions of persistent monitoring that heighten professional pressure (Perrotta & Selwyn, 2020). The shift from periodic evaluation to more continuous forms of monitoring parallels changes experienced by students, reinforcing the possibility that assessment-related stress is becoming more systemic than episodic.

Parents, another key stakeholder group identified by Mulvenon et al., are also experiencing changing forms of engagement in AI-mediated environments. With greater access to real-time learning analytics and performance tracking tools, parents may become more directly involved in monitoring student progress. While such transparency can support achievement, it may also contribute to heightened expectations and increased pressure dynamics similar to those identified in earlier research (Ifenthaler & Yau, 2020). The immediacy of data access shifts parental involvement from primarily reactive to more continuous forms of oversight.

Principals and counselors, though less emphasized in subsequent research, remain important actors in shaping institutional responses to assessment. In contemporary contexts, these stakeholders are increasingly responsible for interpreting data outputs, ensuring compliance with accountability frameworks, and addressing the socio-emotional implications of technology use. Their roles now often include mediating between human judgment and algorithmic decision-making, introducing new forms of institutional pressure and ethical complexity (Tsai et al., 2020).

Despite its enduring contributions, the Mulvenon et al. framework is limited by its pre-AI context and focus on relatively static testing environments. Assessment in 2005 was largely characterized by standardized, high-stakes tests administered at discrete intervals. In contrast, many contemporary systems incorporate more dynamic and continuous forms of evaluation embedded within digital platforms. This shift suggests a need to reconsider key constructs such as anxiety and pressure. Rather than being tied primarily to specific events, these experiences may increasingly emerge through ongoing interactions with technological systems.

Moreover, the original framework did not account for the role of data as an active factor in shaping perceptions and behaviors. In AI-influenced environments, data is not merely a byproduct of assessment but a central mechanism through which performance is defined and interpreted. This introduces new dimensions of accountability and transparency that affect all stakeholders. For instance, students may internalize performance metrics as indicators of identity, while teachers may adjust instructional strategies in response to algorithmic recommendations, sometimes with implications for professional autonomy (Holmes et al., 2023).

In summary, while Mulvenon et al. (2005) provided a valuable multi-stakeholder lens for understanding test anxiety, the evolution of assessment technologies calls for an updated interpretation. The core insights—particularly the distinction between anxiety and pressure and the importance of stakeholder perspectives—remain relevant. However, the distribution, intensity, and nature of these experiences appear to be shifting in AI-mediated environments. Anxiety is less confined to discrete testing moments and may be more diffusely embedded in ongoing interactions, while pressure is increasingly shaped by both human and algorithmic influences. Revisiting this framework through a contemporary lens enables a more nuanced understanding of assessment in digitally mediated education.

The Rise of AI in Assessment

The integration of artificial intelligence (AI) into educational assessment is increasingly reshaping how learning is evaluated, measured, and acted upon. Unlike traditional systems that rely primarily on periodic, high-stakes examinations, many AI-enabled environments support more continuous forms of evaluation embedded within everyday learning processes. This shift is associated with advances in adaptive testing, real-time feedback systems, and predictive analytics, which contribute to a more dynamic and data-rich understanding of student performance (Holmes & Tuomi, 2022; Siemens & Baker, 2024).

AI-enabled assessment systems are often characterized by their capacity to personalize evaluation at scale. Adaptive testing technologies, for example, adjust the difficulty and sequencing of questions in real time based on a learner's responses, allowing for more precise estimation of ability while reducing inefficiencies associated with one-size-fits-all models (van der Linden & Glas, 2023). Such systems may improve measurement precision and create more responsive assessment experiences. However, this personalization is not neutral; it reflects algorithmic design choices that influence what is measured and how performance is interpreted.

Real-time feedback is another defining feature of AI-supported assessment. Digital platforms increasingly provide immediate responses to student inputs, enabling learners to refine understanding and adjust strategies without delay. This contrasts with traditional feedback cycles, where responses may be delayed. Research suggests that timely feedback can enhance learning outcomes and support metacognitive development, particularly when it is specific and actionable (Shute & Rahimi, 2021). At the same time, frequent feedback may create a sense of ongoing evaluation, blurring the boundary between learning and assessment and potentially increasing cognitive load.

Predictive analytics further extend the capabilities of AI in assessment by using historical and real-time data to forecast future performance. These systems can identify patterns associated with academic success or risk, enabling more proactive forms of intervention. For example, early warning systems may flag students who are likely to struggle, allowing targeted support before failure occurs (Gašević et al., 2023). While such tools offer benefits in terms of efficiency and responsiveness, they also raise concerns about determinism and bias. Predictions based on incomplete or skewed data may reinforce existing inequalities, particularly when used in high-stakes decision-making contexts.

Together, these technologies contribute to a broader shift from episodic testing toward more continuous forms of evaluation. In traditional models, assessment is concentrated in discrete events—such as midterms or standardized tests—that serve as primary indicators of learning. In contrast, AI-mediated systems can distribute assessment across time, generating streams of data that reflect ongoing engagement and performance. This shift repositions assessment as a process rather than a singular event, emphasizing learning trajectories and behaviors over isolated outcomes (Ifenthaler & Schumacher, 2022). While continuous evaluation can offer a more holistic view of learning, it also introduces challenges related to data interpretation, overload, and student autonomy.

A key development associated with this shift is the emergence of algorithmic accountability. As AI systems increasingly mediate assessment, they also influence how performance is evaluated and how decisions are made within educational institutions. Algorithmic accountability refers to expectations that such systems operate transparently, fairly, and in alignment with educational goals (Kizilcec & Lee, 2024). However, many AI models function as "black boxes," making it difficult for educators and students to understand how outputs are generated. This lack of transparency can complicate efforts to ensure fairness and may undermine trust in assessment processes.

Closely related is the rise of data-driven performance monitoring. In AI-enabled environments, students and teachers may be evaluated through dashboards, analytics reports, and performance indicators. For students, this can include metrics such as time-on-task, accuracy rates, and progression patterns. For teachers, evaluation may incorporate student outcomes, engagement metrics, and comparative benchmarks. While these tools can support informed decision-making, they may also create conditions of increased visibility and surveillance (Selwyn & Jandrić, 2023). Such conditions can influence behavior, encouraging alignment with measurable outcomes while potentially narrowing the scope of learning.

Importantly, this shift toward data-driven monitoring is not solely technical but also cultural. It reflects a broader movement toward quantification in education, where complex learning processes are translated into measurable indicators. This may create tensions between what is easily measured and what is educationally meaningful. For example, constructs such as creativity, critical thinking, and collaboration are more difficult to capture through automated systems, yet remain central to educational goals (Williamson & Eynon, 2020). As a result, AI-driven assessment systems may privilege certain forms of knowledge while marginalizing others.

In sum, the rise of AI in assessment is reshaping educational practices in significant ways. Adaptive testing, real-time feedback, and predictive analytics contribute to a shift toward more continuous evaluation, influencing how learning is experienced and measured. At the same time, the emergence of algorithmic accountability and data-driven monitoring introduces challenges related to transparency, equity, and the nature of educational judgment. Understanding these dynamics is essential for developing assessment systems that balance technological innovation with ethical and pedagogical considerations.

Table 1
Conceptual comparison of traditional assessment and AI-mediated assessment environments

Dimension	**Traditional Assessment (Mulvenon et al., 2005 context)**	**AI-Mediated Assessment (Contemporary context)**
Timing of assessment	Episodic (midterms, finals, standardized tests)	Continuous, embedded in learning activities
Mode of evaluation	Primarily human judgment	Algorithmic evaluation supported by analytics
Nature of stress	Visible, event-based test anxiety	Embedded, ongoing “invisible anxiety”
Feedback cycles	Delayed, periodic	Immediate, real-time feedback
Data characteristics	Limited, point-in-time snapshots	Extensive, longitudinal, high-frequency data
Accountability structure	Institution- and teacher-driven	Algorithmic accountability and data-driven monitoring

Stakeholder pressure	Concentrated (mainly on students)	Distributed across students, teachers, parents, administrators
Role of teachers	Primary evaluators	Data interpreters and mediators of AI outputs
Role of parents	Limited visibility into performance	Real-time access and increased monitoring
Decision-making	Reactive and retrospective	Predictive and proactive (analytics-informed)

Note. This table presents a conceptual comparison based on Mulvenon et al. (2005) and recent literature on AI-mediated assessment systems.

Table 1 synthesizes key differences between traditional and AI-mediated assessment systems by highlighting structural, temporal, and experiential shifts. One notable change is the movement from episodic to more continuous forms of evaluation, which redistribute assessment across time and embed it within everyday learning interactions. This temporal shift may influence how pressure is experienced: rather than being concentrated around discrete testing events, anxiety can become more diffuse and persistent.

The table also illustrates a transition from predominantly human-centered judgment to forms of evaluation increasingly informed by data analytics and automated systems. This development introduces new forms of accountability, often described as algorithmic accountability, in which aspects of performance are continuously monitored and quantified. As a result, pressure may become less localized and more distributed across stakeholders, affecting not only students but also teachers, parents, and administrators.

Another key insight involves the transformation of stakeholder roles. Teachers may shift from sole evaluators to interpreters of data, while parents move from limited awareness to more immediate access to performance information, potentially shaping expectations. Administrators, in turn, may rely more heavily on predictive analytics, influencing institutional decision-making processes.

Overall, the table supports the article's central claim that AI does not eliminate test anxiety. Instead, it suggests that anxiety may be reconfigured into more continuous, system-mediated forms. These forms are shaped by factors such as data use, increased visibility, and the immediacy of feedback.

Reframing Test Anxiety in AI Contexts

The integration of artificial intelligence into educational assessment is increasingly reshaping the nature, distribution, and visibility of test anxiety. Rather than eliminating anxiety, AI-mediated environments may reconfigure it into more continuous, systemically embedded forms that operate across multiple stakeholders. Traditional conceptualizations of test anxiety—centered on discrete, high-stakes testing events—may be insufficient for capturing the more diffuse and persistent pressures associated with algorithmically influenced evaluation systems. A contemporary reframing therefore needs to consider how AI reshapes emotional, cognitive, and institutional dynamics in assessment contexts.

Students

For students, AI-enabled assessment systems may contribute to a reduction in traditional forms of test anxiety associated with single, high-stakes examinations. Adaptive platforms and continuous assessment models distribute evaluation across time, potentially reducing the intensity of episodic stress events (Heilweil, 2024). Students may experience less acute pressure from "one-shot" testing scenarios, as performance is increasingly measured through multiple low-stakes interactions embedded within learning activities. This shift aligns with research suggesting that frequent, formative feedback can support learning and reduce fear of failure (Shute & Rahimi, 2021).

However, this apparent reduction in episodic anxiety may be accompanied by new forms of psychological strain. Continuous evaluation can increase cognitive load, as students must regularly process feedback, adjust strategies, and maintain awareness of performance. The persistent presence of assessment may lead to what has been described as "evaluation fatigue," characterized by sustained mental effort due to limited separation between learning and testing (Kovanović et al., 2021). In this context, anxiety may become less visible but more enduring.

This pattern can be conceptualized as "invisible anxiety," a diffuse and ongoing state of performance vigilance that differs from episodic test stress. Unlike acute test anxiety, which is temporally bounded, invisible anxiety operates through continuous interaction with digital systems. Students may not explicitly report anxiety in conventional terms, yet remain subject to ongoing evaluative pressure shaped by real-time metrics and feedback loops (Ifenthaler & Yau, 2020). This shift suggests a need to reconsider how anxiety is defined and measured in AI-mediated environments.

Teachers

For teachers, the transformation of assessment systems may shift the locus of pressure from classroom-based evaluation to more continuous, data-informed monitoring. In traditional settings, teacher evaluation was often periodic and based on observations, student outcomes, and professional judgment. In contrast, AI-supported systems can generate continuous streams of performance data, aggregated into dashboards and analytics tools used to assess instructional effectiveness (Perrotta & Selwyn, 2020).

These metrics may introduce new forms of accountability pressure. Teachers are increasingly evaluated using quantifiable indicators such as student engagement, progression rates, and assessment outcomes. While such data can support instructional improvement, it may also encourage alignment with measurable outcomes rather than broader learning goals (Williamson & Eynon, 2020). The visibility and persistence of these metrics can contribute to increased stress, particularly when linked to high-stakes decisions such as promotion or contract renewal.

A related concern is the potential impact on instructional autonomy. As AI systems provide recommendations for pacing, content delivery, and assessment design, teachers may experience constraints on professional discretion. In some contexts, algorithmic suggestions may function as implicit directives, particularly where data-driven decision-making is emphasized (Selwyn & Jandrić, 2023). This dynamic can create tension between pedagogical expertise and technological guidance.

Parents

Parents, as key stakeholders, are also experiencing shifts in their relationship to assessment. AI-enabled platforms increasingly provide real-time access to student performance data, including grades, engagement metrics, and predictive indicators (Ifenthaler & Schumacher, 2022). This transparency can reduce uncertainty and enable closer monitoring of academic progress.

However, greater access to information may also encourage more continuous oversight. Parents may respond to real-time data with increased involvement or heightened expectations, potentially contributing to pressure on students (Kizilcec & Lee, 2024). This shift from intermittent to ongoing monitoring can alter the dynamics of parental engagement.

Additionally, the availability of detailed analytics may contribute to expectation escalation. Continuous visibility of performance data may emphasize incremental improvement and optimization, sometimes at the expense of intrinsic motivation or exploratory learning. In this context, parental pressure—identified by Mulvenon et al. (2005) as influential—may be intensified by the immediacy and granularity of AI-generated information.

Administrators (Principals and Counselors)

For administrators, including principals and counselors, AI is expanding both the scope and complexity of decision-making processes. These stakeholders increasingly rely on data systems and predictive models to inform resource allocation, identify at-risk students, and design intervention strategies. Learning analytics platforms can aggregate data across classrooms and institutions, offering insights that were previously difficult to obtain (Gašević et al., 2023).

This data-informed approach can enhance the capacity for targeted intervention, enabling administrators to allocate support more efficiently and respond proactively to emerging challenges. For example, predictive models may identify students who are at risk of disengagement or underperformance, allowing earlier intervention through counseling or academic support. Such capabilities align with broader institutional goals related to retention and student success.

However, reliance on AI systems also introduces important risks. One concern is the potential for overreliance on algorithmic outputs. Predictive models are inherently constrained by the quality and scope of the data on which they are trained and may not fully capture contextual factors influencing student performance. Decisions based primarily on these outputs can lead to misclassification, bias, or unintended consequences (Tsai et al., 2020).

Administrators must also navigate ethical and practical challenges associated with integrating AI into institutional processes. These include ensuring data privacy, maintaining transparency, and balancing efficiency with human judgment. The expectation to act on data-driven insights may create a form of institutional pressure, where decision-makers feel accountable not only to stakeholders but also to the perceived authority of algorithmic systems.

In sum, AI does not eliminate test anxiety but may redistribute and transform it across stakeholders. Students may experience reduced episodic stress alongside increased cognitive load and less visible forms of anxiety. Teachers may encounter intensified accountability and potential constraints on autonomy under conditions of data-driven monitoring. Parents may shift from uncertainty to more continuous oversight, potentially shaping expectations. Administrators, in turn, gain new decision-making tools while also facing risks related to overreliance and ethical complexity. Reframing test anxiety in this context requires a system-level perspective that accounts for the evolving interplay between technology, psychology, and institutional practice.

Algorithmic Accountability as a New Pressure System

Algorithmic accountability is increasingly recognized as a defining feature of AI-mediated educational environments, reshaping how assessment, evaluation, and responsibility are structured. Broadly defined, algorithmic accountability refers to expectations that automated systems—particularly those driven by artificial intelligence—operate in ways that are transparent, explainable, fair, and aligned with institutional goals (Kizilcec et al., 2022). In education, this concept extends beyond technical performance to include how algorithms influence judgments about student learning, teacher effectiveness, and institutional outcomes. As AI systems become more integrated into assessment processes, they introduce an additional layer of accountability that interacts with, and in some contexts may challenge, traditional human-centered evaluation.

A useful way to understand this shift is through comparison with traditional assessment systems. Historically, assessment has been organized around periodic tests—midterms, finals, and standardized exams—that concentrate evaluation into discrete moments. These events are typically interpreted through human judgment, with teachers, administrators, and examiners playing central roles. In this model, stress is often visible and episodic, peaking around testing periods and then subsiding.

In contrast, AI-mediated systems can support more continuous forms of monitoring. Assessment is less confined to specific events and more embedded within ongoing interactions between learners and digital platforms. Engagement metrics, responses, and activity data may contribute to evolving performance profiles. Evaluation is increasingly informed by algorithmic processes that analyze patterns and generate indicators in near real time (Gašević et al., 2023). This transition does not remove subjectivity but may relocate it into the design, assumptions, and operation of technological systems.

One consequence of this shift is a movement from highly visible stress to more embedded forms of pressure. In traditional systems, stress is tied to identifiable events, making it easier to recognize and address. In AI-mediated environments, pressure may be distributed across time and operate less visibly. Students, teachers, and other stakeholders may experience ongoing performance awareness due to more continuous evaluation (Selwyn, 2022). This form of pressure may be less intense at any single moment but potentially more persistent, given the absence of clear boundaries between evaluation periods.

From this comparison, it can be argued that AI does not eliminate anxiety but may redistribute it. Rather than concentrating stress in high-stakes testing events, AI-influenced systems may diffuse it across everyday practices. Students may experience less anxiety tied to individual exams but greater concern with maintaining consistent performance across multiple indicators. Teachers may encounter reduced pressure from formal observations alongside increased demands associated with data-driven monitoring. Parents and administrators similarly engage in environments where accountability is more continuous and data-informed. In this sense, anxiety may increasingly function as a structural feature of the system rather than solely as a response to discrete events (Williamson, 2023).

Proposed Framework: AI-Mediated Multi-Stakeholder Anxiety Model

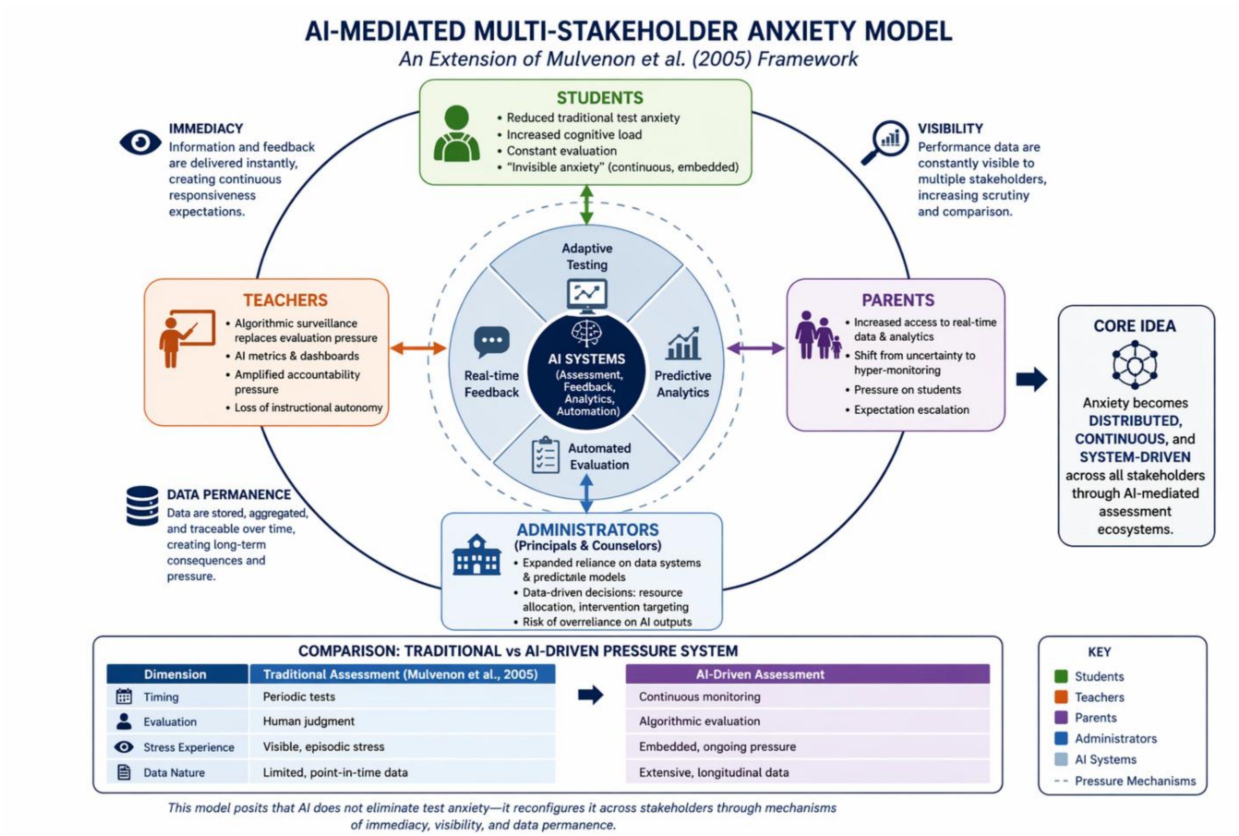
Building on Mulvenon et al.'s (2005) multi-stakeholder framework, a contemporary model of assessment-related anxiety should incorporate the role of AI systems as influential agents in shaping experiences of pressure and evaluation. The proposed AI-Mediated Multi-Stakeholder Anxiety Model extends the original framework by integrating three core components: stakeholders, AI systems, and pressure mechanisms. This model offers a system-level perspective intended to reflect key features of digitally mediated educational environments.

The first component, stakeholders, retains the categories identified by Mulvenon et al.—students, teachers, parents, and administrators—while reconceptualizing their roles within AI-influenced contexts. Each group interacts with assessment systems in different ways, yet all are affected by algorithmic processes. Students engage with adaptive platforms and feedback systems; teachers interpret and respond to performance data; parents monitor progress through analytics dashboards; and administrators may use predictive models to inform decision-making. These interactions are interconnected, forming a network of shared accountability and influence.

The second component, AI systems, refers to the technological infrastructure that mediates assessment. This includes feedback mechanisms that provide near real-time responses, analytics tools that aggregate and interpret data, and automated processes that generate evaluations and recommendations. These systems function not only as tools but also as mediating structures that influence what is measured, how it is interpreted, and how it is acted upon (Holmes et al., 2022). Their presence may introduce new dynamics of authority, as algorithmic outputs increasingly inform human judgment.

The third component, pressure mechanisms, captures how AI systems may shape and distribute anxiety across stakeholders. Three mechanisms are particularly relevant: immediacy, visibility, and data permanence. Immediacy refers to the rapid feedback and evaluation cycles enabled by digital systems, which can accelerate decision-making and reduce opportunities for reflection. Visibility involves the increased accessibility of performance data to multiple stakeholders, potentially expanding the scope of evaluation. Data permanence highlights the enduring nature of digital records, where past performance remains accessible and may influence future judgments (Ifenthaler & Schumacher, 2022).

Figure 1. AI-mediated multi-stakeholder anxiety model: Reconfiguring test anxiety through algorithmic accountability



The figure visualizes the AI-Mediated Multi-Stakeholder Anxiety Model as a system in which anxiety is less confined to individuals or discrete events and more distributed across interconnected stakeholders and technologies. At the center, AI systems—comprising adaptive testing, real-time feedback, predictive analytics, and automated evaluation—function as a core mechanism supporting more continuous forms of assessment. This positioning suggests that AI operates not only as a tool but also as a mediator influencing how performance is measured, interpreted, and acted upon.

Surrounding the AI core are four stakeholder groups: students, teachers, parents, and administrators. The circular arrangement emphasizes interdependence rather than hierarchy, with each group experiencing distinct but related forms of pressure. Students may experience reduced episodic test anxiety alongside increased cognitive load and less visible forms of ongoing pressure. Teachers may encounter a shift from periodic evaluation to more continuous, data-informed monitoring, with implications for accountability and autonomy. Parents may move from limited visibility to more immediate access to performance data, potentially shaping expectations, while administrators may rely more heavily on predictive systems for decision-making, balancing efficiency with concerns about overreliance.

The outer layer—immediacy, visibility, and data permanence—represents key mechanisms through which AI systems may shape and sustain pressure. Immediacy reflects accelerated feedback cycles; visibility expands the audience and scope of evaluation; and data permanence extends the temporal influence of performance records (Ifenthaler & Schumacher, 2022). Together, these mechanisms help explain how anxiety may shift from episodic stress toward more continuous, embedded forms of pressure.

The comparison table complements this interpretation by contrasting traditional assessment (periodic, human judgment, visible stress) with AI-mediated systems (more continuous, data-informed, and less visibly bounded pressure). Overall, the model integrates technological, psychological, and institutional dimensions into a unified conceptual framework.

Taken together, these elements suggest that anxiety in AI-mediated environments may be more distributed, continuous, and system-influenced. Pressure is distributed across stakeholders, as each group experiences it in interconnected ways; it is more continuous, as evaluation occurs across time rather than at fixed intervals; and it is system-influenced, as the structure and logic of AI systems shape how pressure is generated and experienced.

This reframing has important implications for research and practice. It suggests that addressing assessment-related anxiety requires moving beyond individual-level interventions to consider broader technological and institutional contexts. Designing effective and ethical assessment systems therefore involves not only improving accuracy and efficiency but also attending to the psychological and social consequences of more continuous evaluation. By extending Mulvenon's framework into AI-mediated contexts, the proposed model offers a more comprehensive perspective on how anxiety may operate in contemporary education.

Implications

The rapid expansion of AI-mediated assessment systems carries important implications for instructional design, teacher roles, and educational policy. These implications extend beyond technical implementation to include ethical, psychological, and organizational considerations. As AI becomes more integrated into everyday learning environments, stakeholders must navigate tensions between innovation and responsibility, ensuring that technological developments support rather than undermine core educational values.

Instructional Design

Instructional design in AI-supported environments should balance automation with human judgment. While AI systems offer capabilities such as adaptive sequencing, real-time feedback, and predictive insights, overreliance on these tools may lead to overly deterministic learning pathways that constrain student agency (Holmes et al., 2023). Designers are therefore encouraged to ensure that AI augments rather than replaces pedagogical decision-making, preserving opportunities for creativity, exploration, and instructor discretion.

A related concern is the potential emergence of over-surveillance environments. Continuous data collection, while useful for personalization, may create conditions in which students feel persistently monitored. Research suggests that such environments can negatively affect motivation, trust, and engagement, particularly when learners perceive constant evaluation (Selwyn & Jandrić, 2023). Instructional design may therefore benefit from incorporating intentional “off-grid” moments—spaces where learners can reflect, experiment, and engage without immediate assessment. These design choices can help mitigate continuous pressure and support psychological well-being.

Designers must also consider how feedback is delivered. While immediacy can be beneficial, not all learning processes require instant correction. Strategic delays and opportunities for self-assessment may foster deeper cognitive engagement and reduce dependence on automated guidance (Shute et al., 2022). In this sense, effective instructional design involves not only leveraging AI capabilities but also determining appropriate limits to their use.

Teacher Roles

The integration of AI into assessment systems is influencing the role of teachers, who increasingly act as interpreters of data and mediators of algorithmic outputs. Educators may be expected to analyze dashboards, interpret analytics, and translate data into instructional decisions (Gašević et al., 2024). This shift suggests the need for competencies that extend beyond traditional pedagogical skills.

Central to this transition is AI literacy. Teachers benefit from understanding how AI systems function, including their assumptions, limitations, and potential biases. Without such understanding, educators may either overtrust or underutilize algorithmic outputs, both of which can hinder effective practice (Kizilcec & Lee, 2024). AI literacy supports critical evaluation of data and more informed, context-sensitive decision-making.

At the same time, teachers play an important mediating role between students and AI systems. They are responsible for interpreting data in ways that are meaningful and supportive, rather than reductive. This requires balancing quantitative indicators with qualitative judgment to ensure that students are not defined solely by metrics. As a result, the teacher’s role becomes more complex, involving the integration of technological, pedagogical, and ethical considerations.

However, this shift also raises concerns related to workload and professional autonomy. Continuous engagement with data systems may increase cognitive and administrative demands. Institutions therefore need to provide appropriate support, including professional development, time allocation, and clear guidelines for data use, to ensure that AI integration does not negatively impact teacher well-being (Williamson & Eynon, 2020).

Policy

The rise of AI-mediated assessment systems highlights the need for policy frameworks addressing regulation, fairness, and transparency. One key area involves the governance of AI-driven evaluation. Policies should clarify how algorithmic systems are used in high-stakes decisions, such as grading, placement, and teacher evaluation, and ensure alignment with educational objectives (OECD, 2023).

Data use represents another critical policy domain. AI systems rely on extensive data collection, raising concerns about privacy, consent, and ownership. Educational institutions must establish guidelines that protect student and teacher data while enabling responsible innovation. This includes defining what data can be collected, how it is stored, and who has access to it (Regan & Jesse, 2019).

Ensuring fairness and transparency remains essential for maintaining trust in AI-mediated systems. Algorithmic bias is a persistent concern, particularly when systems are trained on datasets reflecting existing inequalities. Policies may require regular auditing of AI systems to identify and mitigate bias, as well as mechanisms to improve explainability of algorithmic decisions (Kizilcec et al., 2022). Transparency, in this sense, is not only technical but also relational, shaping how stakeholders understand and engage with AI technologies.

Limitations and Future Research

Despite growing interest in AI and assessment, much of the existing literature remains conceptual, underscoring the need for further empirical validation. Theoretical models provide useful frameworks for understanding emerging dynamics, but they benefit from testing through studies that examine how AI systems influence learning outcomes, stakeholder experiences, and institutional practices. Experimental and quasi-experimental designs can offer insights into causal relationships, while qualitative approaches can capture the nuanced experiences of users.

Longitudinal research is particularly important for understanding the longer-term effects of continuous evaluation and algorithmic accountability. Short-term studies may not fully capture how sustained engagement with AI systems shapes motivation, identity, and well-being over time (Ifenthaler & Schumacher, 2022). Tracking these effects across multiple academic cycles can reveal patterns that are less visible in shorter timeframes.

Future research may also examine how AI-related anxiety manifests across different contexts. Educational systems vary in resources, culture, and policy environments, all of which influence how AI is implemented and experienced. Comparative studies across institutions, regions, and demographic groups can help clarify how contextual factors shape the distribution and intensity of anxiety (Luckin et al., 2022).

In addition, there is value in exploring how AI-related anxiety intersects with other forms of educational stress, such as performance pressure, digital fatigue, and equity-related concerns. Examining these interactions can support more comprehensive approaches to assessment design and policy development.

In conclusion, the implications of AI in assessment are substantial, influencing how learning is designed, how teaching is practiced, and how education is governed. Addressing these implications likely requires coordinated efforts across stakeholders, grounded in empirical evidence, ethical considerations, and a commitment to balancing technological innovation with human-centered values.

Conclusion

Mulvenon et al.'s (2005) multi-stakeholder framework remains a valuable foundation for understanding assessment-related anxiety, particularly in its recognition that pressure is distributed across students, teachers, parents, and administrators. However, the rise of AI-mediated assessment systems calls for a critical reinterpretation of this framework. While the original model was grounded in periodic, high-stakes testing environments, contemporary education is increasingly influenced by more continuous, data-driven forms of evaluation. This shift does not invalidate Mulvenon's insights but extends them into a more complex, technologically mediated context.

AI influences not simply whether pressure exists, but how it is experienced. Traditional test anxiety was often episodic—intense but time-bound—associated with identifiable assessment events. In contrast, AI-supported systems may embed evaluation more deeply into everyday learning processes, contributing to forms of pressure that are more ongoing and less visible (Selwyn, 2022). Students may experience reduced anxiety tied to single examinations while also encountering sustained cognitive and evaluative demands. Teachers may face increased accountability through data-informed monitoring, while parents and administrators engage with real-time analytics that shape expectations and decision-making (Gašević et al., 2023). In this context, anxiety may shift from isolated moments of stress to more continuous engagement with performance systems.

The central implication is that AI does not eliminate test anxiety but may reconfigure it. Anxiety may be redistributed across stakeholders, diffused across time, and increasingly mediated by algorithmic processes that shape how performance is measured and interpreted. This perspective suggests the need to move beyond traditional conceptions of test anxiety toward a system-level understanding that accounts for technological influences. Addressing assessment-related pressure in AI-mediated environments therefore involves not only improving technological tools but also attending to design, ethical governance, and human-centered educational practices (Williamson, 2023).

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