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How teachers perceive AI in their profession and classroom: professional visions and practical problems

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HOW TEACHERS PERCEIVE AI IN THEIR PROFESSION AND CLASSROOM: PROFESSIONAL VISIONS AND PRACTICAL PROBLEMS

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DEDICATION

To my grandparents, in loving memory. If you could see who I have become, I know you would be proud.

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ABSTRACT

Although artificial intelligence (AI) technology has long existed, only recently has it broken into public consciousness. The hopes and fears surrounding it range from catastrophic nightmares to utopian dreams. As a communication and information technology, AI is particularly relevant to the educational enterprise. Already, there's much discussion about what the proper role should be of AI in education and how it will affect the roles of teachers. Given the big stakes, it's important for communication scholars to devote attention to this emerging technology. To take up this challenge, this study explores how teachers perceive AI in education, focusing on its impact on professional identity, values, and pedagogical autonomy. Traditional functionalist models like the Technology Acceptance Model (TAM) often overlook the deeper psychological and contextual factors shaping educators' attitudes. The study adopts an interdisciplinary approach that integrates the sociology of professions with functionalist models under a critical realism (CR) framework. This approach provides a multi-layered lens to explore educators' acceptance or resistance to AI, addressing factors that single-paradigm models overlook.

Methodologically, the research employed semi-structured interviews with 51 K–12 educators, followed by a CR-guided thematic analysis to uncover underlying patterns and causal mechanisms. The analysis was augmented by an innovative use of large language models (LLMs) to assist in qualitative coding and theme identification under careful researcher oversight, demonstrating a novel AI-assisted approach to data analysis within a CR paradigm. Findings reveal that teachers' professional identity, which includes their sense of autonomy, ethics, and purpose, emerged as a key causal mechanism influencing attitudes toward AI. When educators perceived AI tools as reinforcing their professional values and enhancing their autonomy, they were inclined to adopt them; if the tools threatened these values or autonomy, educators showed resistance.

Based on these insights, the study proposes a refined conceptual model of AI adoption in education that combines task-oriented factors (e.g. perceived usefulness, ease of use, organizational support) with profession-oriented factors (e.g. value alignment, professional identity, ethical considerations). This model significantly extends conventional technology acceptance theories by embedding the moral and professional dimensions of teaching into adoption frameworks. Theoretical contributions include expanding educational technology (EdTech) adoption models with professional identity and ethics constructs, while a key methodological contribution is illustrating how LLM-assisted qualitative analysis can be conducted rigorously under a CR approach. Practically, the findings provide insights for teacher training, school leadership, and policymaking. They highlight that successfully integrating AI into K–12 schools requires

targeted professional development programs that clearly illustrate how AI can enhance teaching practices while preserving teacher autonomy and student-teacher relationships. Additionally, schools should establish explicit ethical guidelines and policies to ensure responsible AI use aligned with teachers' professional values, particularly concerning academic integrity, fairness, and student privacy. It is also essential to foster collaborative professional communities that enable educators to experiment with AI, share effective practices, and collectively address emerging ethical concerns. Finally, ensuring equitable access to AI resources across diverse school settings is critical to preventing the widening of gaps in educational equity.

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LIST OF ABBREVIATIONS

AI.....Artificial Intelligence

API.....Application Programming Interface

CR.....Critical Realism

DOI .....Diffusion of Innovations

EdTech.....Educational Technology

GUI.....Graphical User Interface

IT .....Information Technology

K–12.....Kindergarten through Grade 12

LLM.....Large Language Model

MOOC.....Massive Open Online Course

QDA.....Qualitative Data Analysis

SEM.....Structural Equation Modeling

SES.....Socioeconomic Status

TAM .....Technology Acceptance Model

TOE .....Technology–Organization–Environment Framework

TPB .....Theory of Planned Behavior

TRA .....Theory of Reasoned Action

US/U.S.....United States

UTAUT .....Unified Theory of Acceptance and Use of Technology

Chapter 1 Introduction

The rapid emergence of artificial intelligence (AI) in K–12 education has sparked significant debate regarding its opportunities and challenges in educational settings (Alsolami, 2025; Cobing, 2024; Huang et al., 2024, 2025; Huang & Katz, 2025; Luckin & Cukurova, 2019; Ta & West, 2023). Following the public release of generative AI tools, such as OpenAI's ChatGPT in late 2022, educators and policymakers have grappled with critical considerations about embracing AI as a transformative aid for teaching and learning or restricting its use due to concerns about academic integrity, equity, and potential erosion of human expertise. Early responses exhibited considerable variation. By early 2023, several major school districts implemented bans or tight restrictions on generative AI in response to concerns related to academic dishonesty and inappropriate content (Mearian, 2023; Ta & West, 2023; Zalaznick, 2023). Notably, New York City Public Schools, initially among the first to restrict ChatGPT, reversed its ban within months, adopting a cautious integration strategy supported by teacher training and oversight (Mearian, 2023). This rapid policy shift highlighted a growing recognition among educational leaders that outright prohibitions were neither practical nor educationally beneficial in the long term. Consequently, many began exploring ways to leverage AI's potential advantages, such as personalized learning support and improved administrative efficiency, while addressing associated risks through structured guidance and professional development initiatives (Banks, 2023; Duer, 2023; Henry, 2023).

By 2024, governmental and professional organizations actively engaged in these discussions. As of the first half of 2025, at least 26 U.S. states and territories had

established official guidance or policies regarding the use of AI in K–12 education (AI for Education, 2025). These policies generally stress that AI should serve as an enhancement rather than a replacement for human educators. For instance, guidelines from the state of Alabama explicitly indicate that AI systems must supplement rather than supplant human instruction, with teachers mandated to verify AI-generated content (AI for Education, 2025). These provisions reflect a prevailing perspective that despite advancements in educational AI, the centrality and irreplaceable nature of the teacher's role remain fundamentally intact.

Amid the rapid policy shifts and technological advancements, it has become increasingly evident that teachers play a pivotal role in successfully integrating AI into educational settings. Teachers' perceptions and practices regarding AI significantly influence its effectiveness and adoption within classrooms. School administrators and educational researchers increasingly acknowledge that successful implementation of AI tools requires more than directives from leadership; it necessitates genuine engagement and careful application by classroom teachers. In recognition of this, several progressive schools have chosen to provide educators substantial autonomy regarding the use and management of AI in teaching. For example, a preparatory school in Florida implemented a system allowing teachers to individually determine guidelines for AI usage in student assignments, ranging from complete restriction to full permission, rather than enforcing a universal policy (SAIS, 2024). This strategy maintained teacher autonomy and enabled educators, initially cautious about AI, to incrementally experiment and build familiarity with these tools over an academic year (SAIS, 2024). Such initiatives underscore the

importance of teacher autonomy and professional discretion in the effective integration of AI.

In summary, the current educational landscape reflects both enthusiasm and cautious deliberation. While AI technologies continue to expand within schools, there is widespread consensus that their implementation must align closely with core educational values and rely upon teachers' professional expertise and ethical considerations. Within this context, the present study examines K–12 educators' perceptions of AI integration into their professional roles and explores the factors influencing their acceptance or resistance to adopting these emerging technologies.

In light of the above developments, this study centers on the perspectives and choices of teachers regarding AI. It is motivated by initial observations that not all teachers readily adopt even those AI applications deemed pedagogically useful or user-friendly. This raises research questions about teachers' mindsets and the underlying reasons for their choices. Specifically, the study seeks to answer the two research questions:

RQ1: How do K–12 educators perceive the integration of AI into their classroom practice and professional role?

RQ2: What factors shape teachers' decisions to embrace or resist AI tools in their work?

These questions aim to probe both teachers' general outlook on AI as part of teaching, and the particular influences that encourage or discourage them from using AI-based tools in practice. By addressing these questions, the research seeks to shed light on an

emergent phenomenon in education at a time when schools worldwide are grappling with how to balance innovation with professional values.

Addressing these issues holds significant practical and scholarly relevance. From a practical standpoint, understanding educators' perceptions of AI is vital for shaping effective policies and implementation strategies. Teachers serve as critical gatekeepers in the adoption process of educational technologies. Even highly advanced AI tools will achieve limited impact without meaningful integration into instructional practices by educators. Consequently, insights into factors influencing teachers' reluctance or resistance toward AI adoption, despite apparent benefits, can assist school administrators, teacher educators, and policymakers in creating more effective support structures. For instance, concerns that AI could undermine students' creativity or compromise educators' professional integrity suggest that mere technical training may be inadequate for successful adoption (CO-EDP, 2025). Recent studies on faculty resistance to AI highlight that such resistance often encompasses ethical, professional, and identity-related considerations beyond mere practicality or ease of use (Shata, 2025). Therefore, professional development and integration initiatives must address foundational issues such as ethics, authenticity, and professional identity, not solely technical proficiency. By exploring educators' underlying values and concerns, this study aims to inform the creation of AI integration strategies that educators perceive as acceptable and empowering. Ultimately, aligning AI implementation with educators' professional values has the potential to promote more sustainable and meaningful adoption, fostering innovations that authentically enhance educational practices rather than being

superficially utilized or actively resisted.

The scholarly significance of this study arises from its challenge to and expansion of existing models of technology adoption in education. Established research on educational technology adoption has predominantly relied on frameworks described as functionalist or utilitarian. For instance, frameworks such as the Technology Acceptance Model (TAM) operate on the premise that educators will adopt technology if it is perceived as easy to use and beneficial for their instructional tasks. The fundamental constructs of TAM, perceived usefulness and perceived ease of use, have consistently demonstrated predictive power regarding technology adoption across various settings (Dele-Ajayi et al., 2019). However, previous research indicates that the foundational elements of TAM alone are typically insufficient for fully explaining technology adoption behaviors, particularly within educational contexts where individual and contextual factors significantly influence adoption decisions (Tarhini et al., 2013, 2014).

Responding to the call for more context-specific explorations of educational technology adoption (Tarhini et al., 2013), this study examines influences extending beyond functional advantages offered by AI tools. Consequently, the research contributes to scholarly discourse by incorporating educators' professional identities, ethical considerations, and personal values into the analysis of technology acceptance. Examining these frequently overlooked factors provides a broader and more nuanced theoretical perspective on educational technology adoption. Such an expanded approach moves beyond an exclusive focus on practical utility toward a comprehensive understanding of factors driving educators' technology choices. This broader theoretical

perspective is particularly timely, as the introduction of AI may necessitate new or refined theoretical models to adequately capture how educators respond to technological innovation.

Initial findings from this research and other recent studies indicate that educators' decisions regarding artificial intelligence (AI) adoption are influenced by factors that extend beyond the parameters of conventional technology adoption models. Preliminary interviews conducted in this study revealed that several K–12 teachers recognized the utility and ease of use of specific AI applications, such as tools capable of rapidly generating quiz questions or drafting lesson plans. Despite acknowledging these functional benefits, teachers nonetheless actively chose not to incorporate these tools into their instructional practice. The reasons provided by these educators did not pertain to technical obstacles or concerns about the tools' effectiveness; rather, they related more closely to profound professional values and convictions. One experienced educator, for instance, articulated a preference for personally developing lesson plans instead of delegating this responsibility to an algorithm, despite recognizing the potential efficiency gains from using AI. To this educator, lesson planning represented more than a task aimed merely at efficiency—it constituted a fundamental aspect of professional identity and responsibility toward students. The educator expressed concerns that relying on AI could diminish the authenticity of instructional practices and undermine a sense of ownership in the classroom process. Another teacher expressed reservations about using AI for tasks such as generating progress report comments, equating such use to a compromise of professional standards and integrity. This perspective reflected an implicit

belief that the effort involved in teaching possesses intrinsic value and should not be delegated to automated processes. These examples underscore that educators may resist integrating AI technology into their practices not due to doubts about its capabilities, but rather due to the broader implications of technology use concerning their professional roles and values.

Such motivations for resistance cannot be fully captured by technology adoption models that depict the process primarily as a function of perceived usefulness and ease. The reasoning offered by teachers in these instances pertains less to the practical functionality of the AI tools and more to their professional values, ethical considerations, and sense of identity. This phenomenon aligns with existing literature concerning teacher identity and technology integration. Research exploring technology use in teaching contexts has documented instances where educators deliberately avoided digital tools perceived to interfere with their personal teaching styles, values, or preferred methods of student engagement, even when these tools offered apparent educational advantages (Shelton, 2018; Westberry et al., 2015). Similarly, studies examining higher education faculty responses to AI have highlighted tensions related to identity, specifically among educators whose professional identities are closely linked to original intellectual effort. These educators often experience discomfort when delegating any portion of their creative or intellectual tasks to AI, perceiving such delegation as undermining their authenticity and professional integrity (CO-EDP, 2025). Consequently, resistance to technological innovations may emerge when these innovations conflict with educators' definitions of effective teaching or their professional identity, even if the innovations

possess significant usability and functional benefits. Traditional diffusion and acceptance models typically overlook these normative and identity-related dimensions. Therefore, such models may inaccurately predict higher adoption rates, assuming that educators will readily embrace AI based solely on functionality and ease of use. Conversely, these models may underrepresent principled non-adoption behaviors, which stem from deeper professional beliefs and ethical considerations.

To fully understand the dynamics involved, it is essential to adopt a broader analytical perspective. Factors such as professional identity, ethical considerations, and perceived threats to teacher autonomy and expertise emerge as central elements influencing technology adoption. Educators function not merely as users of technological tools but as professionals committed to specific educational values that AI implementation may affect. Additionally, there may be apprehensions about the long-term implications for their profession. Some educators express concerns that excessive reliance on AI might erode their pedagogical skills or potentially threaten their job security. Recent research examining AI's impact on teacher identity identified both enthusiasm and apprehension among educators (Puja et al., 2025). While many educators appreciate AI's ability to alleviate workload burdens and personalize learning experiences, they also report significant concerns regarding reduced pedagogical autonomy and the risk of professional obsolescence associated with extensive AI use (Puja et al., 2025). Such concerns indicate perceived risks to teacher autonomy and professional expertise, potentially leading educators to feel marginalized or undervalued due to increased automation. In scenarios where AI implementation occurs in a top-down

manner, constraining professional judgment—such as mandatory AI-driven curricula or monitoring systems—educators may experience feelings of disempowerment and surveillance rather than empowerment and support (Puja et al., 2025). Conversely, when teachers receive adequate support and the flexibility to adapt AI to their instructional needs, they typically perceive AI as a beneficial collaborator rather than as a threat (Puja et al., 2025). This comparison emphasizes that the context and approach of AI integration, particularly regarding alignment with teachers' professional identities, significantly shape educators' acceptance or resistance to technological innovations.

Given these complexities, existing frameworks of technology adoption may prove insufficient, highlighting the need for new conceptual approaches. Models centered solely on individual cognition or assuming technological neutrality do not fully capture the reality that educational technology operates within social and ethical contexts. Teachers are more than mere end-users; they are custodians of pedagogical values and agents of student development. Consequently, their decisions regarding AI integration reflect broader considerations about consistency with their professional roles and adherence to educational principles. The limitations of prevalent models suggest the necessity of incorporating insights from teacher professional identity, educational ethics, and sociology of technology. This integration would yield frameworks acknowledging both surface-level motivators of adoption, such as efficiency and effectiveness, and deeper mechanisms including normative beliefs, role identities, and power dynamics that significantly influence teacher behaviors.

In summary, this study investigates why certain K–12 teachers, despite recognizing the utility and ease of use of AI tools, choose not to adopt them. Addressing this issue requires surpassing a purely functionalist perspective and adopting an approach that views teachers holistically, situated within their professional cultures. It involves examining how technology aligns with or challenges educators' professional identities and values. By addressing this broader dimension, the research aims to close critical gaps in understanding technology integration in schools. Instances of teachers independently engaging in tasks despite available AI support indicate important clues that theoretical models must expand to account for educators' lived experiences and deeper considerations of purpose, values, and identity.

Recognizing the complexity of this phenomenon underscores the importance of adopting a multilayered analytical framework. Examining both observable behaviors—such as adopting or resisting AI—and underlying factors like beliefs, institutional norms, and identities requires bridging empirical observations and conceptual analysis. To accomplish this, the study employs Critical Realism, a philosophical framework that conceptualizes reality as layered and seeks to identify underlying mechanisms shaping observed behaviors. This philosophical stance, detailed further in Chapter 2, facilitates exploration into how deeper structural factors intersect with individual agency in the context of educators' technology use.

Chapter 2 Philosophical and Methodological Groundings

Critical Realism

This dissertation aims to contribute to the understanding of technology adoption in education by moving beyond existing functionalist models. While these models offer valuable insights, they often fail to fully capture the intricate interplay among individual, systemic, and contextual factors influencing adoption. Furthermore, relying exclusively on grounded theory (Glaser & Strauss, 1967) as a methodological approach presents notable limitations. Guerrero Puerta and Lorente García (2024) highlight several challenges doctoral students encounter when utilizing grounded theory for dissertations, including difficulties with coding, theory development, integration of theoretical frameworks, time constraints, and addressing theoretical conflicts. Recognizing these limitations, this study employs a more balanced methodological approach.

The present research draws upon functionalist models and integrates perspectives from the sociology of professions. This interdisciplinary synthesis represents a novel approach that has not previously been applied to investigating teachers' adoption of AI in professional practice. It is argued here that this synthesis provides a richer and more comprehensive explanation of AI adoption among educators, addressing gaps that neither functionalist models nor grounded theory alone sufficiently resolve.

Critical realism serves as the philosophical foundation for the theoretical and methodological framework of this study. Critical realism provides a robust justification for integrating diverse theoretical constructs while ensuring coherence and rigor. It aligns effectively with the study's objective of comprehending the reasons and processes

underlying teachers' adoption of AI by emphasizing the layered nature of reality, a point elaborated further within this manuscript.

Subsequent sections of the dissertation explain why integrating disparate theoretical constructs offers greater value and validity than adherence to singular existing theoretical frameworks. Additionally, the methodological design is articulated in detail, illustrating alignment with the ontological and epistemological principles of critical realism at each stage.

Critical Realism as a Philosophical Framework

CR, developed by Roy Bhaskar from the 1970s (Archer et al., 2013; Bhaskar, 1975), offers an alternative to positivist and constructivist paradigms (Fletcher, 2017). At its core, CR proposes that reality operates on three interconnected levels: the empirical (what we observe), the actual (events that occur, whether observed or not), and the real (the underlying mechanisms driving those events). This stratified view of reality enables CR to go beyond surface-level observations, allowing researchers to uncover the deeper causes behind complex social phenomena.

Fletcher (2017) identifies three fundamental principles of CR: stratified ontology, epistemic fallibility, and causal mechanisms. Stratified ontology suggests that reality is made up of interconnected layers that dynamically influence each other. In the context of this study, for example, the empirical level could be the teachers' reported experiences of using AI tools, such as its ease of use or challenges encountered in the classroom. The actual level could be organizational changes in a school system that influence AI adoption might happen without being directly recognized by the teachers. The real level

could be institutional pressures, professional norms, or systemic inequities that influence teachers' decisions about AI adoption.

Epistemic fallibility highlights the inherent limitations of human knowledge. While human understanding of reality is inevitably shaped by existing theories and perspectives, it is never absolute. CR embraces this uncertainty, advocating for the ongoing refinement of theories to bring us closer to an accurate representation of reality. Finally, causal mechanisms refer to the inherent powers within social structures that interact with human agency under specific conditions to produce observable outcomes. CR aims to identify these mechanisms, as well as the contexts in which they operate, to provide a deeper and more nuanced understanding of how and why events occur.

Problems for Using Single Functionalist Model

A single functionalist model often falls short of explaining the diverse influences on teachers' perceptions of AI, which are shaped by technological, institutional, and socio-psychological factors. Each theoretical framework contributes valuable but incomplete perspectives, which highlights the need for a more integrative approach. I discussed in details four representative functionalist models—Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovations (DOI), and Technology—Organization—Environment (TOE) framework—in Chapter 4 and the theoretical construct I brought into discussion—sociology of professions in Chapter 3.

Validity of Combining Theories

CR offers a robust justification for combining theories, as it emphasizes theoretical pluralism while maintaining ontological and epistemological rigor. First, CR analyzed research questions as theory-laden, but not theory-determined (Fletcher, 2017). By employing multiple theoretical lenses, this study remains open to revising initial assumptions based on empirical findings, ensuring alignment with observed phenomena. For example, a finding that teachers resist AI due to concerns about autonomy might initially align with TAM (e.g., they perceive AI as not useful). However, further exploration through the lens of the sociology of professions could reveal systemic influences, such as fear of deprofessionalization or loss of control over pedagogy.

Second, CR provides retroduction as a core methodological approach that helps researchers starting with observed phenomena and working backward to hypothesize the causal mechanisms that produce them (Fletcher, 2017). This approach ensures that theoretical concepts are applied selectively and iteratively based on empirical findings. For example, when a teacher expressed reluctance to use AI for grading assignments, the initial interpretation through the TAM might be that the tool was not perceived as user-friendly or effective for grading tasks. Retroduction, however, could uncover that the reluctance stemmed from a deeper concern that using AI for grading undermines professional judgment and devalues expertise. The following section explains how critical realism guided the design of the interview script and the data analysis process.

Development of the Interview Script

First, the semi-structured interview questions are layered on empirical, actual and real level. Empirical level questions focus on teachers' direct experiences with AI (e.g., “Can you describe a specific instance where AI was used in your classroom?”). Actual level questions explore broader patterns and trends (e.g., “What changes have you observed in teaching practices since AI tools were introduced?”). Real level questions investigate underlying mechanisms (e.g., “What do you think motivates the integration of AI into teaching practices?”).

Second, participant input was employed to critique, validate, or extend existing knowledge, reflecting a fundamental principle of critical realism (Fletcher, 2017). Participants reflected on their professional values, teaching philosophies, and broader institutional constraints within their schools or districts, thereby identifying potential causal mechanisms influencing their attitudes toward AI. For example, a teacher’s preference for collaborative lesson planning could be analyzed through the Theory of Planned Behavior (TPB), examining how perceived behavioral control interacts with external limitations, such as insufficient training or resources, influencing their intention to adopt AI. Teachers might feel competent in using AI but still indicate institutional obstacles like limited technical support significantly hinder their willingness to integrate the technology. Furthermore, the same preference for collaborative lesson planning can be analyzed using the UTAUT, specifically investigating how performance expectancy and facilitating conditions shape perceptions of AI utility in collaborative scenarios. For instance, if educators recognize AI tools as effective in simplifying collaborative tasks

such as resource sharing or lesson coordination, UTAUT attributes these positive perceptions to strong performance expectancy and favorable facilitating conditions. Conversely, perceptions of complexity or inadequate institutional support could diminish behavioral intentions to use AI for collaborative activities.

Third, questions were designed to be theory-laden but open (Fletcher, 2017). For example, while TAM might initially frame questions about the usability of AI tools, emergent data could highlight systemic inequities in resource distribution that are better explained by structural theories like the sociology of professions. Similarly, though TAT may guide exploration of how AI enables specific pedagogical practices, unexpected themes—such as resistance stemming from perceived threats to professional identity—may emerge. For instance, a teacher might report that while AI tools effectively streamline administrative tasks like grading or attendance, they also create feelings of reduced professional agency when AI-generated suggestions override teachers' pedagogical decisions. Therefore, this resistance might be better explained by the sociology of professions, which highlights how the adoption of AI might clash with deeply held professional values and norms, such as the need for autonomy and personalized instruction. This openness ensures that the study remains responsive to participants' lived experiences, integrating emergent findings to refine theoretical interpretations and produce a holistic understanding of AI adoption.

Data Analysis Steps

While some existing studies advocate for the use of grounded theory methods in CR research (Maxwell, 2012; Oliver, 2012; Redman-MacLaren & Mills, 2015; Yeung,

1997), I adopt a more flexible deductive approach suggested by Fletcher (2017), which aligns better with the CR's ontology and epistemology. Fletcher (2017) argued that grounded theory is not ideal for CR studies for two mean reasons. First, grounded theory avoids active engagement with existing theories during analysis, focusing instead on inductively developing theories grounded solely in data. In contrast, CR requires active engagement with existing (though fallible) theories to find the best explanation of reality, even before the research begins. This is also the reason why I think CR fit better for my project goals. Second, grounded theory primarily employs inductive reasoning, which is data-driven. CR, however, relies on abduction and retroduction, involving a more theory- and researcher-driven analytical process.

According to Fletcher (2017), CR-informed data analysis involves an iterative process combining identification of demi-regularities, abduction, and retroduction. The first step is to identify demi-regularities. Initial coding focuses on identifying recurring patterns or trends in teacher narratives. For example, multiple teachers may express concerns about how AI impacts their professional autonomy, such as feeling that AI-driven lesson plans reduce their creative input or decision-making authority. This recurring concern represents a demi-regularity—an observable pattern that suggests underlying causal mechanisms, such as institutional mandates or AI design decisions, limiting teachers' agency. These patterns guide deeper analysis into the systemic constraints shaping these perceptions, using theories like the sociology of professions to contextualize the data. Similarly, recurring positive patterns might emerge, such as how AI tools alleviate administrative burdens, allowing teachers to focus more on

personalized instruction. This positive trend serves as another demi-regularity, pointing to the enabling mechanisms of AI, such as time-saving affordances and resource allocation. Deeper analysis might explore how these mechanisms vary depending on contextual factors, such as access to training or technical support.

The second step is abduction. Empirical findings are reinterpreted using theoretical concepts from functionalist models and the sociology of professions. For instance, narratives about AI's perceived ease of use might initially appear as isolated technical concerns but are recontextualized within broader professional and systemic dynamics. For example, when teachers describe ease of use, it may highlight their limited time to experiment with new tools due to institutional pressures, aligning with findings from the sociology of professions that emphasize systemic constraints on professional autonomy. Similarly, while ease of use may reflect practical considerations (as TAM suggests), it could also indicate perceived organizational priorities, where the institution's support or lack thereof influences these perceptions. This layered reinterpretation integrates surface-level findings with deeper systemic mechanisms, ensuring a comprehensive understanding of the data.

The third step is retroduction. Analysis moves beyond observable patterns to infer the causal mechanisms enabling or constraining AI adoption. For example, a teacher's resistance to AI might be traced to systemic pressures, such as a lack of institutional support manifested through inadequate funding for AI training programs or the absence of IT support staff in schools. These systemic issues create a structural barrier that limits teachers' ability to effectively integrate AI into their practices. On the psychological side,

fear of obsolescence might stem from narratives within the teaching community about AI replacing human educators, leading to anxiety and skepticism toward adopting these tools. This interplay of systemic and psychological factors is further influenced by contextual variables, such as whether the school serves underprivileged communities where resource limitations exacerbate these challenges. By connecting these patterns to deeper mechanisms, the analysis reveals the layered realities impacting AI adoption.

The fourth step is iterative coding and refinement. This study applied a deductive coding framework informed by CR, with categories like “structure,” “agency,” and “context.” For instance, “structure” might include institutional factors such as policies mandating AI integration or resource availability, while “agency” could cover teacher-driven initiatives, such as adapting AI tools creatively to suit classroom needs. Codes are refined through multiple cycles of analysis, ensuring alignment with CR’s ontological and epistemological commitments. For example, in the first coding cycle, a teacher’s statement about feeling unsupported when implementing AI might be coded under “structure: lack of training resources.” In subsequent cycles, this might be expanded to reflect intersecting factors, such as “context: rural school setting” and “agency: reliance on peer collaboration for learning AI.” These iterations allow for the progressive refinement of themes, ensuring a detailed and interconnected understanding of the data that incorporates CR's emphasis on the interaction between layers of reality.

Using LLMs for Qualitative Data Analysis

Large language models (LLMs) such as OpenAI’s GPT series have recently been explored as powerful tools to augment or even automate qualitative data analysis (QDA).

Traditionally, QDA of interview transcripts and other textual data is a labor-intensive human endeavor, involving coding text into themes or categories through methodologies like thematic analysis, grounded theory, and content analysis. Since around 2022, researchers have begun examining whether LLMs, including generative models like GPT-3/4 and even earlier transformer-based models like BERT, can take on some of these analytical tasks. Over forty empirical and methodological studies across domains have applied LLMs to qualitative datasets to assess their performance in coding and theme identification.

This section reviews the current state of this emerging literature. It synthesizes empirical findings on LLM-assisted qualitative coding, methodological innovations, tool developments, critiques of LLM-driven analysis, and best practices. Both human-in-the-loop (assistive) applications and fully automated approaches are discussed, covering key qualitative methods (thematic analysis, content analysis, grounded theory) and highlighting the promises and pitfalls of using LLMs for analyzing interview transcripts. Major themes include how well LLMs emulate human coders in identifying themes, the efficiency gains achieved, interpretive and ethical challenges (e.g. hallucinations, context loss, bias), and recommended practices to responsibly integrate LLMs into qualitative research workflows. All in all, the literature to date suggests LLMs can substantially accelerate coding with moderate to high agreement with human analysts, but they are not a wholesale replacement. Instead, they function best as assistive partners under human oversight. The following sections elaborate these findings in detail.

LLM Applications in Qualitative Analysis Methods

Thematic Analysis. The most common application of LLMs in QDA is inductive thematic analysis, following frameworks such as Braun and Clarke's six-phase approach. Numerous studies have tested GPT-3, GPT-4, and similar models on coding interview transcripts to derive themes and sub-themes. For example, Zhang et al. (2023) used ChatGPT to assist in a six-phase thematic analysis of interview data, finding that the model could generate initial codes and candidate themes that aligned with human-derived themes in many cases (Zhang et al., 2023). Similarly, Wachinger et al. (2024) compared ChatGPT's thematic coding of a health interview to a human researcher's analysis; they reported substantial overlap in major themes, with ChatGPT proposing many of the same codes and even suggesting plausible theoretical connections, though notably, a human had to vet and refine the outputs (Wachinger et al., 2024). Studies have shown that LLMs can reliably capture the most salient or obvious themes in textual data, essentially reproducing the "main themes" identified by human analysts. However, LLMs are less adept at identifying subtle, latent, or contextually nuanced themes that require deep interpretation. Researchers note that while an LLM might quickly generate a thematic codebook for a set of transcripts, it tends to miss or misinterpret finer-grained insights such as underlying metaphors, emotional undertones, or culturally specific meanings that a skilled human analyst would catch (Sakaguchi et al., 2025). Thus, LLM-based thematic analysis works well for expediting the identification of dominant patterns in the data, but human expertise remains crucial for interpreting and contextualizing those patterns, especially in rich interview narratives.

Content Analysis and Deductive Coding. A number of studies have employed LLMs in more structured qualitative analysis scenarios, such as deductive coding using a predefined codebook (a form of content analysis). In these tasks, the model is given a set of code definitions or examples and asked to categorize text segments accordingly. For instance, Chew et al. (2023) introduced an "LLM-Assisted Content Analysis" approach using GPT-3.5: the LLM was prompted with an existing codebook and then applied those codes to multiple datasets, including interview excerpts, to mimic a human content analyst (Chew et al., 2023). The results indicated moderate to high agreement between the code assignments of the LLM and human coders, particularly when codes were clearly defined. In many instances, the model achieved coding accuracy between 70 and 80 percent relative to human benchmarks. Similarly, Xiao et al. (2023) used GPT-3 with expert-defined codebooks for deductive coding of open-ended survey responses and interview snippets; they reported a substantial inter-coder reliability (Cohen's κ around 0.6—0.7) between GPT-3's labels and those of human researchers, demonstrating the feasibility of an assistive, semi-automated content analysis workflow (Xiao et al., 2023). One advantage noted in such deductive applications is consistency: given a clear coding schema, an LLM will apply codes uniformly, unaffected by fatigue or shifting interpretations, which can sometimes result in higher consistency than human coders for straightforward classification tasks (Long et al., 2024). However, challenges remain that LLMs can be confused by ambiguities that a trained human would resolve using context, and they may overgeneralize codes if a piece of text only loosely fits a category. Overall, the literature suggests that LLMs can effectively perform deductive coding when given

high-quality codebooks, making them valuable for speeding up content analysis of large text datasets, though critical categories and borderline cases still need human review to ensure validity (Tai et al., 2024).

Grounded Theory and Other Qualitative Methods. Researchers have also begun experimenting with LLMs in more open-ended, inductive frameworks like grounded theory. Grounded theory requires iterative open coding, constant comparison of data and codes, and theory-building. Some preliminary studies (Übellacker, 2024; Zhou et al., 2024) have attempted to have ChatGPT or similar models conduct portions of a grounded theory analysis. For example, Zhou et al. (2024) tested a guided ChatGPT workflow to perform risk analysis via grounded theory coding; they found that ChatGPT could generate a list of open codes from text and even suggest how those codes might relate, but human researchers had to supervise and refine at each step to ensure the emerging "theory" made sense (Zhou et al., 2024). Übellacker (2024) developed an open-source system based on instruction-tuned LLMs to automate specific aspects of grounded theory, including transcript coding and concept grouping. The study reported that while the system effectively proposed reasonable conceptual categories, final theoretical development and abstraction still relied on human analytical interpretation. Beyond grounded theory, other qualitative traditions have seen exploratory use of LLMs: for instance, discourse analysis of classroom dialogue (Garg et al., 2024), phenomenological analysis of interview data (e.g., applying an LLM to follow a structured phenomenological coding method), and narrative analysis. These are still nascent efforts. Early results indicate that while LLMs can handle descriptive coding or simple

categorization in these contexts, they struggle with the deeper interpretation, sense-making, and theoretical integration that methods like grounded theory or phenomenology demand. In summary, LLMs are being applied across a range of qualitative methodologies, but their performance varies: they excel at rapid descriptive coding and theme extraction, yet in methods requiring high interpretive depth, they currently serve only as preliminary aids rather than independent analysts.

To illustrate the breadth of LLM applications, Table 1 summarizes key qualitative analysis tasks and how LLMs have been used in each, along with representative studies.

Qualitative Task/Method	LLM Application Examples	Key Findings and Notes
Thematic Analysis (Inductive)	LLMs (GPT-3.5/4) used to generate codes and themes from interview transcripts (Zhang et al., 2023; Qiao et al., 2025; Wachinger et al., 2024)	LLMs can identify most major themes similar to human analysts, significantly accelerating coding. However, they may miss subtle or context-dependent themes, so human validation is required for interpretive depth.
Deductive Coding / Content Analysis	LLMs apply predefined codebooks to text (Chew et al., 2023; Xiao et al., 2023; Long et al., 2024)	When given clear code definitions, LLMs achieve moderate to high agreement with human coders (e.g., $\kappa \approx 0.6–0.8$) and maintain consistency across large datasets. They enable rapid coding with minimal fatigue, though ambiguities still need human judgment.
Grounded Theory (Open Coding)	Experimental use of LLMs for initial coding and categorization (Zhou et al., 2024; Übellacker, 2024)	LLMs can suggest open codes and tentative groupings, helping brainstorm concepts. Yet, human analysts must lead the constant comparison and theory-building; LLM outputs require careful interpretation and cannot replace human insight in theory generation.

Other (Discourse, Narrative, etc.)	Early trials in discourse analysis (Garg et al., 2024) and cross-cultural analysis (Sakaguchi et al., 2025)	LLMs can perform basic coding of structured dialogues or narratives and have shown high-speed coding even in non-English data. However, capturing pragmatic nuances, speaker intent, or cultural context remains challenging, often requiring expert interpretation to augment the LLM's output.

Note. LLMs have been most effective in thematic and content-oriented analyses, while more interpretive approaches demand significant human involvement.

Table 1. Qualitative Analysis Tasks Addressed by LLMs.

Modes of LLM Integration: Assistive vs. Automated Approaches

Researchers distinguish between two broad modes of using LLMs in qualitative analysis: (1) assistive or human-in-the-loop use, where the LLM acts as a collaborator to a human researcher; and (2) fully automated use, where the LLM attempts to perform coding or theme extraction with minimal human intervention. The literature indicates that these modes have different strengths and limitations, and many authors advocate a hybrid approach as the safest and most effective practice.

Assistive (Human-in-the-Loop) Workflows. In assistive scenarios, an LLM is employed as a "coding partner" or intelligent assistant to expedite parts of the qualitative analysis, while a human analyst retains control over the process. This can take many forms. For example, an analyst might ask ChatGPT to suggest possible codes or summarize a batch of interview excerpts, then decide which suggestions are useful. Alternatively, the LLM might generate an initial thematic outline which the human refines. Dai et al. (2023) describe an LLM-in-the-loop framework in which GPT-3.5 was used iteratively. In this process, the model generated draft codes from data, a human refined those codes and fed the revisions back into the model, and the cycle was repeated

to develop a high-quality codebook (Dai et al., 2023). Such collaborative processes have shown that LLMs can dramatically speed up the early phases of coding, which the researcher can then merge with their own insights. Studies report that these assistive workflows can yield coding quality comparable to human-only analysis for straightforward tasks, while cutting down the manual effort substantially (e.g., one study found an analyst+GPT team coded short texts with agreement on par with independent human coders, but in a fraction of the time). Crucially, the human-in-the-loop approach lets the researcher correct any LLM mistakes, inject domain knowledge, and ensure that interpretation remains sound. Many authors assert that this approach "maximizes benefit while allowing expert correction". In practice, assistive use of LLMs can include: using LLMs to do a first round of open coding, to summarize or cluster codes, to draft analytic memos or summaries of themes, or to even converse with the researcher about the data (e.g. asking the model analytic questions to see if it surfaces insights). The consistent finding is that LLMs excel at accelerating mundane or repetitive parts of analysis, but final decisions and deep interpretations must be confirmed by humans. As a result, a strong recommendation in the literature is to use LLMs as supportive tools, rather than as an autonomous analyst if one's goal is a trustworthy, rigorous qualitative study (Ashwin et al., 2025; Qiao et al., 2025).

Fully Automated Analysis. More ambitiously, researchers have explored fully automated pipelines where an LLM (or a set of LLM-based agents) performs end-to-end qualitative coding and theme identification with minimal human input. In these setups, the human's role is often limited to providing the raw data and perhaps a prompt or

codebook, and then letting the LLM generate coded output or thematic reports. Early proof-of-concept studies indicated that LLMs could autonomously follow thematic analysis procedures, including reading transcripts, generating initial codes, clustering codes into themes, and producing narrative summaries for each theme (De Paoli, 2023). De Paoli (2023) showed that GPT-3.5, when guided through Braun & Clarke's phases for a set of interviews, was able to reproduce most of the main themes identified by human analysts in those interviews. This was a striking finding: it suggested that for relatively structured qualitative data, an LLM might handle a thematic analysis from start to finish with outcomes not entirely dissimilar to a human-conducted analysis. Building on this, fully automated approaches have been tested in various contexts. For example, Rasheed et al. (2024) developed a multi-agent system where separate LLM agents handled coding, theme aggregation, and report writing, effectively simulating a team of "AI analysts" conducting a qualitative analysis without human intervention (Rasheed et al., 2024). Other projects (Xu et al., 2025; Qiao et al., 2025) have also implemented end-to-end pipelines: transcripts are automatically chunked and fed to an LLM for coding, then another LLM process synthesizes those codes into higher-order themes and even drafts narrative outputs or visualizations of the thematic structure.

The fully automated paradigm, though technically impressive, has demonstrated mixed results and considerable risks. On one hand, it is technically feasible and moderately accurate for structured tasks. For example, Dunivin (2025) found that an automated GPT-4 coding pipeline, utilizing careful chain-of-thought prompting, could achieve agreement levels close to human inter-coder reliability in certain cases. On the

other hand, when dealing with unstructured, complex qualitative data, fully autonomous LLM analysis often falls short in interpretive validity and error rates. Common issues include the LLM erroneously assigning codes because it lacks true understanding of context, or generating plausible-sounding themes that are actually unsupported by the data ("hallucinated" themes). Several evaluations have documented that unsupervised LLM coding can drift off-topic or introduce biases. For instance, Ashwin et al. (2025) observed that when left to code interview data by itself, an LLM not only made biased coding decisions (correlated with sensitive attributes of participants) but also was inconsistent unless carefully prompted. As a result, even proponents of automation stress the need for caution: fully automated LLM QDA might be acceptable for low-stakes, exploratory analysis or when validating against a known coding scheme, but reliable published research still requires a human analyst in the loop to verify and interpret the results (Prescott et al., 2024; De Paoli, 2023). A consensus in the field is emerging that fully autonomous LLM analysis should be used sparingly, or at least always double-checked by human experts, especially in "nuanced or high-stakes qualitative research".

Evaluation of LLM Performance in Qualitative Coding

A crucial aspect of this research area is evaluating how well the analyses produced by LLMs align with those of human qualitative researchers. Studies have employed both quantitative metrics to assess reliability and accuracy and qualitative assessments to evaluate interpretive validity in gauging LLM performance.

Reliability and Agreement Metrics. Many empirical studies use inter-coder agreement statistics to compare LLM-generated codes or themes with human-coded data.

Common metrics include Cohen's kappa (κ), Krippendorff's alpha, F1-scores, Jaccard similarity, and simple percent agreement. Across the literature, LLM—human agreement is typically in the "moderate to substantial" range. For instance, multiple independent experiments report Cohen's κ values on the order of 0.4–0.7 when comparing an LLM's coding of text segments to a human reference coding. In deductive coding scenarios with clearly defined categories, agreement tends to be on the higher end of that range (κ often ~0.6 or above, indicating substantial agreement). In more open-ended inductive coding, agreement may be moderate (κ in the 0.3–0.5 range) if the themes are somewhat subjective. For example, in a study analyzing social media comments, an LLM's inductive coding reached about $\kappa = 0.5$ with the human coder, a respectable level considering the ambiguity inherent in the data (Breazu et al., 2024). On the other hand, some tasks have yielded lower reliability: one education study found ChatGPT's codes had only slight agreement (κ ~0.2–0.3) with expert codes when analyzing very nuanced pedagogical interviews (Jiang Yan et al., 2025). These outliers highlight that LLM performance depends on the nature of the task. Straightforward coding tasks produce higher consistency, whereas more interpretive coding results in lower consistency. It is also common to compute overlap percentages, which measure the proportion of the LLM's codes that were also assigned by a human and vice versa. Substantial overlap (often 60–80%) has been observed in many cases, confirming that LLMs do pick up the majority of prominent themes or categories that humans identify. However, perfect agreement is rarely achieved, and indeed even two human coders might not fully agree on qualitative codes. Thus, moderate agreement is a promising sign that LLMs can

approximate human judgments to a useful degree, at least for initial coding.

Notably, a few studies have directly compared multiple LLMs. Prescott et al. (2024) evaluated both OpenAI's and Google's models on coding a set of text messages. The study found that while both LLMs were faster than humans, their agreement with human coders differed, with one model achieving higher fidelity than the other. These results highlight that model choice can influence outcomes (Prescott et al., 2024). Another study compared GPT-3.5 vs. GPT-4 on German interview data and found GPT-4 achieved better agreement with humans (as expected given its more advanced training), though neither was perfect (Kirsten et al., 2024). Early transformer models like BERT, when fine-tuned for coding, have also been used as baselines; LLMs like GPT-3/4 generally meet or exceed the performance of such older classifiers in these QDA tasks, especially because GPT models can leverage semantic context more fluidly via prompting. In summary, LLM-based coding can often approach human coding reliability, but results vary by context.

Time Efficiency and Cost. Perhaps the clearest advantage of LLMs in QDA is speed. Virtually every study that tracks time reports dramatic efficiency gains when using LLMs for coding tasks. In many cases, coding that would take a human analyst days or weeks can be completed by an LLM in minutes or hours. Qiao et al. (2025), for example, applied ChatGPT to inductively code a set of lengthy interview transcripts and reported an 81% reduction in analysis time compared to manual coding. Likewise, Long et al. (2024) found that GPT-4 could code classroom dialogue transcripts in a fraction of the time it took experts, achieving high agreement while reducing annotation time by well

over 50%. Several reports cite 80–90% time savings as a typical outcome when using LLM assistance for coding large datasets. These efficiency gains are not only due to raw speed but also the ability of LLMs to work continuously without fatigue on tedious tasks like scanning for code occurrences. From a cost perspective, if using commercial application programming interfaces (APIs), the computational cost of having an LLM analyze hundreds of pages of text can be non-trivial (and needs consideration in project budgets), but it often remains lower than the labor cost of human coders for comparable volume. Theelen et al. (2024) note that even with API fees, using ChatGPT-3.5 to assist coding was cost-effective given the reduction in human coding hours.

Quality of Themes and Interpretive Validity. Beyond metrics, scholars evaluate the substantive quality of themes and insights produced by LLMs. They assess whether these AI-generated codes are coherent, meaningful, and useful within the research context. Generally, studies suggest that LLMs perform well in identifying clearly evident themes, those explicitly and frequently mentioned in the data, but may struggle with subtler elements. For instance, Wachinger et al. (2024) observed that although ChatGPT identified many surface-level themes from a health interview similarly to a human researcher, it failed to capture deeper interpretive insights. Specifically, ChatGPT overlooked the nuanced theme regarding the erosion of the participant's sense of agency, which emerged only through human interpretation, even though the model offered useful supporting codes. This illustrates a pattern that LLMs tend to generate themes that are plausible and relevant, but sometimes too general. They might converge on generic labels (e.g., "communication issues") whereas a human might frame it more

sharply (e.g., “perceived communication barriers with providers due to language differences”; Breazu et al., 2024). Some works evaluate theme quality by using expert judges: for instance, in an experiment by Breazu et al. (2024), experts rated whether the themes produced by GPT-4 from YouTube comments on hate speech were coherent and insightful; the model’s themes were found to be mostly coherent and matched the dataset’s content, but they missed some nuance that human analysts identified.

One encouraging finding is that LLM-generated codes and themes are often more interpretable and user-friendly than those from traditional automated text analysis methods. Unlike topic modeling or clustering algorithms that output keywords or opaque factors, LLMs output human-language descriptions that can read like a qualitative researcher’s notes. For example, Wosny and Hastings (2024) found that GPT-based analysis yielded themes that were more aligned with expert interpretations than those produced by an LDA topic model on the same interview data. This suggests LLMs might offer a bridge between quantitative text mining and qualitative insight, producing results that are immediately understandable. Nonetheless, the interpretive fidelity of LLM outputs remains a concern. Researchers often perform a secondary qualitative check: reading through transcripts and LLM-generated codes to see if the codes truly reflect participants’ meanings. In many studies, human review has caught instances where the LLM slightly misinterpreted a quote or oversimplified a sentiment. Therefore, while LLMs can reliably surface the main content of the data, human analysts are needed to ensure that the resulting themes accurately represent the complex realities expressed in qualitative data. Best practice involves treating LLM outputs as draft interpretations that

must be verified and refined, rather than final truths (De Paoli, 2023; Qiao et al., 2025).

Methodological Innovations and Best Practices

Given the challenges of using AI in qualitative research, a significant portion of the literature is devoted to developing methodological techniques and best practices to improve LLM performance and integrate these tools into research workflows. Key areas of innovation include prompt engineering strategies, workflow design, specialized tools and interfaces, and protocols for maintaining research transparency and ethics.

Prompt Engineering and Workflow Design. How one asks an LLM to perform coding has a large impact on the quality of results. Early experiments often started with simple prompts like "Read this interview and list the themes," but it has become clear that more sophisticated prompting yields better, more reliable outputs. One effective approach is using chain-of-thought prompting: breaking the task into smaller steps and instructing the LLM to reason stepwise (e.g., first identify significant text segments, then generate a code for each, then group codes into themes; Dunivin, 2025; Wei et al., 2022). This reduces the chance of the model skipping context or making leaps. Studies have found that chain-of-thought or multi-step prompts improved the consistency of codes across responses. Another strategy is role prompting (Zhang et al., 2023), where the prompt frames the LLM as a certain persona, such as: "You are an experienced qualitative researcher analyzing these transcripts…" This tends to make the LLM's output more aligned with professional practices and terminology. Incorporating codebook definitions directly into the prompt is crucial for deductive coding; Xiao et al. (2023) achieved good results by literally concatenating the code descriptions and examples into

the prompt so the model had clear guidelines. Few-shot prompting (providing examples of text and corresponding codes) is also widely used to "teach" the model the coding style or thematic framework expected. In thematic analysis applications, a segmented approach is recommended: if an interview transcript is long, it should be broken into smaller chunks (e.g., by question or topic) and the LLM should analyze each chunk, then a second-pass prompt can synthesize the chunk-level codes into overall themes. This mitigates the context window limitations of current models and prevents important details from being lost in lengthy text. Researchers often implement custom workflows. For example, Raza et al. (2025) described a pipeline using LangChain to automatically chunk long interviews and feed them in sequence to GPT-4, preserving state between chunks so the model maintains context across the entire interview. Such workflows resemble an analyst who reviews interview data in portions while keeping track of earlier observations. Ultimately, carefully engineered prompts and structured workflows, including iterative refinement processes where prompts undergo multiple rounds of revision, or ensemble prompting that aggregates results from different prompts or models, significantly improve the reliability and depth of coding produced by LLMs. Current guidelines recommend that researchers using LLMs for qualitative data analysis thoroughly document their prompt strategies and conduct preliminary tests to determine the optimal prompting approach for their particular datasets.

Tool Support and Automation Platforms. To facilitate adoption of LLM-assisted QDA, developers have created various tools, libraries, and interfaces. One prominent example is QualiGPT (Zhang et al., 2023), an open-source tool that wraps

GPT's API into a user-friendly interface for qualitative coding. QualiGPT provides a graphical user interface (GUI) where researchers can upload transcripts, define codes or ask for inductive coding, and then see the model's suggestions with options to accept or edit them. In their evaluation, Zhang et al. (2023) reported that QualiGPT significantly improved coding efficiency and that users appreciated the ability to see the AI's reasoning (it provided rationale for each coding, enhancing transparency). Another line of development is multi-agent systems for qualitative analysis, essentially, orchestrating several LLM "agents" with different roles. Xu et al. (2025) introduced the TAMA framework, where one agent generates initial codes, another agent reviews and refines the codes, and a third agent compiles themes, with human oversight at key decision points. This division of labor is based on the way a team of researchers might collaboratively analyze data. Initial results suggest that multi-agent LLM systems can improve reliability, as one agent can identify another's errors, and can better simulate human analytical processes. There are also efforts to integrate LLMs into existing QDA software: prototypes for plugins or API connections to software like NVivo or Atlas.ti have been mentioned. For example, one could imagine selecting a set of quotes in NVivo and invoking an LLM to auto-code them or suggest a thematic summary, which the researcher could then adjust in the software. While such integrations are still experimental, they point to a future where LLM assistance is a seamless part of the qualitative analyst's toolbox. Across these tools, usability and transparency are key concerns – designers aim to make the LLM's suggestions easy to review, with features like highlighting text corresponding to each code (so the user can see why the model gave

that code). Some tools log every AI suggestion and the user's action (accept/modify/reject), creating an audit trail that can be used to reflect on the AI's influence on the analysis. This relates to a broader best practice: maintaining a reflexive stance and documenting how the AI was used, to ensure the research community trusts findings that were machine-assisted.

Transparency, Reproducibility and Ethics. A recurring theme in methodological discussions is the need for transparency when using LLMs in research. Because the analytic processes of LLMs are not directly observable, making the generation of codes opaque to researchers, extra care must be taken in documenting how the model was utilized. Several studies have expressed concern that early research did not consistently report critical details such as the specific prompts provided, the exact model versions, transcript segmentation methods, or the frequency with which researchers modified or rejected AI-generated outputs. Without such information, reproducing or trusting these findings becomes challenging. Consequently, there is now increased emphasis on establishing clear standards. Researchers are encouraged to provide detailed appendices containing complete prompts, examples used to guide the model, relevant parameters such as the temperature settings, and selected portions of the model's output logs. Additionally, since LLMs may undergo updates or further refinements over time, researchers highlight the importance of clearly specifying the date or precise version of the model used in analyses. Some have called for journals to mandate this level of documentation for AI-assisted studies to ensure reproducibility, as even slight prompt alterations might yield different codes.

On the ethical front, using LLMs with qualitative data raises concerns about confidentiality and bias. Interview transcripts often contain sensitive personal information. Uploading such data to a third-party AI service (like an API) can violate ethical agreements or privacy laws if not handled properly. Best practice dictates that researchers should anonymize transcripts before using LLM services and ensure compliance with data protection standards or use on-premise models when dealing with highly sensitive data. There is also the issue of AI bias: if the LLM has biases (and many large models have documented biases in how they respond to certain demographic or ideological content), these could skew the analysis. Ashwin et al. (2025) provided a stark reminder, finding that an LLM introduced systematic bias in coding interviews about refugees. Specifically, it gave different coding emphasis based on whether a statement came from a refugee or a host, even when content was similar. This kind of bias could seriously compromise research findings. The recommended mitigation is to keep humans in the loop to detect anomalies and to possibly fine-tune models on domain-specific data if needed to reduce unwanted biases. Some innovative suggestions have emerged, such as using the LLM to critique itself: e.g., after coding, ask the model to reflect on whether any biases could have influenced its analysis (though this is experimental). Another idea is to incorporate reflexivity prompts, where the model is prompted to justify each code with evidence from the text. This allows researchers to verify whether the resulting codes accurately reflect the data or are merely artifacts of the model's inaccuracies.

In summary, the community is coalescing around best practices that mirror core principles of qualitative research: transparency (document your process), reflexivity (be

aware of how the tool might shape the analysis), and ethical vigilance (protect participants' data and be alert to biases). When these principles are followed, LLMs can be used in a manner that upholds the integrity of qualitative research rather than undermining it.

Challenges and Limitations of LLM-Based QDA

Despite the promising capabilities of LLMs, researchers consistently underscore several challenges, limitations, and risks associated with their use in qualitative analysis. These issues highlight why LLMs are not a panacea and must be applied carefully.

Loss of Context and Nuance. One fundamental limitation is that LLMs, due to fixed input length and their training, often struggle to maintain context over very long narratives. Interview transcripts can be lengthy and nuanced, but models like GPT-4 have token limits that force analysts to truncate or chunk data. Important context might be lost between chunks, leading the model to misconstrue a statement's meaning. Even within a single response, LLMs tend to focus on the most salient patterns and may gloss over subtle cues like irony, tone shifts, or implicit assumptions that a human reader might notice. As a result, deeply contextual or latent themes are frequently missed by automated analysis. For example, an LLM might code an interview segment at face value ("participant is talking about schedule constraints") whereas a human might see a deeper theme ("power imbalance in the workplace") that requires reading between the lines. This limitation is essentially an AI's lack of true understanding and cannot reliably infer unspoken subtext or sociocultural nuance beyond what its training data frequency suggests. Researchers trying LLMs in cross-cultural settings found that models had

difficulty with culturally specific concepts or idioms, sometimes misinterpreting them or ignoring them (Sakaguchi et al., 2025). Thus, when rich interpretation is needed, heavy human involvement remains non-negotiable.

Hallucinations and False Outputs. LLMs have a recognized tendency to hallucinate, meaning they may generate information that is not present in the original input (Martino et al., 2023). In qualitative analysis, this can mean generating codes or themes that have no basis in the actual data. De Paoli (2023) reported instances of GPT-3.5 inventing themes that sounded plausible but, upon checking, were not actually supported by any participant quotes. This likely happens because the model, aiming to be helpful, draws on general knowledge or patterns from its training rather than sticking strictly to the given text. A related issue is that if asked to provide explanations or examples from the data, an LLM might fabricate a quote or detail to fit the theme it produced. Such artificial consistency is dangerous in research that it can mislead analysts into thinking a theme is grounded in data when it is not. To mitigate this, some workflows force the model to output quotes from the text as evidence for each code (and then the human checks those quotes). If the model can't produce a real quote, that's a red flag the theme may be spurious. Still, hallucination remains a serious concern, particularly in fully automated modes where a human might not catch the fabrication. It underlines the refrain: LLM outputs must be verified against the source data to ensure trustworthiness (De Paoli, 2023; Wachinger et al., 2024).

Bias and Overgeneralization. As noted earlier, LLMs can introduce biases in analysis. Ashwin et al. (2025) demonstrated how an LLM systematically coded refugee

interview data differently based on the speaker's identity, reflecting societal or training-data biases rather than the content itself. More generally, if the training data of an LLM contains stereotypes or dominant cultural narratives, the model might overemphasize certain themes. For example, an LLM might be more likely to label text as "angry" or "negative" if it comes from a minority group, if such bias existed in its training. This raises ethical issues of fairness and requires careful bias audits. Moreover, LLMs often overgeneralize in their coding as they tend to apply broad categories even when the data might call for a more specific interpretation. The model might default to themes like "positive experience" vs "negative experience" which flattens the richness of what participants actually said. Overgeneralization partly results from patterns within the training data and partly reflects the model's attempt to remain cautious by avoiding nuanced interpretations. This can pose a risk of losing sight of specific, meaningful issues when themes become overly broad or generic. Researchers counteract this tendency by refining prompts to encourage more detailed and specific themes, even if such themes appear infrequently. Alternatively, they manually subdivide overly broad themes identified by the AI. Nevertheless, the danger of overlooking minority or divergent themes remains significant, as the AI might disregard perspectives expressed by only a few individuals, even when those insights hold considerable value. In contrast, human qualitative researchers often intentionally focus on highlighting minority voices in their analyses.

Prompt Sensitivity and Reproducibility. Another limitation is the sensitivity of LLM outputs to how the prompt is phrased or how the input is ordered. Studies have

found that changing a single word in the prompt or presenting interview responses in a different sequence can lead to different codes being generated. This instability is problematic for reproducibility. If an independent researcher cannot replicate the exact prompt and model conditions, they might get a different set of themes from the same data. Even using the same model a few weeks later (after an update) could produce variation. De Paoli (2023) identified this as a significant concern, observing that results produced by AI are less stable compared to traditional qualitative analysis. In conventional analysis, consistency is expected when the same researcher applies identical methods repeatedly. However, AI-generated results might vary unpredictably or be influenced by incidental textual details. To mitigate this, consistent prompting protocols and version control are recommended, as mentioned earlier. But users should recognize that LLM-based analysis has an inherent stochastic element, especially if using non-zero temperature settings or if the model is not deterministic. As a consequence, LLMs might be better for generating initial insights, with the understanding that those insights need confirmation rather than being treated as final reproducible results on their own.

Transparency and Black-Box Reasoning. Qualitative research emphasizes transparency in how researchers derive codes and themes. In human-led analyses, researchers typically describe their analytic processes and include raw data excerpts to support each identified theme, which builds trust in their conclusions. In contrast, when using LLMs, the internal reasoning process remains largely opaque. Researchers obtain outputs such as codes and themes but lack access to explicit reasoning or justifications behind these outcomes. This lack of explainability is a limitation because it can be hard to

justify why a theme was created by the AI. Some attempts to address this include prompting the model to provide a justification or to output its intermediate reasoning steps (chain-of-thought). Indeed, a benefit of chain-of-thought prompting is that it produces a kind of trace of how the model moved from data to code. Still, these traces are themselves generated text and not a guaranteed faithful explanation of the model's actual internal computation. Without caution, researchers could be lulled into a false sense of security by an AI-generated explanation. The field is grappling with how to treat AI-driven findings: some suggest treating the AI as another coder and calculating inter-rater reliability, which is fine, but beyond that, understanding why the AI coded something differently can be challenging. This ties into the earlier point about documenting processes and perhaps even saving model outputs for audit.

Generalizability to Diverse Data. Most studies so far use English-language data and often fairly structured interviews or textual responses. A limitation is whether these findings generalize to more diverse qualitative data contexts: e.g., narratives in other languages, highly idiomatic or metaphorical text, or very unstructured conversational data. Early evidence in non-English contexts shows that LLMs can work (Sakaguchi et al., 2025, with Japanese data), but cultural and linguistic nuances pose additional challenges. LLMs trained predominantly on English internet text might miss culturally specific themes or require region-specific fine-tuning. Low-resource languages are particularly uncertain territory as the state-of-the-art LLMs might not have sufficient proficiency to analyze such data accurately. Additionally, certain qualitative data like visual or multimedia data (video interviews, etc.) is beyond current text-only LLM

capabilities (unless transcripts are provided). Thus, the approach is not one-size-fits-all and researchers must validate an LLM's performance in their specific context.

In light of these limitations, the literature strongly advocates maintaining human oversight and critical reflection whenever LLMs are used. Rather than discouraging use outright, most authors suggest these challenges can be managed with proper checks: always cross-check AI-generated codes with original data, use the AI as a starting point not the final judge, be alert to possible biases, and transparently report any issues encountered. The next and final section will conclude by synthesizing the overall recommendations and future outlook drawn from the reviewed studies.

Conclusion

LLMs have rapidly emerged as influential tools in qualitative data analysis, offering new possibilities for handling the labor-intensive task of coding and theme development in interview studies. The literature reviewed in this chapter demonstrates that LLMs can significantly augment qualitative analysis, They drastically reduce the time required to code large volumes of text and can produce thematic outputs that align moderately well with those of human researchers. In domains from health research to education and policy, researchers have successfully employed LLMs to assist in both inductive thematic analysis and deductive content analysis of interview transcripts, generally finding that these models capture the predominant patterns in the data and can serve as a useful "second coder" or a preliminary analytic tool. The evidence base is growing robustly, with dozens of empirical studies, tool prototypes, and methodological papers published between 2022 and 2025, reflecting a broad interest in the potential of AI

to streamline qualitative research.

At the same time, a clear message in the literature is that LLMs are best utilized as assistive, not fully autonomous, agents in qualitative analysis. Human expertise remains indispensable for interpreting nuanced meanings, ensuring the trustworthiness of findings, and providing ethical oversight. Fully automated LLM analyses, while tempting for their efficiency, currently carry too many risks, including misinterpretation of context, hallucination of unsupported information, and the injection of subtle biases. Thus, the consensus among researchers is to adopt a human-in-the-loop paradigm: leveraging the speed and breadth of LLMs to generate initial codes or theme drafts, but always having a skilled qualitative researcher guide the process, correct the AI's mistakes, and make the final analytic judgments. This collaborative approach has been shown to maximize the benefits of LLMs (efficiency, consistency, breadth of suggestion) while mitigating their weaknesses.

In terms of methodology, the field has advanced quickly. Best practices now include thoughtful prompt engineering (e.g., iterative and chain-of-thought prompts), careful chunking of data to handle long transcripts, and providing the model with codebook instructions to improve accuracy. New tools like custom AI coding assistants and multi-agent analysis frameworks offer user-friendly ways to apply LLMs, making this technology accessible even to researchers without programming backgrounds.

Importantly, scholars stress transparency to maintain rigor and allow others to understand and reproduce AI-assisted analyses. Ethical guidelines are also developing, urging caution around data privacy (e.g., anonymizing data before using cloud-based

LLMs) and vigilance for biased outputs.

Looking ahead, the application of LLMs in qualitative research is likely to expand as models improve (e.g., future models may handle longer contexts or be fine-tuned for qualitative tasks) and as more researchers become comfortable with these tools. There are clear opportunities, such as using LLMs to rapidly analyze open-ended survey responses or to assist in cross-language qualitative analysis by translating and coding in one step. However, the core lesson from current literature is that qualitative data analysis is not merely a technical act of coding words, but an interpretive act requiring human sense-making. LLMs, no matter how advanced, do not possess the lived experience, empathy, or critical perspective that human researchers bring to qualitative inquiry. They cannot determine research significance or ethical import. Therefore, the prudent path is to view LLMs as powerful aids, rather than as replacements for the qualitative researcher. As one review concluded, LLMs are "credible accelerators" for QDA but should operate under the "methodological pillars" of human validation and transparent reporting.

In conclusion, the integration of LLMs into qualitative analysis is an exciting development that holds much promise for improving efficiency and breadth in handling textual data. Empirical studies to date show that with proper use, LLMs can produce coding outputs that align well with human analyses, and they can reveal patterns quickly, making them a valuable part of the qualitative toolkit. However, realizing this potential responsibly requires adhering to best practices, acknowledging the technology's limitations, and centering the irreplaceable role of human judgment in making meaning of qualitative data. By combining the strengths of LLMs (speed, consistency, linguistic

breadth) with the strengths of human researchers (interpretive depth, ethical discernment, contextual understanding), the field can advance toward more efficient yet rigorous qualitative data analysis in the era of AI. The chapter's review of current research underscores both the achievements and the cautionary lessons learned, providing a foundation for researchers who wish to experiment with LLMs in their own qualitative work, and pointing to the need for ongoing critical evaluation as these tools become more widespread.

Chapter 3 Professions, Professionalism, and Teaching: Identity and Evolving Boundaries

Teaching has long stood in an ambivalent position in the sociology of professions literature. On one hand, teaching shares many features of classical professions—specialized knowledge, a service ethic, and a role in socializing the next generation (Alsup, 2006). On the other hand, it has often been labeled a "semi-profession," reflecting a perceived gap between teaching and paradigmatic professions like medicine or law in terms of autonomy, prestige, and control over work (Larson, 2014). This chapter explores the K–12 teaching profession through five interconnected themes, including the general concept of professions and professionalism, historical and contemporary shifts in professionalism's meaning and boundaries, teaching as a semi-profession, teachers' professional identity, philosophy, and aspirations, and the impact of technology-driven change on the teaching profession. The literature review discussion primarily draws upon insights from the sociology of professions, focusing particularly on U.S. K–12 teaching while incorporating international and interdisciplinary perspectives to provide additional context. Foundational theories, empirical research, and historical trends are examined to illustrate how the professional status and identity of teaching have evolved over time.

Sociology of Professions

Classic sociological definitions of a "profession" emphasize a distinct body of specialized knowledge, a lengthy period of training or education, a service orientation or ethical code, and a high degree of autonomy and authority in practice (Evetts, 2011a, b).

Early studies often enumerated such "trait" lists that distinguished professions from other occupations (Freidson, 2001). Over time, however, scholars shifted from static trait definitions to more dynamic analyses of how occupations attain professional status. One influential perspective is Andrew Abbott's (1988) system of professions, which views professions as engaged in ongoing jurisdictional competition—battles to control specific areas of work or expertise. Rather than a checklist of traits, Abbott (1988) emphasizes how professions achieve and maintain jurisdiction over tasks in an "ecology" of occupations. This approach highlights that professional status is not inherent to a job title but is actively won and defended through claim-making to expertise and exclusive rights to perform certain work.

In contemporary sociology, "professionalism" is understood not only as an occupational attribute but also as an ideology or discourse that can be employed by different stakeholders (Evetts, 2009; 2011a, b). Julia Evetts (2011a) distinguishes between occupational professionalism, rooted in collegial authority, discretionary judgment, and ethical standards developed by professionals themselves, versus organizational professionalism, characterized by external control through managerial standards, performance targets, and accountability measures. This distinction is crucial for understanding teaching: historically, teachers aspired to occupational professionalism (self-regulation based on teacher-developed norms of good practice), but in recent decades, elements of organizational professionalism have become more prominent in education policy. Evetts (2011a, b) and others observe that what counts as "professional" can be co-opted by bureaucratic or market logics, for instance when administrators

impose standardized curricula, evaluation rubrics, and surveillance technologies under the banner of "professional standards." Thus, professionalism can function as a rhetorical tool: sometimes empowering practitioners with autonomy, and other times legitimizing tighter control over their work (Freidson, 2001). Freidson (2001) argued that professionalism constitutes a "third logic" of organizing work (distinct from market or bureaucratic logics), wherein trust in practitioners' expert judgment prevails over both profit motives and top-down rules. The degree to which teaching operates under this third logic, as opposed to being governed by market competition or bureaucratic mandates, is a central question that recurs throughout this chapter.

Historical and Contemporary Shifts in Teaching Professionalism

Early Professionalization Efforts. Historically, teaching underwent waves of professionalization efforts throughout the 20th century. In the early- to mid-1900s, teaching in the U.S. was a predominantly female occupation, relatively low in status and often supervised by administrators in a hierarchical school system. This era saw the rise of normal schools and university-based teacher education as attempts to raise the knowledge level of teachers. Professional associations and teachers' unions also emerged as collective vehicles to improve teachers' working conditions and assert professional interests. By the mid-20th century, scholars and reformers were asking whether teaching could or should become more like the established professions (Vanassche & Kelchtermans, 2014; Varghese et al., 2005). However, despite requiring college degrees and certifications, teaching remained constrained by bureaucratic oversight (with school principals and superintendents directing much of teachers' work) and by public

perceptions that did not equate teachers with doctors or lawyers in prestige (Evetts, 2011a; Larson, 2014). Early sociological analyses often cited gender dynamics as one reason for teaching's liminal professional status: as a field dominated by women (especially at the elementary level), teaching suffered from gendered assumptions that it was an extension of mothering or a nurturing vocation rather than a scholarly profession (Larson, 2014). These ingrained cultural perceptions made it easier for education authorities to justify lower pay and stricter controls on teachers compared to male-dominated professions.

Managerialism and Accountability in Late 20th Century. A major shift in the meaning of teacher professionalism occurred from the 1980s onward, coinciding with a global rise of neoliberal and managerial ideologies in public sector governance. In education, this was epitomized by policies that introduced rigorous accountability systems, standardized testing, and performative measures of teacher effectiveness. In the United States, landmark federal initiatives like No Child Left Behind (2001) and Race to the Top (2009) ushered in an era where teacher quality was closely monitored through student test scores and evaluations tied to quantifiable outcomes. This era has been characterized by some scholars as a move from occupational professionalism to organizational professionalism (Evetts, 2011a), meaning that what it meant to be "professional" was increasingly defined by adherence to externally imposed standards and metrics. Empirical studies document that teachers experienced an erosion of autonomy in this period: curriculum became more scripted, assessments more frequent, and teachers' own judgments often subordinated to data-driven directives (Brass &

Holloway, 2019). Researchers Wills and Sandholtz (2009), for example, described the phenomenon of "constrained professionalism" in high-stakes testing environments, where teachers felt compelled to narrow their practice to align with test requirements. In sociological terms, this can be seen as a form of deprofessionalization or a "proletarianization" of teachers' work, reducing a once discretion-laden role into tasks that could be dictated and audited by management.

Shifts in Professional Boundaries. The contemporary period also witnesses continual renegotiation of the boundaries of the teaching profession. With the expansion of specialized support roles in education (such as instructional coaches, school psychologists, curriculum specialists, and data analysts), some responsibilities traditionally in teachers' domain have been either outsourced or shared. For instance, who "owns" the task of student well-being? In some contexts, school counselors or social workers take lead, potentially narrowing the scope of what teachers do, whereas in other contexts teachers are expected to fulfill quasi-parental or counseling roles in addition to instruction. Studies in countries like Sweden have shown jurisdictional tensions between teachers and school social workers regarding overlapping roles in student welfare, highlighting that professional boundaries are fluid and often contested (Isaksson & Larsson, 2017, as cited in Hordern, 2024). In the U.S., the growth of standardized curriculum packages and education consulting industries has similarly encroached on areas that teachers once autonomously controlled (such as lesson planning or material design). According to Abbott's framework, whenever external bodies lay claim to tasks central to teaching, the profession's jurisdiction is weakened unless teachers develop new

areas of expertise to counterbalance that shift. One response has been an emphasis on teacher leadership roles and specialized certifications (for example, mentor teachers, National Board Certification) to reassert teachers' expertise and differentiate within the occupation.

International Variations. It is important to note that these shifts are not uniform worldwide. Comparative research illustrates that nations have experienced the professionalization or deprofessionalization of teaching differently. For example, Finland is often cited as a case of high professional status for teachers: Finnish teachers must earn a research-based master's degree, enjoy considerable classroom autonomy, and benefit from strong public trust, all of which align with a classic professional model (Sahlberg, 2011). Japan, too, historically accorded teachers a respected status and considerable control within a framework of lesson study and peer-led improvement. In contrast, countries like the United States, England, and Australia since the 1990s have exemplified the managerialist trend, with heavy emphasis on standards, testing, and accountability measures that some argue have deprofessionalized teaching (Becher, 2024; Hordern, 2024). Indeed, Brass and Holloway (2019) characterize recent U.S. reforms as producing a "new professionalism" in which teachers are expected to continuously up-skill and adapt to metrics, while losing some collective voice. Interestingly, some nations have attempted to "re-professionalize" teaching by borrowing models from other professions or by restoring trust in teachers. For instance, there have been movements to make teacher education more clinically oriented (similar to medical training) in the U.S. and UK, or policies to give accomplished teachers mentorship roles and higher pay to keep

them in the classroom as experts. These efforts have met mixed results—often improving certain conditions or prestige slightly, but not fully reversing the underlying trends of standardization and external control (Becher & Lefstein, 2021). The balance between teacher autonomy and accountability continues to evolve, and with it, the very meaning of professionalism in teaching remains hotly debated and context-dependent.

Teaching's Semi-Professional Status

Magali Sarfatti Larson conceptualizes professional status as the outcome of a "professional project," wherein occupational groups translate their expertise into credentials, market monopolies, and social prestige (Larson, 2014). Building on Larson's earlier work (1977), Larson describes professionalization as a historically situated process that involves creating licensing rules, credential requirements, associations, and codes of ethics, thus achieving market closure and professional autonomy. However, Larson critiques the generality of her earlier work, highlighting that it underestimated the internal diversity and external institutional dynamics within professions. Teaching, in Larson's nuanced view, has achieved only partial professionalization and is characterized as a "semi-profession," not merely because of weak closure mechanisms but also due to structural domination from bureaucratic authorities, limited autonomy, gender discrimination, and systemic inequalities in education (Larson, 2014).

Teaching typically has shorter training periods, less stringent entry barriers, and less societal prestige compared to "the professions" such as law or medicine (Evetts, 2011a, b; Larson, 2014). Teaching historically lacked a unique knowledge base that was universally acknowledged as complex and specialized; instead, teachers applied

knowledge often seen as an extension of general education or subject-matter learning (Larson, 2014). Shulman (1987) addressed this critique by introducing pedagogical content knowledge, which combines deep subject-area expertise with teaching strategies uniquely characteristic of educators. Shulman argued that this knowledge could strengthen the professional knowledge base of teaching, bringing it closer in stature to professions such as medicine or law. Shulman (1987) also posited that teaching requires specialized understanding of how to convey content to learners, which is an expertise in itself. This notion helped shift thinking toward viewing teaching as knowledge-intensive intellectual work. Nonetheless, even with stronger knowledge claims, teachers' autonomy remained constrained. Unlike doctors or lawyers, teachers did not historically control licensing or have the final say over standards of practice; school boards, state regulators, and administrators had significant authority. Abbott's (1988) perspective suggests that teachers' jurisdiction over key tasks (like curriculum design or student assessment) has been continuously challenged or shared with other actors (curriculum experts, psychologists, testing companies, etc.). Overall, the sociology of professions establishes a conceptual backdrop in which teaching has many professional characteristics but also clear structural limitations on its professional autonomy and authority. The next sections build on this foundation to explore how teachers develop their professional identities, and how technologies transform this profession.

Teacher's Professional Identity and Aspirations

Professional Identity as a Social Construction

Professional identity refers to how individuals perceive and enact their roles as members of an occupation. In the case of teachers, this identity is not a fixed personal trait or static label; rather, it is socially constructed and continually negotiated in response to contextual factors like policies, institutional norms, and cultural expectations (Brass & Holloway, 2019; Day et al., 2006; Flores & Day, 2006). Sociological research emphasizes that teachers' sense of "who they are" as professionals emerges through interactions with the education system and society's narratives about teaching more than through any one individual's personality or psychology. For example, reform discourses may alternately portray teachers as empowered change agents or as technicians who are expected to implement standardized curricula (Sachs, 2001). When accountability policies cast teachers as primarily responsible for student test scores, educators may internalize or resist aspects of that role as they form their professional self-concept. Conversely, when educational ideals emphasize the teacher as a reflective practitioner and moral leader, a different professional identity is cultivated. In short, teachers continually negotiate their identities amidst policy demands, community expectations, and their own values (Brass & Holloway, 2019; Sachs, 2001).

This process of identity formation is also shaped by interactions within the profession itself. Mentorship, induction programs, and professional learning communities can implicitly socialize teachers into particular ways of thinking about their role—whether teaching is viewed as an intellectual inquiry, a craft improved through reflection,

or a set of technical competencies to be efficiently delivered (Brass & Holloway, 2019; Sachs, 2001). All of these social and organizational forces contribute to a dynamic professional identity rather than a static one.

Competing Discourses of Professionalism

Multiple, sometimes competing, discourses of what it means to be a "professional" teacher coexist in education, offering divergent visions of a "good teacher." Judyth Sachs (2001) identifies two prominent narratives or teaching philosophies in this regard: "managerial professionalism" and "democratic (or activist) professionalism." Managerial professionalism aligns with top-down accountability and performance management—teachers in this view are expected to be efficient deliverers of curriculum and to meet externally imposed standards and targets. Democratic professionalism, in contrast, emphasizes teacher collaboration, ethical commitment, social justice, and community engagement—teachers are seen as experts who work with peers and the public to improve education and address students' broader needs. These discourses are not merely abstract theories; they actively influence teachers' daily thinking, their aspirations for their work, and how they talk about what they do in the classroom.

Empirical studies illustrate how these competing narratives shape teacher identity and can cause internal conflict. For instance, early-career teachers often enter the field with ideals of making a difference in children's lives and advancing equity, reflecting a more democratic or moral-calling orientation (Becher, 2024). Over time, however, if they face pressure to "teach to the test" or to adhere strictly to scripted lessons, they may

experience tension or even identity conflict between their initial philosophy and the managerial role that is imposed on them (Brass & Holloway, 2019; Sachs, 2001). Some teachers manage to integrate elements from both discourses—for example, embracing data-driven instructional techniques (a managerial element) while reframing them as tools to better serve each student's individual needs (a democratic, student-centered rationale). The coexistence of multiple professionalism narratives means that teachers' identity formation is often a site of struggle. Educators must pick, choose, and sometimes hybridize elements from the available discourses in order to construct a sense of professional self that feels authentic to them and sustainable in their work environment.

Aspirations and Moral Purpose in Teaching

Teaching has frequently been described as a profession "with a calling," and many teachers articulate their professional purpose in strongly moral and civic terms. Unlike some occupations where professional identity centers on technical expertise alone, teachers commonly invoke aspirational narratives about developing young people, fostering good citizenship, and contributing to social betterment as core to their professional identity (Becher, 2024). These aspirations serve not only as personal motivation but also as a justification for professional autonomy. For example, a teacher who sees their mission as nurturing critical thinking and democratic values in students might argue for greater latitude in curriculum choices in order to fulfill that mission authentically. Even amid an era of standardization and accountability, teachers often assert broader purposes for education: promoting equity, educating the "whole child,"

and acting as advocates for underserved students (Becher, 2024; Brass & Holloway, 2019). Such broad educational aspirations underpin a vision of teaching as more than just a technical job—instead, they frame it as a profession grounded in ethical commitments and care for learners. This moral dimension of teaching can be a source of resilience for teachers' professional identity, reminding educators why teacher judgment, discretion, and passion matter.

At the same time, a strong sense of moral purpose can lead to tension when institutional directives seem to contradict teachers' values or aspirations. For instance, a teacher who aspires to practice culturally responsive and inclusive teaching may feel that rigid, standardized curricula impede that goal, creating dissonance in their professional identity. How teachers navigate these tensions often depends on the support and culture around them. As noted above, teacher communities and mentors play a role: how new teachers conceptualize their role can be reinforced or reshaped in social contexts such as mentoring and professional learning communities that emphasize particular values. In sum, teachers' professional identities and teaching philosophies are dynamic, continually shaped by an interplay of external discourses and internal moral commitments. Understanding these identity dynamics is crucial because they influence how teachers respond to reforms and how they define "professional" behavior in their practice.

Socioeconomic Contexts and Teacher Aspirations

While a drive to do right by students is nearly universal among teachers, the specific aspirations teachers hold for their students—and the way teachers frame their professional purpose—can vary markedly depending on the socioeconomic context of the

school community. In other words, what teachers hope for and expect of their students is powerfully shaped by whether they teach in high-poverty or low-poverty school settings. All teachers may share a general commitment to student success, but the content, tone, and professional framing of their aspirations tend to diverge in context-specific ways. Large-scale quantitative studies that treat socioeconomic status (SES) merely as a background variable risk obscuring these nuances. In contrast, qualitative research foregrounds SES as a decisive lens through which teacher aspirations are formed, articulated, and enacted. This body of research highlights that teacher aspirations in high-poverty schools often look very different from those in more affluent schools, reflecting the distinct challenges, resources, and cultural values of each environment (Holloway & Pimlott-Wilson, 2011; Martinez et al., 2022).

Teacher Aspirations in High-Poverty School Settings. In high-poverty contexts, teachers frequently frame their aspirations for students in terms of overcoming structural adversity and accessing opportunities that might otherwise be out of reach. The content of these aspirations skews toward tangible goals of academic achievement and career success as avenues for social mobility. For example, a study examining primary teachers in disadvantaged English communities found that educators consciously promoted middle-class aspirations, such as attending university and pursuing ambitious career paths, to challenge prevailing assumptions about the limited aspirations held by students' families (Holloway & Pimlott-Wilson, 2011). In these contexts, teachers regard raising students' aspirations as central to their moral responsibility, encouraging pursuits such as higher education, stable employment, and expanded life opportunities to help

students escape cycles of poverty. Goals related to personal growth and character development, including fostering resilience, self-efficacy, and civic engagement, are also evident but tend to be embedded within broader academic and professional objectives rather than pursued separately. In other words, teachers in high-poverty schools tend to view scholastic success and personal growth as intertwined necessities for empowering their students. Consistently across studies in low-SES settings, there is an emphasis on "academic success and college/career readiness" as the primary locus of teachers' aspirations for their students.

The tone of teacher aspirations in high-poverty schools combines idealism with a form of clear-eyed realism. On one hand, many teachers sustain idealistically high hopes for their students despite the long odds their communities may face. For instance, Martinez et al. (2022), in a study of urban high schools, describe teachers' profound emotional investment in fostering a "college-going culture" and their determination to "maintain high aspirations even amid urban poverty." Educators in these contexts often speak in hopeful, at times visionary, terms about their students' futures, reflecting a deep moral commitment to equalizing opportunities. On the other hand, teachers in under-resourced schools are typically also acutely aware of the constraints their students face. Their aspirations may be "recalibrated" by a realistic recognition of structural barriers—limited resources, unstable home lives, systemic inequities—even as these teachers strive to leverage schooling as an engine of mobility for their students. One analysis characterizes educators in low-SES schools as operating in a "persistent tension" between deficit-based and asset-based outlooks (Forrester et al., 2022). In practice, this means

teachers balance their aspirations with a realistic understanding of what can be accomplished in the short term, without losing sight of broader ideals about transformative success for their students. This balance results in a tone of measured optimism. Teachers communicate enthusiasm about students' futures but frame their encouragement in practical, achievable steps. For instance, qualitative research conducted in English primary schools indicates that teachers strive to expand their students' opportunities and actively support their aspirations, while simultaneously acknowledging barriers arising from limited resources. Such grounded optimism characterizes the discourse of teachers in high-poverty schools, reflecting a sense of moral commitment, as teachers view themselves as advocates of hope working to counteract the injustices confronting their students.

The professional framing of aspirations in high-poverty contexts often aligns with a social justice ethos. Teachers (and school leaders) in disadvantaged communities frequently cast their aspirations for students as part of a larger struggle against inequality. They frame their work as mission-driven: not simply delivering curriculum, but "making a difference" in children's lives by expanding their life chances and advocating for them. For example, principals in highly disadvantaged Australian schools describe their vision for students in terms of equity and justice, aiming for high academic and personal outcomes as a way to redress social disadvantage (MacDonald, 2023). This rhetorical framing underscores that educating in high-poverty contexts is, for many practitioners, a profoundly moral endeavor: their professional identity is entwined with the notion of advocacy for the underprivileged. At the same time, researchers caution that even this

well-intentioned discourse can carry subtle pitfalls. MacDonald's (2023) study found that alongside noble intentions, leaders' language sometimes betrayed deficit assumptions, implicitly doubting their communities' capacities even as they advocated for students. Scholars have observed this paradox within teachers' narratives, noting that a strong commitment to supporting students can inadvertently reinforce subtle deficit perspectives. Emphasizing the need to elevate students' aspirations may implicitly suggest that families and students from impoverished backgrounds initially hold limited aspirations (Zipin et al., 2015). Thoughtful educators consciously address this complexity by embracing an asset-based approach, which highlights community strengths and students' existing cultural capital, rather than framing students exclusively in terms of their disadvantages. Indeed, some examples illustrate this asset-focused approach: in certain underprivileged contexts (for instance, rural Ghana), teachers enact culturally responsive pedagogy and forge community partnerships to leverage local knowledge in support of student aspirations. In summary, the moral purpose driving teacher aspirations in low-SES settings tends to be two-fold: to combat structural injustices and to honor and draw upon the existing strengths of students' communities. This professional stance casts the teacher as both an advocate and an ally, a professional identity stretching beyond instructor to include roles such as mentor, social worker, and community builder.

Teacher Aspirations in Low-Poverty (Affluent) School Settings. In low-poverty, more affluent school settings, teachers' aspirations for students manifest with a different emphasis, reflecting the relative abundance of opportunity and support that characterizes these contexts. Students in affluent schools typically enter with high levels

of prior achievement and strong parental support for education; consequently, teachers do not generally need to instill in students the desire to succeed academically so much as to channel, enrich, and personalize that success. The content of teacher aspirations in high-SES environments therefore often extends beyond the standard metrics of grades or college admission (outcomes which are commonly presumed). With basic academic achievement virtually assured, teachers in these schools are freer to emphasize holistic development, encouraging critical thinking, creativity, character growth, and civic engagement as key goals for their students. Research indicates that even in these well-resourced contexts, academic and career outcomes remain a "default or baseline aspiration" that teachers hold for every student, but educators place additional weight on personal growth domains that round out a student's education. For instance, a teacher in an affluent suburban school might describe their goal as developing "well-rounded individuals who are not only strong scholars but also good citizens." This contrasts with the high-poverty context, where such personal or character-related aspirations, while present, tend to be overshadowed by the immediate urgency of academic and economic concerns. In affluent settings, by contrast, teachers can foreground values and personal competencies—such as leadership skills, empathy, or global awareness—knowing that academic success will likely occur as a matter of course. Comparative studies in the UK underscore this contextual difference: in "middle-class" schools, aspirational narratives largely revolve around the transmission of already high expectations and the maintenance of students' existing cultural capital, whereas in low-SES schools they center on *raising* aspirations under conditions of constraint. In short, teachers in low-poverty schools aspire

for their students to excel and flourish, not merely to overcome challenges. The nuance lies in the assumption of excellence and the goal of pushing the boundaries of enrichment, rather than the challenge of combating disadvantage.

The tone of teacher aspirations in affluent contexts is notably optimistic and often unapologetically idealistic. Free from the weight of immediate socio-economic crises, teachers in high-SES schools can afford to project a confidence that their students will achieve great things. Their language frequently mirrors the high expectations held by the students' families and communities. For example, educators in elite schools might speak of their students as future innovators, leaders, or changemakers, expressing an implicit faith in students' ability to reach lofty outcomes. This idealism does not need to be as cautiously tempered by realism as in high-poverty schools, because the structural barriers to student success are significantly fewer. Indeed, when educators in advantaged settings discuss their students' futures, the conversation is less about whether students will succeed and more about how and in what domains they will find success. The ethos in these schools is one of limitless possibility, aligning with a moral optimism that every child can self-actualize given the ample resources and support at hand. It bears noting that the research literature has comparatively less to say about teacher aspirations in affluent schools—perhaps because such aspirations are taken for granted as unproblematic or expected. Many large studies of teacher expectations include high-SES schools only as reference groups and do not probe their aspirational dynamics in depth (Chambers et al., 2019). Nevertheless, by contrasting narratives across contexts, we can infer that the tone in these schools is one of assured aspiration: an expectation of

excellence that is "baked in" to the school culture. Teachers in such contexts express their aspirations with a tone of professional confidence rather than urgency. For instance, expecting all students to attend college is routine and assumed, which allows the teacher's aspirational energy to focus on encouraging students to pursue meaningful and fulfilling pathways (such as finding a personal passion or developing a sense of purpose), rather than simply ensuring basic upward mobility. In sum, the idealism in high-SES schools is buoyed by structural advantage: teachers can dream with their students, rather than mainly dreaming for them, since the students' own ambitions are typically well-formed and well-supported by their environment.

The professional framing of teacher aspirations in low-poverty schools tends to be more understated and aligned with traditional notions of the teacher's role as a cultivator of individual potential. Unlike their counterparts in disadvantaged schools, teachers in affluent settings generally do not conceive of themselves as social crusaders or agents of urgent change; instead, they often frame their aspirations in terms of personalized educational guidance and maximizing each student's opportunities. Their professional identity in these contexts is that of the expert facilitator who ensures that each already-advantaged student can make the most of their talents and resources. This often involves a strong emphasis on enrichment: teachers aspire to ignite passions, stretch students' thinking, and broaden their perspectives beyond the baseline curriculum. For example, a teacher in a high-SES context might frame her goal as "producing future leaders and problem-solvers," which reflects a professional commitment to the stewardship of talent and privilege. The moral purpose in affluent school teaching, while no less sincere than in

high-poverty schools, manifests as a commitment to excellence and to nurturing responsibility in the next generation of societal leaders. In practice, teachers in privileged contexts often aim to instill in their students a sense of duty to use their education for good, effectively, to "give back" to society or to lead with integrity. Thus, even in affluent contexts, teachers frame aspirations in moral terms, but without the rhetoric of rescue or social reform that prevails in high-poverty settings. One could say that in affluent schools the moral dimension of teacher aspirations is oriented toward individual ethics and self-fulfillment (ensuring that students become principled, well-rounded people), whereas in high-poverty schools it is oriented toward social justice and collective uplift (helping to change the socio-economic trajectories of children and communities in need). Both orientations are expressions of teachers' deeper moral purpose, but they operate at different levels: the former at the level of individual self-actualization, the latter at the level of community and societal change.

Integrating Identity, Philosophy, and Context

The contrasting patterns of teacher aspirations across socioeconomic contexts underscore how teachers' professional identities, teaching philosophies, and moral purposes are adaptive and context-dependent. A teacher's sense of purpose is not static but evolves in response to the needs of the students and communities they serve, shaped by the broader discourses circulating in education. In high-poverty schools, for example, a teacher's identity often expands to encompass roles of advocate and protector, fueled by an ethic of social care and justice. Their moral purpose is enacted through battling structural injustices one child at a time, and their teaching philosophy may align with an

activist or democratic professionalism that prioritizes collaboration and community empowerment. In low-poverty schools, by contrast, a teacher's identity tends to center on being an enabler of potential and a guardian of each student's individual journey, consistent with a more facilitative or traditional professional stance. Their moral purpose is fulfilled by guiding those who are already socially advantaged to become responsible, enlightened adults, and their philosophy focuses on cultivating each student's personal excellence and character.

Crucially, neither set of aspirations and identity commitments is inherently "higher" or "lower" in merit. Rather, each represents a rational and heartfelt response to the context of teaching. As research on teacher aspirations emphasizes, SES is a "framing lens" that decisively shapes how aspirations are voiced and pursued, but the underlying motive of wanting the best for students is universal. What changes with context is the definition of "the best" and the strategies considered necessary to achieve it. Teachers thus negotiate evolving professional boundaries: in one setting, their role might stretch into the socio-cultural realm to combat disadvantage (taking on tasks that go beyond instruction, such as advocacy and social support), while in another setting their role might focus on intellectual and personal enrichment within a culture of plenty. Appreciating this contextual variation is vital for a comprehensive understanding of teacher professionalism. It reminds us that teacher identity and professional practice are not one-size-fits-all; rather, they are situated and responsive, with moral purpose taking on different hues across the spectrum of advantage and disadvantage (MacDonald, 2023; Zipin et al., 2015).

In summary, teachers' professional identities and aspirations for their students are shaped by an interplay of broad educational discourses and the concrete realities of their teaching contexts. A teacher in a struggling rural school might emphasize hope, resilience, and basic opportunity as guiding ideals, whereas a teacher in an affluent suburban school might emphasize innovation, leadership, and character development. Yet both are ultimately driven by the desire to do right by their students. This illustrates the rich moral ecology of teaching: educators everywhere aim to "make a difference," but they do so in conversation with the particular realities and dreams of the worlds around them.

Technological Transformation and the Teaching Profession: The Role of AI

Digital Technologies, Datafication, and Shifting Professional Boundaries

In recent years, digital technologies have proven to be a double-edged sword for the teaching profession. On one hand, data-driven tools promise to enhance instruction by providing richer information on student learning and automating routine tasks. On the other hand, these same technologies can function as instruments of increased surveillance and standardization, potentially eroding teachers' professional autonomy. The rise of pervasive data collection in education—often termed "datafication"—has introduced "technologies of control" that narrow the scope of teacher decision-making (Brass & Holloway, 2019; Williamson et al., 2020). For example, algorithmic grading software and scripted adaptive learning programs might dictate the pacing and content of lessons, effectively reducing teachers to supervisors of pre-set routines rather than designers of learning experiences. In such cases, expertise and discretion begin to shift from the

teacher to the technology. When a teacher's own assessment of a student is overridden by an externally generated test score or when a recommendation engine prescribes the "next" lesson, trust in the teacher's judgment is undermined. Indeed, empirical studies have found that teachers often feel conflicted about data-driven instructional systems: they appreciate the data insights but resent the loss of professional discretion these systems entail (Daliri-Ngametua et al., 2022). The net effect of many accountability-oriented technologies is a sense of deprofessionalization, as teachers' work becomes focused on fulfilling metrics that the technology monitors rather than exercising professional judgment. Such developments raise concerns that heavy emphasis on data and surveillance in education may dilute the traditional autonomy and creative agency that define teaching as a profession.

A growing body of analysis suggests that these trends in education parallel developments in other professions, foreshadowing potential boundary encroachment by advanced technologies such as AI. In fields like medicine and law, AI-driven systems are beginning to handle tasks once reserved for highly trained professionals—diagnosing medical images or reviewing legal documents, for instance—prompting debate about the future role of doctors and lawyers. In education, observers speculate about similar possibilities: AI-powered tutoring systems and personalized learning platforms could theoretically take over certain instructional duties. To date, large-scale evidence of AI "replacing" teachers is sparse; educational technology has not advanced to a point where human teachers are anywhere near redundant. Yet the theoretical possibility of such "algorithmic encroachment" on teaching has been widely discussed in the literature

(Hordern, 2024). Researchers note that as machine learning technologies in education continue to advance, including AI systems capable of adapting to student responses or assessing emotional engagement, certain aspects of teaching may increasingly be managed by automated tools or specialists outside the traditional teaching role. If, for instance, a future AI platform could reliably teach a subject like algebra via intelligent tutoring, the role of the human teacher in that domain might shift toward facilitation or pastoral support rather than direct content delivery.

As mentioned in the above sections, classic sociology of professions theory (Abbott, 1988) suggests that when new technologies arise, they often provoke jurisdictional disputes over who has the expertise and authority to perform certain tasks. In the context of education, the advent of sophisticated AI invites the question: who will design, control, and interpret these educational algorithms? According to Abbott's framework, if technical experts (software developers, data analysts, EdTech companies) claim a share of tasks that used to lie squarely within teachers' pedagogical domain, a professional boundary conflict emerges. There have already been early signs of this — technology companies and external "learning scientists" increasingly influence curriculum design and assessment through the tools they create, potentially usurping aspects of teachers' professional jurisdiction. Thus far, teaching's core work — motivating, mentoring, and responding to the nuanced needs of students — remains deeply human and relational, which provides the profession with some immunity from wholesale automation. However, the profession is proceeding with caution. Teachers and their advocates frequently call for clear guardrails on educational technology, insisting

that technology should assist rather than replace the teacher's own professional judgment (Becher, 2024). In other words, the consensus in the field is that AI and other tools must remain subordinate to pedagogical expertise, serving as support systems that amplify teachers' capabilities instead of supplanting them.

The infusion of digital technology into schools has also introduced new professional roles and with them, new ambiguities in professional boundaries. Positions such as instructional technologists, data coaches, learning analytics specialists, and online curriculum designers have emerged to support the integration of technology in education. In some cases, these roles collaborate with teachers and enhance the professional community. For example, a data coach might work alongside teachers to interpret student performance data and co-develop strategies for instruction, an activity that can elevate teachers' data-informed decision-making. In other cases, however, such roles may be perceived as encroaching on teachers' expertise. A data coach who is positioned as a monitor to ensure teachers are using data "properly," or an outside consultant who designs a comprehensive e-learning curriculum that teachers are expected to implement, can be seen as undermining teachers' authority over curriculum and assessment. Hordern (2024) describes these scenarios as part of an ongoing "jurisdictional struggle" for the teaching profession. To maintain their professional authority, teachers increasingly need to assert their role in domains that did not traditionally fall within their expertise, such as data interpretation, digital content curation, and even the ethical guardianship of student data in technology-rich environments. Some scholars argue that the very definition of teacher professionalism must evolve in response to such changes, expanding to include

fluency with educational technology and data literacy so that teachers remain the authoritative interpreters of technological tools rather than passive implementers of pre-packaged solutions (Lee et al., 2024; Mandinach & Gummer, 2016; Ndukwe & Daniel, 2020). In fact, one emerging area of responsibility for teachers is shaping the ethical use of technology in the classroom (e.g. deciding how student data should be handled, or vetting the fairness of algorithmic recommendations). As Becher (2024) points out, in an era of public mistrust and rapid technological change, teachers can strengthen their professional claim by championing ethical standards for new practices. By advocating for student privacy, questioning the validity or biases of algorithmic systems, and emphasizing transparency and fairness in technology use, teachers position themselves not as anti-technology, but as critical experts who integrate technology into education while upholding core pedagogical values. This proactive stance can be seen as a strategy for the profession to retain its moral and technical authority amidst technological disruption.

It should be noted that scholarly understanding of technology's impact on teacher professionalism is still developing. Compared to fields like healthcare or law—where research on "technology and the professions" is more mature—education has lagged in producing empirical studies that directly link innovations like AI to changes in teachers' professional identity, status, or power (Hordern, 2024). This gap in the literature represents an important area for future research, as schools increasingly experiment with AI tutors, learning analytics platforms, and virtual classrooms. Key questions remain open: Will teachers gradually cede some of their instructional territory to algorithms,

refocusing their role more on mentorship and socio-emotional support (thereby redefining their professional identity)? Or will teachers integrate technology in ways that enhance their expertise—such as offloading mundane administrative tasks to AI so that they can devote more time to creative, higher-order teaching work? At present, any answers are speculative. What is clear is that technology has become a key frontier in the continuing evolution of professional boundaries in teaching. How the teaching profession navigates this frontier—whether by asserting professional leadership in technology integration or by resisting certain technological incursions—may significantly influence public perceptions of teachers as professionals in the years to come. In this context, the rise of AI in education is especially salient, as it encapsulates the most advanced and perhaps most disruptive set of technologies on the horizon. The following sections therefore turn to AI specifically, analyzing its implications for the teaching profession through several sociological constructs: professional autonomy, identity work, ethical jurisdiction, and moral authority.

AI and the Teaching Profession: Sociological Perspectives

AI is at the cutting edge of technological transformation in education, and it brings into sharp relief the dilemmas and opportunities discussed above. To understand educators' responses to AI, it is useful to apply lenses from the sociology of professions that illuminate how professionals negotiate change. Four key constructs in this regard are professional autonomy, identity work, ethical jurisdiction, and moral authority (Abbott, 1988; Brass & Holloway, 2019; Hordern, 2024; Becher, 2024). Each construct highlights a different aspect of how teachers interpret and adapt to AI in their practice. Below, we

examine how AI in education interacts with each of these dimensions of the teaching profession, and how these interactions influence whether teachers embrace or resist AI-based tools.

Professional Autonomy and the Challenge of AI. Professional autonomy refers to the degree of control and discretion that members of an occupation have over their work practices (Abbott, 1988; Frostenson, 2015). In classic sociology-of-professions theory, autonomy is often cited as a defining hallmark of true professions (Funck, 2012). It entails the recognized right of the professional to exercise expert judgment in their domain without undue external interference (Hordern, 2024). In education, professional autonomy manifests as teachers' latitude to make pedagogical decisions based on their training and understanding of their students. This autonomy is not absolute; it exists as part of an implicit social contract in which society grants professionals a degree of self-regulation in exchange for the profession upholding high standards and serving the public interest (Funck, 2012). In other words, teachers' autonomy is intertwined with public trust: schools (and by extension, society) trust teachers to make sound decisions for students, and in return teachers expect their professional judgment to be respected in policy and practice.

The advent of AI in education is testing this professional autonomy in new ways. Educators now often evaluate any proposed AI system whether this technology supports or undermines their professional discretion in the classroom. Experience from analogous domains suggests that professionals tend to resist technologies perceived as threats to their autonomy. For instance, in healthcare, doctors have been known to reject

information systems that overly constrain clinical judgment, with “perceived threat to professional autonomy” emerging as a key factor in low technology acceptance (Walter & Lopez, 2008). In the education sphere, similar patterns may occur. AI tools that prescribe instructional actions or algorithmically determine which students receive certain interventions could be seen as encroaching on teachers’ decision-making space. If an AI system comes with strict protocols that teachers are expected to follow — for example, a learning analytics dashboard that dictates when to reteach a topic or an algorithmic tutor that decides the next activity for each student — teachers might perceive that their expertise in tailoring lessons is being impinged upon by a “black box” decision process.

When teachers perceive an AI application as potentially reducing their role to simply carrying out predetermined scripts or merely implementing algorithms created by others, they are likely to resist. Abbott’s (1988) analysis of professions helps explain this response, highlighting that when external systems define professional work too rigidly, the creative autonomy central to professional practice diminishes. Executing directives entirely established by others eliminates the essential discretionary judgment inherent in professionalism (Winch, 2010), potentially leading to deprofessionalization (Hordern, 2024). Practically speaking, teachers may interpret highly prescriptive AI platforms as undermining the professional skill and judgment required by their roles, thereby diminishing the overall professional status of teaching (Lauridsen, 2024; Mack, 2025). Such perceptions could provoke resistance, either indirectly through minimal compliance and subtle efforts to preserve autonomy, or directly through openly criticizing these

technologies during professional development sessions or advocating with administrators for greater flexibility (Achinstein & Ogawa, 2006; Akdeniz & Konakli, 2022). For example, if an education department mandates the use of an AI that auto-generates lesson plans as the default curriculum, teachers might comply superficially but still find ways to inject their own judgment into the process, or they might collectively advocate for the AI to be optional and adjustable.

Conversely, if AI tools are introduced in a manner that supports teacher autonomy, educators are much more likely to adopt them. An AI application can support autonomy by serving as a non-intrusive aid that teachers control and customize, rather than a rigid supervisor. For instance, an AI might offer suggestions or analytics that a teacher can choose to use (or not) at their discretion, rather than dictating decisions. When teachers are given configurable options and can opt into how they use an AI system, the technology is seen as empowering rather than constraining. In such cases, teachers often welcome the AI as it augments their capabilities without undermining their agency. In sum, professional autonomy remains a central filter through which teachers view AI. Teachers' willingness to integrate AI tilts toward acceptance if they perceive that their autonomy is preserved or even expanded (for example, by offloading tedious tasks and giving them more time for creative teaching), and toward rejection if they feel their role is reduced to carrying out automated instructions. Thus, any AI initiative in schools that seeks teacher buy-in must contend with this autonomy calculus at the outset.

Identity Work: Teacher Identity in the AI Era. Teachers' decisions regarding AI are shaped by their professional identities, reflecting how they perceive themselves

and wish to be perceived as educators. Every teacher holds a professional identity, which includes their values, pedagogical beliefs, and their understanding of effective teaching (Beijaard et al., 2000; 2004). Such identities are dynamic, as educators continuously engage in identity construction to establish, sustain, or reshape their professional self-concept (Beijaard et al., 2000; 2004; Izadinia, 2013), particularly when confronted with new challenges or innovations (Lai & Jin, 2021; Liu & Geertshuis, 2016).The introduction of AI into educational settings acts as a catalyst for identity negotiation among teachers. Educators consider, either implicitly or explicitly, what their choice to embrace or reject a technology reveals about their professional selves. Such reflection illustrates how decisions around AI adoption can serve as opportunities for teachers to articulate, affirm, or reinforce their professional identities.

Research supports the notion that professional identity is a major factor in technology adoption in schools. Liu and Geertshuis (2016), for example, argue that teachers' professional identities influence how they perceive the characteristics of an innovation, which subsequently impacts their willingness to adopt the technology. This means that whether an AI tool is perceived as beneficial or threatening depends largely on how closely it aligns with their understanding of themselves as professionals. Additional studies similarly emphasize that professional identity guides teachers in interpreting their roles and practices, thereby shaping their attitudes toward integrating technology into their work and determining how they engage with such innovations (Lai & Jin, 2021; Liu & Geertshuis, 2016; Rosdi et al., 2020). In practical terms, if an AI application aligns with a teacher's image of effective and honorable teaching, the teacher

is more inclined to view it positively; if the tool clashes with the teacher's self-image or values, they will approach it skeptically or not at all.

Consider two contrasting examples. A teacher who prides herself on being an innovative, forward-thinking educator may see the introduction of AI as an opportunity to enhance that identity. Using the latest technology can reinforce her self-concept as a cutting-edge professional. Such a teacher might volunteer to pilot new AI tools, share success stories with colleagues, and become a champion or early adopter of AI in education. In adopting AI, she is also performing her identity as a 21st-century educator who prepares students for the future. By contrast, a teacher whose identity is rooted in a traditional, human-centered philosophy of education might perceive extensive use of AI as incongruent with being a "caring, attentive educator." For him, good teaching is fundamentally about the human relationship between teacher and student—empathy, personal feedback, mentorship. If an AI tool seems to mechanize or depersonalize aspects of teaching that he holds dear, he may resist using it or adopt it only in very limited ways. For example, he might tolerate an AI that helps grade multiple-choice quizzes but avoid AI systems that attempt to interact directly with students in a conversational or counseling capacity, because that would encroach on what he sees as the heart of his role.

Teachers also navigate external expectations and peer perceptions as part of their identity work. In some school cultures, there may be an implicit pressure to use the latest technology to appear competent, modern, and up-to-date. Younger teachers or those working in tech-forward districts might worry that not adopting AI could mark them as outdated or less competent in the eyes of their colleagues and administrators. This can

lead to a kind of identity performance where teachers adopt technology at least partly to signal their professionalism and competence. On the other hand, experienced teachers or those with a distinct teaching style may worry that adopting AI extensively could weaken essential aspects of their professional identity, such as being recognized experts in their subject or empathetic mentors to students. For example, if AI technology takes over responsibilities that teachers regard as core to their expertise, such as giving detailed feedback on student essays, teachers might perceive this as encroaching on their mentoring role. Consequently, they may feel that relying on these technologies reduces their professional distinctiveness or value. Aguilar and Wang (2024) illustrated these identity differences: teachers who were more confident in their technological abilities (high tech self-efficacy, which is a component of their professional self-concept) showed less anxiety and more openness toward AI, whereas teachers with lower tech confidence or more skepticism experienced a kind of identity dissonance at the idea of relying on AI. Importantly, that study concluded that teachers are "active participants, grappling with the moral challenges posed by AI," suggesting that educators are actively working through what it means to be a good teacher in the age of AI rather than passively accepting technology. All of this indicates that a teacher's stance on AI is deeply interwoven with their sense of self as a professional.

Educators' Ethical Jurisdiction and Moral Authority in AI Integration. Teachers occupy a unique position of ethical jurisdiction in the classroom, meaning they bear professional responsibility for the well-being, fairness, and development of their students . This responsibility makes educators cautious and discerning about new AI

tools. Unlike tech developers or administrators, teachers directly witness how AI-driven decisions or content can affect individual learners, so they feel duty-bound to vet these tools through an ethical lens. In practice, teachers consider whether an AI application aligns with established educational values, legal obligations, and the best interests of students before embracing it. Their evaluations are grounded in professional codes (e.g. commitments to equity and privacy) and a personal sense of accountability as the adults "in loco parentis" for students. As a result, the adoption or rejection of AI in education is often filtered through educators' ethical frameworks, ensuring technology serves pedagogical goals without undermining students' rights or welfare (Klein, 2024; Soares, 2024).

Several concrete ethical issues commonly shape teachers' attitudes toward AI tools in schools. First, student privacy and data protection. Educators must uphold student privacy laws and confidentiality norms, so they are wary of AI platforms that collect or share sensitive data. For example, many teachers refuse to input identifiable student information into AI systems and avoid delegating tasks like grading or writing individualized education plans to AI, precisely to safeguard privacy (Soares, 2024). There is a well-founded fear that outsourcing data to third-party AI services could expose personal student details without consent or security. Recent incidents underscore these worries: a Los Angeles school district's AI assistant was shut down amid unanswered questions about what happened to the student data it gathered (Seshadri, 2024; Soares, 2024; Young, 2024). Such cases reinforce teachers' resolve to act as protectors of student data. Indeed, studies have found that teachers view themselves as "gatekeepers of

children's data", responsible for shielding students from unwarranted data exposure (Smakman et al., 2021; Van Ewijk et al., 2020). This gatekeeping role often leads teachers to resist AI products lacking transparency about data use, storage, and privacy safeguards.

Second, surveillance and autonomy. AI-powered surveillance tools (e.g. monitoring software for student computers or AI exam proctors) raise moral red flags for many educators. On one hand, these tools promise safety by flagging bullying, self-harm, or violence risks (Lurye & Bryan, 2025). On the other, they can create a culture of constant surveillance that conflicts with the trust and autonomy central to a healthy learning environment. Ayer et al. (2023) revealed that thousands of schools have adopted 24/7 AI surveillance of student devices, yet there is "scant evidence" that such monitoring measurably improves student safety. Instead, severe privacy breaches have occurred (e.g. unprotected logs of students' private messages and mental health crises; Lurye & Bryan, 2025). Moreover, indiscriminate monitoring can unintentionally harm students. For example, an AI safety algorithm inadvertently revealed the private identities of several LGBTQ+ students to school administrators, significantly undermining students' trust (Lurye & Bryan, 2025). . In Durham Public Schools in North Carolina, these concerns led the school board to halt use of a monitoring AI, concluding it wasn't worth "the risk of eroding relationships" between students and teachers (Lurye & Bryan, 2025). Such outcomes reinforce teachers' ethical stance that surveillance tech, if used at all, must be narrowly targeted and combined with human judgment. Educators feel morally obligated to push back on AI practices that treat students like data points under

watch, rather than as young people deserving of respect and a degree of privacy.

Third, algorithmic bias and fairness. Teachers are also concerned that AI systems may carry hidden biases that could unfairly impact certain student groups. AI is only as unbiased as the data it's trained on, and researchers have highlighted how AI image or text generators can reproduce societal prejudices (e.g. picturing a "doctor" only as a white male, or scoring an essay about classical music higher than one about rap due to biased training data; Klein, 2024). Educators recognize that if such biases seep into instructional tools or automated grading systems, they could exacerbate inequities in the classroom. Mote, an educational technology expert, notes that schools must ensure AI never has "the final say" on student decisions, precisely because these tools can mirror and even magnify discrimination (Klein, 2024). In her words, if AI became the ultimate decision-maker, schools would be "taking out the valuable knowledge that educators bring" to nuanced judgments (Klein, 2024). In practice, this means teachers insist on keeping human oversight over AI recommendations. For instance, a teacher might use an algorithm's suggestion as a starting point but will apply their own judgment to accommodate a student's individual context (recognizing, say, that a seemingly "off-track" learner is an English-language learner who needs a different approach rather than remediation). By acting as moral guides, teachers strive to ensure algorithms do not inadvertently amplify biases that education aims to eliminate (Klein, 2024). This cautious stance represents an ethical commitment to equity. Teachers seek to use AI to narrow achievement gaps rather than widen them, frequently advocating for thorough bias assessments and greater transparency from educational technology vendors prior to

adopting these technologies in classrooms.

Fourth, academic integrity and authentic learning. A more immediate moral concern for teachers is how generative AI might enable student cheating or shortcut learning. Maintaining academic integrity is an ethical cornerstone of teaching, tied to values of honesty and personal growth. Unsurprisingly, when powerful AI text generators became freely available, many educators reacted by tightening plagiarism checks and even instituting bans on these tools in class (Blose, 2023). Early surveys in 2023 found that about 1 in 4 teachers caught students using AI to cheat, and numerous school districts blocked access to ChatGPT out of fear it would undermine honest work (Study.com, 2023). Teachers have had to invest extra effort in "AI-proofing" assignments and educating students about plagiarism in the age of AI. From an ethical standpoint, this response is driven by the belief that students must learn to create and think for themselves; allowing AI to do their work not only is dishonest but robs students of learning opportunities. At the same time, some forward-looking teachers have begun to integrate AI into lessons on media literacy and citation, hoping to model responsible use of these tools (e.g. using AI for brainstorming while crediting its contributions) rather than outright prohibition. In either scenario, the teacher's role as mentor and moral example remains central. Teachers assume responsibility for establishing norms for AI use that uphold academic integrity, effective learning, and respect for intellectual property. This careful balancing act, which involves harnessing AI's advantages while preventing potential misuse, illustrates how moral authority shapes teachers' integration of new technologies.

Underpinning all these ethical considerations is the teacher's broader moral authority in the educational environment. Teachers are not only instructors but also caregivers, role models, and mentors who impart values by example. This moral leadership role heavily influences how they appraise AI tools, guiding them to consider whether the technology supports or undermines the values and relationships that are central to learning. One key concern is the potential erosion of the teacher-student relationship. Research consistently demonstrates that human qualities such as empathy, encouragement, and personalized mentorship are essential to student development, yet these attributes remain beyond the capabilities of AI to fully replicate (Waite, 2025). Teachers thus approach AI as a supplement for routine tasks, not a replacement for human connection. By delegating administrative tasks such as grading and scheduling to AI, teachers can gain additional time to focus on individual mentoring, emotional support, and creative teaching practices. These elements represent core aspects of teaching and reinforce teachers' moral authority (University of Illinois College of Education, 2024). In contrast, if an AI tool threatens to diminish meaningful interaction (for instance, an overreliance on AI tutors that might isolate students), educators are likely to resist it in defense of social-emotional learning. Waite (2025) notes that although AI can personalize content and support skill development, it lacks the ability to provide emotional support, such as offering reassurance, celebrating student progress, or guiding them through challenges with empathy. Teachers, as moral agents, see it as their duty to provide that empathetic guidance, and they are unwilling to cede that role to machines.

Chapter 4 Functionalist Models in Technology Adoption Research

Technology adoption research has been dominated by functionalist models, which approach the study of technology use through an objectivist and positivist lens (e.g., Feng et al., 2021; Ghimire & Edwards, 2024). In the typology of Burrell and Morgan (1979), the functionalist models assume an external, objective social reality that can be understood via scientific inquiry and causal models. Applied to technology adoption, this means researchers view the decision to adopt a technology as driven by measurable factors and rational choices, seeking generalizable relationships that predict behavior across contexts. Functionalist models typically conceptualize adoption as a variable-centered process: they identify key independent variables (such as perceived benefits or organizational facilitators) that statistically explain a significant portion of variance in a dependent variable (such as usage behavior or intention; Fish & Turner, 1995; Homburg, 2013). The emphasis is on quantifiable constructs and their causal linkages, aligning with the positivist epistemology of hypothesis testing and the search for law-like generalities in human behavior (DeCarlo et al., 2022). By design, these models focus on how well certain functional factors (e.g. usefulness, ease of use, resources, peer influence) account for adoption outcomes, reflecting a belief that technology acceptance is a rational decision process that can be modeled and predicted (DeCarlo et al., 2022).

Philosophically, functionalist models in adoption research inherit assumptions of structural-functionalism and rational choice theory, treating organizations and individuals as largely rational actors responding to technological innovations in systematic ways. Burrell and Morgan's (1979) framework situates this approach in the objective-regulation

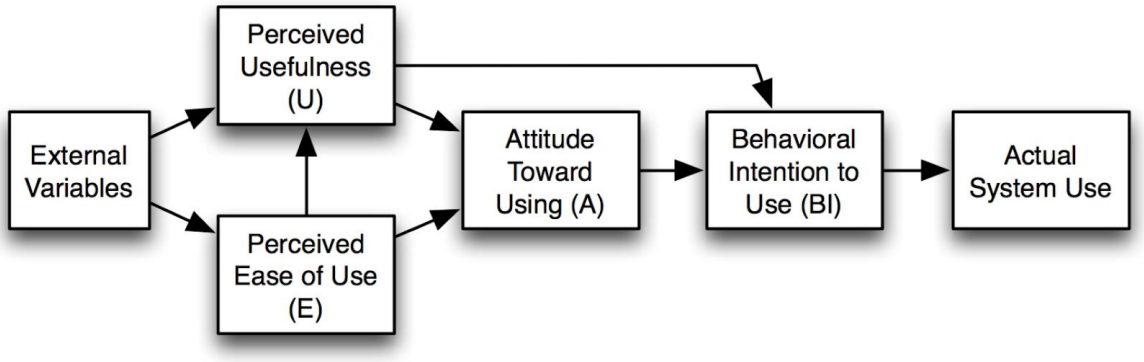
quadrant, meaning it views social systems as essentially stable and regulated by objective structures. Methodologically, studies guided by functionalist models favor quantitative methods—surveys, structured interviews, and experiments—that yield data for statistical modeling. Large-sample surveys and structural equation modeling (SEM) are common techniques used to test the hypothesized factor relationships in these models (e.g., Featherman & Pavlou, 2003; Lu et al., 2024). The goal is often to achieve high explanatory power (variance explained) and robust model fit, thereby validating that the chosen factors functionally "explain" adoption behavior in a broad sense. This positivist, hypothesis-driven approach has been dominant in information systems (IS) and educational technology research, to the extent that by the 2000s it constituted what many saw as the received model for studying technology acceptance. Indeed, a review by Semenova (2020) explicitly notes that frameworks like DOI, TAM, UTAUT, and TOE all operate within the functionalist models as defined by Burrell and Morgan (1979). These models share a commitment to objectivist, factor-oriented explanations and have collectively created an "illusion of progress" in accumulating predictive knowledge about technology use (Benbasat & Barki, 2007). Critics have pointed out that the intense focus on such models has sometimes diverted attention from other research questions and paradigms (Benbasat & Barki, 2007), yet their influence remains deeply ingrained in adoption research, especially in fields like education where practical, outcome-oriented studies prevail.

Key Examples of Functionalist Adoption Models

As mentioned in the above section, several seminal models exemplify the functionalist approach in technology adoption research (Semenova, 2020). In this dissertation, I discussed four of the most influential frameworks—TAM, UTAUT, DOI, and TOE. Each provides a structured, factor-based way to explain why individuals or organizations decide to use new technologies, and each originates from a functionalist impulse to identify general drivers of adoption.

Introduced by Fred Davis (1989), TAM is a landmark model focused on individual adoption of information systems. It posits that two perceptions—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—are the primary determinants of a user's attitude toward a new technology, which in turn shapes their behavioral intention to use it and ultimately their actual usage. TAM was originally adapted from the Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (TPB; Ajzen, 1991) in psychology, but it streamlined that theory by focusing on technology-specific beliefs (usefulness and ease of use) as the key proximal causes of adoption decisions. Figure 1 below illustrates the basic TAM structure, where external variables influence PU and PEOU; these perceptions affect the user's attitude (and sometimes directly the intention in later versions), which then drives the intention to use and usage behavior. Davis (1989) found empirical support for TAM in early studies of computer usage, and subsequent research validated that TAM could explain a sizable portion of the variance in technology use intentions across various contexts (Bekkering et al., 2009; Hu et al., 1999; Yousafzai et al., 2007). Notably, TAM studies frequently report

that perceived usefulness is the strongest predictor of intention to use, more so than ease of use, aligning with the model's theory that users primarily adopt a technology if they perceive it will improve their performance (Bekkering et al., 2009; Li et al., 2008). Over time, TAM has been extended—such as TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008)—to include additional factors like social influence, experience, and trust, but its core assumptions remain within the functionalist tradition of seeking general causal relationships. In education, TAM has been widely applied to study teachers' and students' acceptance of innovations such as e-learning platforms (Natasia et al., 2022), learning management systems (Fathema et al., 2015), or AI-based tools (Wang et al., 2021). Because TAM is parsimonious and empirically tractable, it became "one of the most influential models in IS research" and a default choice for many education technology studies (Bekkering et al., 2009).



Note. The original TAM proposed by Davis (1989) portrays how external factors influence users' perceived usefulness and ease of use of a technology, which shape their attitude toward using the technology, thereby affecting their behavioral intention to use it and ultimately their actual usage.

Figure 1. The Original TAM

Proposed by Venkatesh et al. (2003), UTAUT is a comprehensive model that unifies elements from eight prior technology acceptance theories (including TAM and

DOI) into a single framework. UTAUT identifies four core determinants of behavioral intention and usage: Performance Expectancy (similar to usefulness), Effort Expectancy (similar to ease of use), Social Influence, and Facilitating Conditions (Venkatesh et al., 2003). It also includes up to four moderators (such as age, gender, experience, and voluntariness of use) that condition the impact of those determinants on intention and behavior. As a functionalist model, UTAUT retained the positivist, variable-driven approach of its predecessors but sought greater explanatory power by combining their insights. Venkatesh et al. (2003) demonstrated that UTAUT could account for about 70% of the variance in usage intention in some settings, which was an improvement over the 40% typical of original TAM studies (Bekkering et al., 2009). The model's richness (with many predictors and moderators) has made it a popular choice in studies where researchers want to capture a broader range of influences on adoption. For example, in educational technology research, UTAUT and its extension UTAUT2 have been used to study teachers' adoption of interactive whiteboards (Šumak & Šorgo, 2016), mobile learning (Chao, 2019), and more recently AI-driven tools (Wu et al., 2022), because the model allows consideration of not just usefulness and ease, but also social pressures (e.g. a school's culture or principal's influence) and facilitating conditions (e.g. IT support, training) that are highly relevant in institutional settings.

The inclusion of moderators in UTAUT also recognizes the importance of context. For instance, performance expectancy may influence the intentions of younger teachers differently compared to older, more experienced educators. This reflects a slight broadening of the functionalist approach to incorporate interaction effects and

demographics, but it remains grounded in the idea that the interplay of measurable determinants will yield a general explanation of usage behavior. UTAUT has spawned a large number of follow-up studies; a systematic review by Williams et al. (2015) found UTAUT to be widely applied across domains, including many education-related studies, often with researchers tailoring the model to their specific technology and population . The model's success illustrates the functionalist appetite for integrative frameworks that promise higher explanatory power through the combination of validated constructs.

Originally formulated by Everett Rogers (1962), DOI theory is a foundational model explaining how new ideas and technologies spread in a social system. While broader in scope than TAM or UTAUT, DOI has a strong functionalist element in its emphasis on key attributes of the innovation and the social system that statistically predict adoption rates (Rogers, 1962). Rogers identified five attributes of innovations that influence their rate of adoption. These attributes include relative advantage, compatibility, complexity, trialability, and observability. For example, a technology perceived as highly advantageous and compatible with users' needs (and not too complex) will diffuse faster through the population (Tornatzky & Klein, 1982). DOI also categorizes adopters into groups (innovators, early adopters, early majority, late majority, laggards) based on their propensity to adopt, which is another functionalist classification intended to generalize adopter behavior.

The DOI framework has been especially influential at the institutional and policy level (Massey et al., 2014; Vargo et al., 2020; Zanello et al., 2016). It is considered a functionalist model to the extent that it seeks general laws of adoption (e.g. the S-curve of

adoption over time and the idea that certain attributes universally expedite diffusion) and uses quantitative indicators (surveys on perceived attributes, adoption rates) to explain adoption outcomes. However, DOI also recognizes the role of communication channels and social influence in diffusion, thereby overlapping with more sociological views. In practice, many education studies have blended DOI with other models, such as, using Rogers' attributes alongside TAM's ease of use and usefulness (Al-Rahmi et al., 2019). The strength of DOI in functionalist research is its historical and macro-level perspective: it reminds researchers that adoption is not only about individual cognition (as TAM implies) but also about how innovations travel through communities under the influence of communication and leadership. Still, DOI research usually operationalizes those influences in a positivist way (e.g., counting how many peers have adopted, or rating administrative support), keeping with the theory's quantitative orientation.

Developed by Tornatzky and Fleischer (1990), the TOE framework is a classic model for explaining adoption of innovations at the organizational level. It posits that three contexts—the technological, organizational, and environmental contexts—collectively influence an organization's propensity to adopt new technology. The technological context includes characteristics of the technology itself (similar to Rogers' attributes, e.g. perceived advantages or complexity of the technology). The organizational context involves internal factors like the organization's size, structure, resources, and culture. The environmental context encompasses external pressures such as industry trends, competition, regulations, and support infrastructure. The TOE model does not specify a fixed set of variables, but rather a framework in which researchers identify

salient factors in each of the three categories and examine their impact on adoption decisions (Awa et al., 2017; Tornatzky & Fleischer, 1990).

As a functionalist model, TOE assumes that by measuring relevant factors in each domain (for instance, "top management support" in the organizational context, or "competitive pressure" in the environment), one can predict or explain the likelihood and extent of an innovation's adoption in an organization. A literature review by Oliveira and Martins (2011) notes that the TOE framework became highly popular for firm-level adoption studies because it balances internal and external factors in a single model. In educational research, TOE provides a structured way to consider that a school's decision to implement AI tools could depend on not just the tool's merits, but also on organizational readiness (e.g. teacher training, budget) and environmental pressures (e.g. societal expectations or educational standards; Jiang Liping et al., 2025; Zhou & Zhang, 2025). This broad scope aligns with functionalism's goal of general explanation, though one critique of TOE is that it can become too generic—researchers have great freedom in choosing variables under each category, which sometimes leads to less theoretical consistency (Zhu & Kraemer, 2005). Nonetheless, TOE remains firmly in the functionalist canon as it seeks causal relationships (e.g. "organizations with high technical readiness and strong external pressure are more likely to adopt X technology") and relies on comparative surveys or cross-sectional designs to validate those relationships.

These four examples—TAM, UTAUT, DOI, and TOE—illustrate the evolution of functionalist models from the 1980s to the 2000s. All are factor-based, causal models that

have been widely cited and applied. Other models and theories often discussed alongside these include the TPB (Ajzen, 1991) and its predecessor the Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975), which heavily influenced TAM's development, as well as the Task-Technology Fit model (Goodhue & Thompson, 1995) and the Expectation-Confirmation Model (Bhattacherjee, 2001) in IS use—all of which can be considered part of the "functionalist family" of adoption theories. Collectively, these frameworks provided researchers a toolkit to dissect technology adoption in terms of inputs and outputs: if one can measure the right inputs (user perceptions, organizational factors, etc.), one can reasonably predict the output (adoption or rejection). This toolkit was readily embraced by educational technology researchers, who often wanted to identify why a given educational innovation was or wasn't being taken up by teachers or students. By the early 2010s, dozens of studies had applied TAM or UTAUT in schools and universities, and DOI and TOE were commonly invoked for understanding diffusion of educational innovations at larger scales. The next sections explore how these models have specifically played out in education, what evidence we have from reviews about their efficacy, and what limitations have been noted.

Historical Development and Use in Education

1980s–1990s: Foundations

The functionalist approach to technology adoption took hold in the 1980s with the formulation of foundational theories. Rogers' work on DOI theory had already been shaping thinking since the 1960s, but by the 1980s it was being integrated into information systems research as a way to frame the spread of personal computers and

educational media in organizations. A retrospective review by Fichman (1992) notes that DOI theory had grown into a common reference framework for empirical studies of IT adoption in the 1981—1991 period. In 1989, Davis's TAM emerged as the first model tailored specifically to information technology acceptance, marking a shift from general social-psychological theories (like TRA) to a domain-specific framework. TAM's immediate success in explaining user adoption of office software and other IT innovations led to it being rapidly taken up in various fields. By the early 1990s, education researchers began considering TAM to study the acceptance of computer-assisted instruction and productivity software among teachers. For example, as personal computers entered K–12 schools in the late 1980s, administrators and scholars were keen to understand teachers' attitudes toward these new tools. Functionalist models provided a convenient quantitative approach: surveys could assess a teacher's perceived usefulness of computers for teaching, and those metrics could predict that teacher's likelihood of integrating computers into lessons.

2000s: Expansion and Integration

The turn of the millennium saw an explosion of interest in technology integration in education, coinciding with the rise of the Internet, e-learning, and later Web 2.0 tools. Functionalist models expanded in complexity and number during this period. Venkatesh and Davis (2000) introduced TAM2, incorporating social influence and cognitive instrumental processes into TAM. By 2003, UTAUT was published, unifying TAM with six other models and quickly gaining traction as the "one model to rule them all" for user acceptance research (Venkatesh et al., 2003). Education researchers around this time

began adopting UTAUT to study phenomena like faculty acceptance of learning management systems or student acceptance of online learning platforms, since UTAUT allowed them to examine a richer set of factors (including facilitation conditions like technical support, which were very relevant in school settings). Meanwhile, researchers continued applying and refining TAM within education and other professional contexts. For instance, Venkatesh and Morris (2000) explored gender differences in technology acceptance among workers, highlighting implications for teachers based on gender. Similarly, Yi et al. (2006) combined TAM with TPB and DOI to examine factors influencing medical professionals' acceptance of personal digital assistants. At a broader level, DOI was frequently employed to investigate how specific educational technologies, such as interactive whiteboards or Massive Open Online Courses (MOOCs), spread throughout school systems or universities over time. Researchers often utilized case studies or national surveys to categorize educators according to Rogers' adopter typology. The TOE framework also entered education research in the 2000s for studying institutional decisions such as adopting campus-wide information systems or new classroom technologies; for example, researchers would examine a university's organizational readiness, the technology's fit, and external pressures (like accreditation requirements) to explain adoption outcomes, exemplifying TOE's three domains. By the end of the 2000s, functionalism was the default model for most quantitative studies of educational technology uptake. Scherer et al. (2019) found that the majority of articles in domain reputable journals were TAM-based studies exploring factors influencing the usage of various tools by teachers or students. Importantly, this era also saw functionalist

models being extended and localized for education: researchers added constructs like "perceived pedagogical usefulness" or "teacher self-efficacy" to TAM to better capture educational contexts. But these were still in line with the functionalist tradition, treating those constructs as additional independent variables in the causal model.

2010s: Systematic Evidence and Refinement

The past decade brought maturity to this body of research and a surge of systematic reviews and meta-analyses that synthesized findings across studies. In the education field, scholars responded to the proliferation of TAM/UTAUT studies by conducting large-scale reviews. For example, Granić and Marangunić (2019) conducted a systematic literature review of TAM in educational settings, covering 71 studies from 2003 to 2018. They found that TAM (often with extensions) was repeatedly validated as a useful model for explaining both teachers' and students' acceptance of technologies, ranging from smartboards to learning management systems. They also catalogued the various external factors that studies had incorporated to improve TAM's explanatory power in educational contexts (such as subjective norm, technical support, or computer anxiety). Another review by Granić (2022) expanded this to include multiple models and noted that in 47 studies on educational technology adoption, over 75% utilized a functionalist model (TAM, UTAUT, or a close variant). These reviews reinforced that functionalist models had high empirical prevalence: they became the standard theoretical framework in quantitative EdTech research. Additionally, meta-analytic studies applied advanced techniques to aggregate data from many papers. A landmark example is Scherer et al (2019), who conducted a meta-analytic structural equation modeling of

TAM specifically for teachers' adoption of digital technology. By synthesizing 45 primary studies, their meta-analysis provided robust estimates of the path coefficients in TAM for educational contexts (e.g., on average, the effect of perceived usefulness on behavioral intention, the effect of intention on actual use, etc.) and tested moderators such as subject domain or culture. The results confirmed TAM's core validity among teachers: perceived usefulness had a strong positive effect on intention to use technology, and perceived ease of use had a significant albeit smaller effect (often mediated through usefulness). The amount of variance explained in teachers' intentions was substantial (often around 40–50% in combined analyses), which is consistent with TAM research in other fields. Such evidence solidified the position of TAM/UTAUT as evidence-based models: not only conceptually appealing, they had quantifiable support that they "work" in predicting adoption. In the 2010s, functionalist models continued to be applied to emerging educational technologies. For example, as mobile learning apps and social media became prevalent in classrooms, researchers utilized UTAUT2, an extension of UTAUT that incorporates consumer motivation factors, to study student adoption of tablets and teacher adoption of social media platforms for instructional purposes. The functionalist models demonstrated considerable flexibility, allowing researchers to integrate additional constructs such as trust for cloud-based educational services or perceived value in mobile learning, without altering the underlying model structure. By the end of the 2010s, several systematic reviews focused on specific sectors emerged as well: Liangyong Xue et al. (2021) compiled UTAUT studies in higher education, and Kittinger & Law (2024) reviewed UTAUT-based research in K–12 teacher populations.

Both found that the majority of studies used survey methods and SEM, reinforcing that the functionalist, quantitative approach was nearly universal in those subliteratures. They also highlighted that certain contexts, such as primary school teachers, were still under-researched, suggesting the model was spreading to all education levels. In summary, the 2010s in educational technology adoption research were characterized by consolidation: functionalist models were not only widely used but also rigorously examined through meta-studies, which generally supported their validity but began to hint at diminishing returns and areas for improvement, such as incorporating more context-specific factors or addressing methodological limitations).

2020s: New Technologies and Model Reflections

In the current decade, the rapid rise of emerging technologies—most notably AI in education—has provided a testing ground for the continued use of functionalist models, while also prompting some researchers to reflect on the limitations of these approaches. On one hand, early studies of teachers' and students' adoption of AI tools, such as AI-driven tutoring systems or generative AI like ChatGPT for teaching, have overwhelmingly employed models like TAM or UTAUT, confirming that the functionalist model is being carried forward into new domains. For example, Herzallah and Makaldy (2025) applied an extended TAM to investigate Israeli teachers' acceptance of AI in teaching, finding that technological self-efficacy and a personal disposition called "sense of coherence" significantly predicted teachers' AI adoption intentions. Similarly, Kong et al. (2024) examined Hong Kong school teachers' intention to use generative AI tools using a model based on extended TAM, revealing that self-efficacy,

perceived usefulness, attitude, and subjective norms were among the key drivers. These studies indicate that even as the technology changes, researchers still default to functional, factor-driven frameworks to make sense of adoption. Moreover, a meta-analytic report by McGehee (2024) synthesized findings across many such studies and confirmed that the same classic predictors (e.g., perceived usefulness, ease of use, social influence) remain critical in explaining teachers' willingness to use AI. This suggests a continuity in the research approach: new innovations are often just plugged into the existing models to see if the old predictors hold, and generally they do, at least to some extent. On the other hand, the 2020s have also seen increasing critical commentary on the dominance of functionalist models. A few scholars have explicitly called for a broader paradigm pluralism, urging the field to look beyond the narrow set of quantitative models that have been recycled for decades. For instance, Bagozzi (2007) argued for a "paradigm shift" to incorporate emotions, group dynamics, and deeper theory into technology acceptance research. In the context of educational technology, Selwyn (2010) advocated for increased use of interpretive and critical approaches that address the social and political dimensions of technology adoption in schools, aspects often overlooked by functionalist models. Nevertheless, these alternative approaches remain uncommon. As noted in a recent review article, the field seldom clearly articulates functionalism or provides robust examples of non-functionalist frameworks, indicating that critiques of prevailing paradigms remain relatively undeveloped. The mainstream of research continues to gather data that fit into functionalist models, even as authors in discussion sections might acknowledge that "not all aspects of adoption can be captured by surveys"

or call for mixed methods. Overall, the current state is one of continuity with a dose of introspection: functionalist models are still the workhorse for studying new tech like AI in education, but there is a growing awareness of their limits and an openness to expanding the theoretical toolkit in the future.

Evidence from Systematic Reviews and Meta-Analyses

The extensive use of functionalist models has itself become a subject of study, with scholars conducting systematic literature reviews and meta-analyses to assess how these models perform and how they have been applied in educational technology research. The evidence from these secondary analyses largely underscores the dominance and utility of models like TAM and UTAUT, while also highlighting patterns and gaps in the literature.

Several systematic reviews have mapped the landscape of technology adoption research in education. For example, Granić and colleagues found TAM and its extensions to be a credible and reliable model for assessing acceptance of various learning technologies across higher education and K–12 contexts (Al-Emran & Granić, 2021; Granić, 2022; Granić & Marangunić, 2019; Marangunić & Granić, 2015). They reported that TAM's core constructs (perceived usefulness and ease of use, often augmented by others like subjective norm or facilitating conditions) were consistently significant predictors of behavioral intention in most studies. Their review also catalogued common external variables that had been integrated into TAM in educational settings noting that while these improved explanatory power in individual studies, they did not fundamentally alter TAM's structure. These reviews collectively show that functionalist models have

been replicated across dozens of contexts with broadly consistent results. This consistency is a testament to the models' robustness: despite differences in culture or technology, factors like perceived usefulness tend to emerge as universal drivers of adoption, aligning with the functionalist assumption of generalizability.

Meta-analytic studies have gone a step further by quantitatively synthesizing the magnitude of effects in functionalist models. In the aforementioned meta-analysis on teachers' technology acceptance, Scherer et al. (2019) found that across studies the standardized path coefficient from perceived usefulness to behavioral intention was about 0.50 (medium-to-large effect), and from perceived ease of use to intention was about 0.20 (smaller but significant) when controlling for usefulness. Attitude, when included, mediated some of the effect but interestingly many TAM studies in education omit attitude and find users' perceptions can directly influence intentions. Scherer et al. (2019) also examined actual usage (when data was available) and confirmed intention as a strong predictor of usage (path around 0.45–0.6). One of the insightful contributions of this meta-analysis was to demonstrate that TAM's overall explanatory power in educational contexts was on par with other domains: on average, the model explained roughly 40–50% of the variance in teachers' intentions to adopt technology. This is a respectable figure in social science and indicates that while a large portion of variance remains unexplained, TAM's core variables consistently capture a significant chunk of what drives teachers' tech usage decisions. Another finding was that subjective norms had a weaker but still positive effect on intentions; this suggests that while teachers largely decide based on personal usefulness perceptions, collegial or administrative influences do

have some role, which is a nuance that supports the inclusion of social factors in models like UTAUT for educational research.

Moreover, these quantitative syntheses have allowed comparison between models. Some meta-analyses within the broader information systems field (King & He, 2006; Dwivedi et al., 2019) have compared TAM with alternative models and concluded that no single framework consistently explains more variance than others. Instead, contextual factors and the quality of measurement instruments often exert greater influence on outcomes. Reviews specific to education have similarly noted that UTAUT typically does not substantially outperform TAM, partly because researchers frequently simplify the UTAUT model in practice. For example, Xue et al. (2024) found in their systematic review of UTAUT in higher education that many studies reported R^2 values in the 0.40–0.60 range for intention, similar to TAM, and that researchers frequently drop the moderating variables due to sample constraints. This indicates that in practice the purported advantages of the more complex models are not always realized, possibly because the added complexity (and many more parameters to estimate) poses empirical challenges. Nonetheless, the inclusion of facilitating conditions in UTAUT has proven valuable in educational research. For example, several studies reviewed noted that facilitating conditions significantly influenced actual usage, particularly in situations where teachers intended to use a tool but were unable to do so effectively without adequate support (Wang et al., 2017; Yuan et al., 2023).

Systematic reviews have also shed light on methodological patterns in this body of research. They point out that the vast majority of studies are cross-sectional surveys

(often single-instance self-report questionnaires) analyzed with regression or SEM. Only a small minority use longitudinal designs or objective usage data. This has been critiqued in reviews (e.g., Tarhini et al. 2015) as a limitation—while functionalist models are concerned with variance, their over-reliance on self-reported intention and use may inflate relationships (due to common method bias) and doesn't always translate to long-term adoption behavior (Sadeck, 2022). Some meta-analyses attempt to correct for such biases by looking at studies that included actual usage logs or by statistically adjusting for reliability. For instance, in the healthcare domain, a meta-analysis by Holden and Karsh (2010) on TAM noted that the attitude-intention relationship was weaker when intention and use were measured far apart in time, suggesting that immediate self-reports likely overestimate how well intention leads to sustained use.

In summary, the meta-analytic and review evidence confirms that functionalist models like TAM and UTAUT are not only theoretically influential but empirically well-supported in educational technology research. They consistently identify a core set of factors that explain a meaningful portion of why teachers and students adopt new technologies. These findings give educators and policy-makers evidence-based levers to pull (e.g., improving teachers' perceptions of usefulness through professional development. At the same time, the reviews also highlight shortcomings: the heavy focus on a narrow set of quantifiable factors, potential issues of common method bias, and the need to consider contextual and unquantified factors that lie outside the current models. These observations naturally lead into a discussion of the limitations of functionalist models and the calls for broadening research approaches.

Empirical Studies of AI Adoption in K–12 Education Using Functionalist Models

A growing body of empirical research has applied classical "functionalist" technology adoption models to examine the adoption and use of AI technologies in K–12 teaching and learning contexts (Al Darayseh & Mersin, 2025; Almulla & Adam, 2025; An et al., 2023; Ballenas & Lasco, 2024). Empirical investigations of AI technology adoption in K–12 education using functionalist models have been conducted in a wide range of geographical and educational contexts (Kittinger & Law, 2024; Natasia et al., 2022; Scherer et al., 2019). Across these contexts, the TAM and the UTAUT (and its extensions) are by far the most commonly employed theoretical frameworks, often supplemented or extended with additional constructs (Granić, 2022; Kittinger & Law, 2024). A number of studies have also combined models (e.g. TAM with TPB or TAM with DOI) to capture a broader range of influences on adoption (Al-Rahmi et al., 2019; Gómez-Ramirez et al., 2019; Nguyen et al., 2022). Methodologically, quantitative methods with comparative design, case study, and cross-sectional survey designs were most commonly employed (Baydas et al., 2015).

Common Predictors of AI Adoption in K–12 Settings

Perceived Usefulness (PU) has emerged as the most consistent and powerful predictor of teachers' intention to adopt AI tools in the classroom (Awofala et al. 2025; Scherer et al., 2019). For example, in a TAM-based study of Spanish primary and secondary teachers using chatbots, both PU and perceived ease of use were found to lead to greater acceptance of the chatbot technology (Chocarro et al., 2023). Similarly, Awofala et al. (2025) found that PU was a strong predictor of the adoption of educational

AI tools (EAIT) among science, technology, and mathematics (STM) teachers in Nigeria.

Perceived Ease of Use (PEOU) is another core factor that significantly influences AI adoption, though its role can be both direct and indirect. In many cases PEOU has a positive direct effect on teachers' intention to use AI tools, meaning that if the technology is seen as user-friendly and not overly complex, teachers are more inclined to adopt it (Awofala et al. 2025; Scherer et al., 2019). For example, Chocarro et al. (2023) reported that Spanish teachers' perceptions of chatbot ease of use significantly boosted their intention to use the chatbot. In some studies, the effect of ease of use is mediated through usefulness—that is, easy-to-use AI tools are perceived as more useful, which in turn drives higher intention (Choi et al., 2023) or other factors (Lin et al., 2025). For example, Choi et al. (2023) found that perceived ease of use influenced teachers' intention to use educational AI tools, both directly and by enhancing the chatbot's perceived usefulness. Lin et al. (2025) found that PEOU did not directly impact math teachers' engagement with AI. Instead, its effect was mediated by their mathematics beliefs and AI literacy. Overall, teachers tend to adopt technologies they find easy to work with, especially given their busy schedules and varying levels of technical expertise.

Beyond the core TAM constructs, trust in AI and teachers' pedagogical beliefs have increasingly been integrated into these models and shown to be significant predictors of AI acceptance. For example, Choi et al. (2023) proposed an extended TAM that included perceived trust in educational AI tools and teachers' constructivist pedagogical beliefs. They found that both trust and pedagogical belief orientations significantly affected acceptance: teachers with more constructivist, student-centered

beliefs were more likely to integrate AI, and those who trusted the AI's recommendations found the tools more useful and were more inclined to adopt them. Velli and Zafiropoulos (2024) similarly integrated trust, pedagogical beliefs, and personal innovativeness into a hybrid model combining TAM and UTAUT. They found that trust had a significant positive effect on the perceived usefulness of EAIT, and that innovativeness positively and significantly influenced perceived usefulness, ease of use, and behavioral intention. Although constructivist pedagogical beliefs did not directly affect acceptance of EAIT, educators who favored these approaches were more likely to view EAIT as both useful and trustworthy. Moreover, Awofala et al. (2025) expanded the TAM framework by incorporating trust and instructional beliefs in EAITs. They found that trust, along with perceived usefulness and ease of use, was a strong direct predictor of AI adoption among STM teachers. Additionally, teachers with constructivist instructional beliefs were more inclined to adopt and integrate EAITs into their teaching practices compared to those with more traditional beliefs. These results suggest that the success of AI integration may depend in part on alignment with teachers' pedagogical values, and that professional development encouraging more innovative teaching mindsets could indirectly facilitate AI adoption.

Social influence and facilitating conditions (key components of UTAUT) have shown more mixed but noteworthy effects. Social influence (or subjective norm)—the degree to which teachers feel that colleagues, school leaders, or the broader education community expect or encourage them to use AI—is significant in many studies using UTAUT models, though its strength varies by context (see review Kittinger & Law,

2024; Williams et al., 2015; Yao & Abd Halim, 2023). For example, Zhang and Wareewanich (2024) found that social influence had a positive effect on AI adoption intention. Similarly, Velli and Zafiropoulos (2024) found that social influence was one of the influential factors for Greek teachers' behavioral intention to use EAIT alongside usefulness and innovativeness. However, other studies have found social influence to be weaker or nonsignificant. A systematic review found that, among 18 studies using UTAUT or UTAUT2 with K–12 educators, four reported that social influence had no significant impact on behavioral intention (Kittinger & Law, 2024).

Facilitating conditions similarly are sometimes significant in UTAUT-based analyses. In a survey of 266 Chinese primary school math teachers, for instance, facilitating conditions was a positive predictor of teachers' acceptance of a dynamic mathematics software (Yuan et al., 2023). Yet in other cases, facilitating conditions have not emerged as a strong direct predictor of intention (Park et al., 2011; Venkatesh et al., 2003). For example, Park et al. (2011) found that facilitating conditions provided by an organization, such as its human and technical resources, explained more variability in actual usage behaviors than individual-level facilitating conditions alone. The study further underscores that differences in organizational support structures across groups can substantially affect individual users' acceptance and utilization of new systems. Therefore, it is crucial for organizations to establish comprehensive support not only targeted at individual users but also encompassing group-level resources, to achieve more consistent technology adoption outcomes. This inconsistency suggests that teachers' perceptions and use of facilitating conditions may vary according to school-specific

factors, including resource availability, institutional support, and professional culture.

Several additional variables have been examined across different studies, reflecting attempts to extend the functionalist models for AI contexts. Self-efficacy (teachers' confidence in their ability to use AI) has been found to positively influence adoption (Tekin, 2024; Tram, 2025; Wang et al., 2024). Anxiety about AI or technology was found as a barrier—Tekin's (2024) showed that teacher anxiety about AI had a significant negative effect on both perceived ease of use and on intention, suggesting that reducing fear and uncertainty around AI is important for adoption. Some recent models have introduced AI literacy or knowledge as a construct, especially for understanding adoption of complex AI like machine learning tools. Lin et al. (2025) found that teachers' AI literacy (knowledge and understanding of AI concepts) was an important mediator: those with higher AI literacy were more likely to engage with AI tools in teaching. In Lin et al.'s (2025) TAM-based framework, AI literacy and teaching beliefs together conditioned how PU and PEOU translated into actual engagement with AI, highlighting the value of building teachers' conceptual understanding of AI. Moreover, Zhao et al. (2025) found that some non-traditional factors emerged as influential in AI adoption in middle school level. In particular, compatibility (the degree to which AI tools fit with teachers' existing practices and values) and personal innovativeness were important positive predictors, alongside the usual PU and PEOU. Interestingly, they reported that interpersonal relationships (a proxy for peer influence and networking among teachers) and mass media exposure were among the most influential factors on teachers' willingness to use AI. This suggests that in addition to internal beliefs, broader social and

informational contexts (e.g. hearing about AI success stories through media or colleagues) can drive adoption.

In summary, across the literature a clear pattern emerges: perceived usefulness of AI for teaching is the dominant driver of K–12 teachers' adoption, usually accompanied by a significant role for ease of use, while newer constructs like trust in AI and pedagogical alignment further strengthen the explanatory power of the models. Social and contextual factors play a role to varying degrees, and individual differences in self-efficacy, innovativeness, anxiety, and literacy can modulate adoption outcomes. These findings align well with the core premises of TAM/UTAUT, even as the models are enriched to capture the particular nuances of AI in education.

Limitations and Criticisms of Functionalist Models

While functionalist models have been widely used and validated, they are not without significant limitations. Over the years, scholars have critiqued these models on conceptual, empirical, and practical grounds. Several key criticisms include concerns about the models' theoretical scope and assumptions, their empirical performance and methodological issues, and their applicability to the richer reality of technology use in education.

Conceptual Limitations

One major critique is that functionalist models provide a simplified, mechanistic view of technology adoption that neglects many of the deeper forces at play (Benbasat & Barki, 2007; Islam et al., 2014; Malatji et al., 2020; Zaineldeen et al., 2020). By focusing on a set of predefined variables, these models may miss factors that are hard to quantify

or generalize (Malatji et al., 2020). For example, TAM reduces adoption to individual perceptions of usefulness and ease, but ignores the influence of organizational culture, power dynamics, or historical context. In a school setting, this might mean ignoring how a teacher's professional identity or a school's leadership climate affects technology uptake. Benbasat and Barki (2007) argued that TAM and similar models shift researchers' attention away from other significant issues in technology research. For instance, concentrating solely on initial acceptance often results in neglecting critical aspects of technology use, such as usage quality, adaptation, and discontinuance. They cautioned that the continuous refinement of existing models could produce a misleading perception of theoretical advancement, as minor adjustments or additional variables may enhance predictive power without genuinely contributing new insights. Incorporating variables like trust and enjoyment into TAM may improve prediction marginally but fails to expand theoretical understanding unless these variables are connected to a comprehensive understanding of human behavior and the social context.

Another conceptual issue is the assumption of linear, one-directional causality. Functionalist models typically assume a linear influence of factors on intention and behavior. Real-world adoption, however, can be recursive and dynamic and that people's perceptions can change after use (e.g., initial use might increase perceived usefulness, a phenomenon TAM doesn't capture well because it treats usefulness as exogenous). Some researchers have pointed out that technology adoption is an iterative learning process, but functionalist models usually provide a static, one-shot picture (Islam et al., 2014). Additionally, interdependencies between factors are simplified; for instance, perceived

ease of use and perceived usefulness in TAM are not independent (ease of use can enhance perceived usefulness), yet the basic model doesn't explicitly theorize their interaction beyond a simple causal link. This has led to calls for more complex modeling of relationships—such as moderation and non-linearity. While some TAM/UTAUT studies have begun to explore these areas, they often remain underexamined due to limitations in sample size and analytical complexity.

Empirical and Methodological Limitations

Empirically, although functionalist models have decent predictive power, they also leave a substantial portion of variance unexplained, and their predictions may lack specificity (Legris et al., 2003). Those other factors that help explain the variance in intention could be things that are difficult to measure or generalize, such as a particularly inspiring school principal, or a teacher's personal passion for innovation. Functionalist studies typically acknowledge this in limitations, noting the role of unmeasured factors, but the model itself does not readily incorporate such richness. There is also evidence of diminishing returns: as dozens of TAM-based studies accumulate, meta-analyses show very similar effect sizes, suggesting the model has been validated to the point of saturation. As Bagozzi (2007) provocatively stated, continued application of TAM without new theoretical development had become a kind of "scientific stagnation", and he urged scholars to integrate TAM with theories of emotion, motivation, and group influence to revitalize the research. From a measurement perspective, functionalist models often rely on self-reported measures of intention and usage, which can be problematic (Malatji et al., 2020). Teachers, for instance, might overstate their intended

or actual use of a mandated technology due to social desirability bias. This can inflate the correlations between intentions and self-reported usage because both are collected in the same survey context. Moreover, many studies equate “intention to use” with actual use, yet in practice these can diverge—a teacher might express high intention to use an educational app, but subsequently fail to do so due to unforeseen constraints or loss of interest. Some critics note that TAM’s heavy focus on intention (a convenient proxy for behavior in research) might not fully translate to sustained usage or integration quality in the classroom (one can adopt a tech superficially to satisfy an intention, without meaningful utilization). Additionally, functionalist models generally operate at only one level of analysis, either individual or organizational. In educational contexts, this single-level approach is restrictive because technology adoption frequently involves multilevel dynamics. For instance, an individual teacher’s decision to adopt technology can be influenced simultaneously by school policies at the organizational level and by broader technological strategies established at the education system level. TAM/UTAUT by themselves do not handle cross-level influences well, though TOE tries at the organizational level. This has led to suggestions that multilevel models or mixed-method approaches are needed to truly capture educational adoption phenomena, which the one-level functionalist models cannot do alone.

Practical and Ethical Limitations

Another angle of criticism is whether these models guide practice effectively or just reaffirm the obvious. TAM’s core message that people use technology if they find it useful and easy could be rather commonsensical. While TAM quantifies these effects, it

doesn’t necessarily provide deep insight into how to make technologies more useful or easy beyond what any good product designer or trainer would already consider. In educational settings, recognizing that perceived usefulness is essential raises further questions about which specific educational goals the technology serves and how educators' perceptions of usefulness might be influenced. The model alone does not address these issues, leaving practitioners responsible for developing interventions, such as providing educators with evidence of improved student outcomes to influence their perceptions positively.

Furthermore, functionalist models often ignore outcomes of adoption. But in education, adoption is not the ultimate goal, rather, effective integration and impact on learning are. A narrow focus on acceptance might prompt schools to encourage technology use without sufficiently evaluating whether it is pedagogically appropriate or advantageous for students. This reflects a broader ethical critique suggesting that prioritizing models framing adoption as inherently beneficial and driven purely by rational choice could result in overlooking critical considerations, such as whether technology adoption is appropriate, who ultimately benefits, and who might be disadvantaged. Functionalist models typically do not question the suitability of a technology, implicitly assuming that adoption is beneficial if certain conditions are met. Selwyn (2010) suggested that this creates a pro-innovation bias that researchers end up effectively serving as cheerleaders for technology by focusing on how to increase adoption, rather than also scrutinizing the negative or unintended consequences of technology in schools. While one could argue this is beyond the scope of TAM/UTAUT

themselves, it's a consequence of their widespread use that the research agenda gets skewed toward facilitation of adoption rather than a balanced evaluation of it..

Beyond Functionalism: Toward Paradigm Pluralism

A notable gap in the literature, as highlighted by several reviews, is the lack of non-functionalist alternatives being actively used to study technology adoption in contexts including education. Critics argue that exclusively relying on such models oversimplifies the complexities involved in technology use. The focus on generic predictors and linear causality often ignores the richer social, cultural, and emotional contexts in which technologies are embedded. In fact, many attempts to extend TAM have simply introduced additional variables without fundamentally reconsidering its foundational assumptions, resulting in what Bagozzi (2007) described as fragmented modifications lacking coherence and integration. Consequently, Bagozzi and other scholars advocate shifting away from narrow functionalist perspectives toward paradigm pluralism, approaches that integrate more comprehensive emotional, social, and cultural dimensions into the study of technology adoption (Bagozzi, 2007; Baker et al., 2021; Gioia & Pitre, 1990; Mingers, 2001; Taylor et al., 2012).

Researchers across various fields have begun to answer this call by exploring alternative paradigms that complement or challenge the functionalist model. Interpretive and socio-cultural frameworks provide valuable alternatives. For instance, scholars drawing from structuration theory highlight how technology and human practices mutually shape each other, rather than viewing technology adoption as a straightforward, linear process (Orlikowski, 1992). According to this perspective, technology adoption is

socially constructed, continuously influenced by users' interpretations and interactions with technological tools. Similarly, domestication theory, prominent in media and communication studies, directs attention to how individuals integrate and adapt technologies into their everyday lives (Silverstone & Haddon, 1996). This theory emphasizes both the practical and symbolic dimensions of technology use, demonstrating that understanding how devices become embedded in daily routines involves appreciating their social meanings as well as their tangible functions (Silverstone & Hirsch, 1992; Silverstone & Haddon, 1996). Thus, technology adoption encompasses more than mere practicality; it also involves processes of social negotiation, cultural adaptation, and the interplay of power dynamics within households and communities (Silverstone & Hirsch, 1992). Other scholars adopt critical paradigms, examining how issues of power, identity, and ethics intersect with technology. A handful of critical studies have examined how school policies impose technology in top-down ways or how teachers' resistance can be a form of agency (McFadden, 1995; Sannino, 2010; Selwyn, 2010). Another example is the sensemaking theory (Weick et al., 2005), which is used to study how teachers interpret and give meaning to the introduction of AI in their curriculum. All of these diverse approaches enrich the study of technology by asking questions that functionalist models were never designed to answer. They illustrate the value of paradigm pluralism, the idea that multiple theoretical frameworks (functional, interpretive, critical, etc.) can and should coexist to provide a more holistic understanding.

Among the most compelling examples of a non-functionalist paradigm is the Apparatgeist theory developed by Katz and Aakhus (2002), which centers on the cultural

and interpersonal dimensions of communication technology. Katz's approach diverges from the functionalist tradition by exploring why and how individuals utilize technologies within the broader context of human communication needs, social interactions, and underlying values. The concept of Apparatgeist, meaning the spirit of the machine, captures the fundamental ethos or driving principle shaping both the development of personal communication technologies and the meanings users associate with them. Katz and Aakhus (2002) suggest there are common patterns across cultures in how individuals adopt and interpret technologies. They observe that people, irrespective of their cultural backgrounds, generally move toward standardized infrastructure and seek similar features when engaging with personal communication technologies, indicating a universal inclination toward particular communication tools and practices. This stands in contrast to the functionalist assumption that adoption is solely driven by individual utility maximization. Apparatgeist theory posits that a host of social and psychological forces, which collectively form a shared spirit, influence technology use, leading to surprisingly similar usage behaviors across different contexts (Campbell, 2008). Crucially, this theory emphasizes that technology use is socially constructed, shaped by collective norms and interpretations rather than determined by the hardware alone (Katz & Aakhus, 2002). In other words, people collectively develop shared understandings of what a technology means and how it should be integrated into life, and these shared meanings then strongly influence adoption and use patterns. This socially informed view is a clear departure from the individualistic and utilitarian orientation of TAM.

Katz's human-centered paradigm further introduces concepts such as "perpetual contact," highlighting the interpersonal and emotional motivations underlying technology adoption (Katz & Aakhus, 2002). The idea of perpetual contact describes a cultural aspiration made possible by mobile devices, reflecting a desire for continuous and uninterrupted connectivity with others. Holmes (2005) characterizes this aspiration as an ideal of pure communication, free from bodily constraints. In Katz's view, the popularity of mobile phones cannot be explained only by their functional capabilities; it also stems from this deep-seated desire for constant interpersonal connection and the emotional reassurance of availability. People embrace personal communication technologies to feel present with one another at all times, blurring boundaries between absence and presence in social life. This helps explain behaviors that a purely functional model might overlook, such as, the compulsion to check one's phone frequently or anxiety when a connection is lost. Katz's paradigm accounts for phenomena like the "always-on" culture, where being constantly reachable becomes a social norm (Katz & Aakhus, 2002). It acknowledges that users often assess technologies not just by efficiency, but by how well those tools facilitate human interaction and emotional connection, a dimension largely absent in functionalist metrics.

Another key facet of Katz's paradigm is its attention to identity and self-expression in technology use. Katz and colleagues have demonstrated that personal technologies serve as social and cultural symbols, not just utilitarian tools. For example, Katz and Sugiyama (2006) found that mobile phones function as fashion statements and status symbols among youth, with different phone models and customizations conveying

aspects of the owner's identity. Choosing a particular smartphone, personalizing ringtones or cases, and even the way one uses messaging apps can all signal membership in certain social groups or express an individual's style and values. This insight aligns with the idea in domestication theory that adoption has a symbolic component (Silverstone & Hirsch, 1992), and it challenges the purely functional account of why people adopt new features or devices. From Katz's perspective, technology adoption is partly a process of identity formation and self-presentation, wherein individuals incorporate devices into their self-concept and public persona. A young person might adopt a new social media app not only because of its useful features, but also because being on that platform confers a sense of belonging or modernity that fits their identity. Therefore, Katz's paradigm again moves beyond functionalism by incorporating cultural meaning and context, emphasizing the importance of examining personal and group identities in technology adoption. This perspective encourages researchers to adopt a pluralistic approach, integrating communication theory, sociology, and psychology alongside traditional information systems models.

Importantly, Katz's theoretical framework extends beyond mobile communication, offering insights into emerging technologies such as AI and their associated ethical implications. Katz (2025) emphasizes that AI-based systems reshape communicative interactions and environments, prompting new considerations around issues like agency, identity, trust, and cultural adaptation in societies increasingly mediated by algorithms. This viewpoint surpasses traditional adoption models by examining how integrating AI into communication platforms transforms the nature and

roles of users and communicators. It also encourages inquiry into ethical guidelines needed to ensure AI is developed and implemented in ways that uphold human autonomy and promote social justice. Katz asserts that these ethical and social concerns are inherently linked to communication processes, as AI fundamentally reshapes societal meaning-making and interactions. His analysis addresses challenges such as the unequal distribution of AI's benefits and risks, and the potential for superficial or deceptive ethical claims in AI governance, topics not adequately captured by traditional models focusing solely on utility and ease of use.

Apart from the theories discussed above, there have been a few direct comparisons of paradigms. Semenova (2020), as noted earlier, explicitly juxtaposed a functionalist analysis of blockchain adoption with an interpretive one. Semenova (2020) concluded that functionalist models offer valuable predictive frameworks but fail to explain why certain factors matter in specific contexts, something an interpretive analysis could illuminate by examining actors' perspectives and stories. It is suggested that a mixed-paradigm or mixed-method approach can yield a more holistic understanding. For example, one might use TAM to measure the baseline relationships, and then follow up with interviews to understand discrepancies or surprises in the quantitative data.

It is telling that even comprehensive reviews find virtually no empirical studies that present a full-fledged non-functionalist model as an alternative for technology adoption. In other words, while many papers mention in passing that future work should consider qualitative or contextual factors, few actually do so. One reason is likely the inertia of established research methods and training—doctoral programs in related fields

often emphasize quantitative methods and thus new researchers continue the tradition. Another reason is the appeal of functionalist models' clarity and simplicity, making them easier to apply and publish. Non-functionalist research might be messier or harder to generalize, facing more challenges in publication within venues used to seeing TAM-style studies.

Nevertheless, the need for paradigm pluralism is increasingly recognized. Paradigm pluralism doesn't mean abandoning functionalist models, but rather enriching the research landscape by also valuing studies that that draw on different ontological and epistemological foundations. This dissertation aligns with those calls by aiming to move beyond functionalist models, incorporating the sociology of professions to study teachers' use of AI. It suggests examining teachers not just as users deciding on a tool's usefulness, but as members of a profession with a distinct culture and social role, navigating an AI innovation that might challenge their professional boundaries. Such an approach could yield insights (e.g., concerns about AI devaluing teachers' expertise, or conversely, professional pride in innovating with AI) that standard models would gloss over.

In conclusion, functionalist models have undoubtedly advanced the understanding of technology adoption and given us validated predictors to work with. However, they come with significant limitations in scope and depth. The literature shows a clear imbalance: a wealth of functionalist quantitative research and a dearth of interpretive or critical studies. Addressing complex educational phenomena like teachers' adoption of AI may require stepping outside the functionalist comfort zone. As multiple scholars

have argued, embracing paradigm pluralism—integrating functionalist insights with interpretive understanding and critical awareness—can provide a more nuanced and actionable picture of technology adoption in education. The following chapter of the dissertation will build on this realization, proposing a theoretical framework that combines functionalist findings with concepts from the sociology of professions, aiming to capture both the functional drivers and the social-professional context of teachers' engagement with AI in their practice.

Chapter 5 Method

Research Design

This study adopted a qualitative research design, employing semi-structured interviews to capture the lived experiences and perceptions of teachers regarding AI. A matrix of key attributes—including age, teaching experience, educational level, subject area, and attitude toward AI—guide the sampling strategy.

The study has been approved by the university's Institutional Review Board, and all interviewees were provided with detailed information regarding the purpose of the study and their rights as participants. Verbal informed consent was obtained, and participants had the option to withdraw at any time.

Sampling

This study employed a combination of convenience sampling, snowball sampling, and random sampling to recruit a diverse quota sample of 51 K–12 educators. The goal was to ensure representation across a broad range of perspectives and experiences. Participants were recruited through multiple channels, including public social media groups for K–12 teachers and administrators, the professional and personal networks of the author and her committee, as well as referrals from participants' own professional and personal contacts. Recruitment ended once thematic saturation was reached.

Sampling attributes included age groups, educational levels, attitudes toward AI, professional identities, and personal and contextual characteristics. Given the challenge of identifying certain attributes, particularly professional identities and attitudes towards AI, prior to conducting interviews, the study incorporated a post hoc assessment of these

factors. Utilizing quota sampling ensured adequate representation of critical variables influencing teachers' perceptions, thus providing a solid basis for thematic analysis and interpretation.

Age is an essential demographic factor in the study, as younger teachers (under 40) may approach AI with more openness due to their familiarity with emerging technologies, while older educators (40 and above) may exhibit more skepticism based on established teaching practices and prior experiences with educational reforms. However, as discussed in the literature review section, there are also studies that found that age is not a significant factor of technology usage experiences (Kennedy et al., 2008; Watty et al., 2016). Given the contradictory predictions, I included age as a sampling attribute. Similarly, educational levels served as a key attribute, with participants representing three distinct categories: early childhood (K–3), middle school (grades 4–7), and high school (grades 8–12). This differentiation allows for an examination of how attitudes and perceptions may vary across developmental stages and instructional priorities, as early childhood educators may be more focused on personalized interactions, whereas high school teachers may prioritize content mastery and college readiness, potentially viewing AI as a tool for advanced learning or assessment.

Attitudes toward AI will be another primary focus of sampling, with participants categorized into three groups: pro-AI, neutral, and anti-AI. Pro-AI educators are expected to express optimism about the technology’s potential to enhance educational outcomes, while anti-AI teachers may voice concerns about AI undermining professional autonomy and human interaction in the classroom.

Another critical dimension in the sampling strategy is the inclusion of teachers based on their professional identities, classified into four categories: social and moral educators, cultural facilitators, academic facilitators, and holistic developers. Social and moral educators view their primary role as nurturing students' social skills and ethical behavior, while cultural facilitators prioritize exposing students to diverse worldviews and fostering critical thinking. Academic facilitators focus on delivering a strong academic foundation, believing that content mastery is key to future success, while holistic developers see education as a means of preparing students for various life situations, emphasizing the cultivation of well-rounded individuals. These professional identities are likely to shape how teachers perceive the integration of AI in their teaching practices and its alignment with their pedagogical philosophies.

The classification used in this study—social and moral educators, cultural facilitators, academic facilitators, and holistic developers—is informed by these prior works and aligns with the multidimensional view of professional identity described by Beijaard et al. (2000), Hanna et al. (2020), and Lamote and Engels (2010). Beijaard et al. (2000) categorized teachers' professional identities into three primary roles: subject matter experts, didactical experts, and pedagogical experts. Subject matter experts are teachers who emphasize deep knowledge and expertise in their subject areas, focusing primarily on content delivery. Didactical experts prioritize the methods and strategies for effectively planning, implementing, and evaluating teaching and learning processes. Pedagogical experts, on the other hand, focus on fostering students' social, emotional,

and moral development, emphasizing broader educational goals beyond academic content.

Further elaborating on these categories, Hanna et al. (2019, 2020) expanded the understanding of teachers' professional identities through the dimension of task perception. This includes how teachers view their roles and responsibilities, which are shaped by self-image, motivation, and self-efficacy. Hanna et al.'s (2020) measurement scale provides concrete examples of professional identity tasks, such as: "I think it is my most important task to teach students a critical attitude towards society", "I think it is my main task to teach students social skills", "I think it is my main task to introduce students to different cultures and religions", "I think it is my most important task to transfer students' values and norms", "I believe that students should learn well at school so that they become social successful", and "I believe that if students learn a lot at school, they will later have a smaller chance of being unemployment."

Similarly, Lamote and Engels (2010) explored teachers' professional identities through related constructs, such as their emphasis on social skills, academic success, and career preparedness. Example items from their work include: "At school pupils should learn social skills", "If pupils want to have a successful career later on, they need to learn a lot at school", and "I think it's important for pupils to have high marks."

In addition to these core sampling attributes, the study will consider a range of teacher's personal characteristics to capture the complexity of teacher perspectives, such as ethnicity, career stage, subject specialization.

Contextual variables will further enrich the analysis by considering the socioeconomic status of the schools where participants work, categorized as low-income, middle-income, or high-income. The geographic setting (urban, suburban, or rural) will also be examined, as school environments and community contexts can influence how AI is perceived and implemented. Additionally, student demographics, including schools with high numbers of minority or refugee students, will be factored in to explore whether diverse student populations create unique challenges or opportunities for AI integration.

Data Collection

Data was collected through semi-structured, open-ended interviews via Zoom, which were recorded and transcribed with participants' consent. Each interview lasted approximately 60 minutes, ranging from a minimum of 30 minutes (in four cases) to a maximum of 165 minutes (in one case).

Data was collected in two waves (18 for the first wave, and 33 for the second). The questions asked in the first wave were guided by functionalist models such as their attitudes toward using AI in their professions, motivations, perceived benefits, barriers, and institutional policies. I analyzed the 18 transcripts and found that I observed that teachers frequently linked their views on AI to deeper identity-related issues. Therefore, in the second wave of the interview I added more questions specifically on their professional identity, teaching philosophy, career aspirations, hopes, and fears.

The recordings were transcribed using the Alice.AI transcription software.

Analytical Process and Methodological Steps Using CR

This study employed CR to explore the underlying mechanisms connecting teachers' professional identity to their attitudes towards AI integration in teaching professions. Initially guided by functionalist models of technology adoption, I shifted to a sociological perspective, specifically the sociology of professions, upon recognizing the significance of professional identity in shaping teachers' attitudes. The following detailed steps represent the CR-based analytical method adopted from Fletcher (2017):

Step 1: Data Coding and Identification of Demi-Regularities

The analytical process began by coding the initial wave of interview data (N = 18), guided primarily by functionalist models of technology adoption and relevant literature. During this initial coding phase, provisional codes were developed based on expected themes, such as technology functionality, perceived usefulness, barriers, and institutional policy. However, patterns soon emerged that extended beyond functionalist predictions, indicating linkages between teachers' professional identity, autonomy, and the values they associate with their roles as educators. Specifically, teachers frequently articulated their acceptance or rejection of AI technologies in terms related to their professional purposes, the alignment of AI use with their pedagogical philosophies, and potential threats or enhancements to their professional autonomy.

Recognizing the prominence of these identity-related dimensions, a second wave of interviews (N = 33) was conducted with a revised interview protocol explicitly incorporating questions focused on professional identity, teaching philosophies, professional values, career aspirations, and how these dimensions might intersect with

attitudes toward AI integration. The resulting comprehensive dataset (N = 51 interviews) was then analyzed through a flexible deductive (directed) coding approach. This approach began with an expanded set of provisional codes (N = 20) reflecting insights from both functionalist frameworks and the emerging professional identity themes. The codes were iteratively refined, leading to an extensive coding scheme that enabled identification of significant empirical demi-regularities. Demi-regularities included consistent patterns in teachers' responses, demonstrating how perceived alignments or misalignments of AI with their professional identities affected their enthusiasm, reservations, or outright resistance toward AI integration.

Step 2: Abduction (Theoretical Redescription)

In this step, empirical demi-regularities identified in the coding stage were reinterpreted using theoretical constructs drawn from the sociology of professions literature. The sociological perspective allowed a theoretical engagement with concepts such as professional autonomy, identity threats, professional ethics, and jurisdictional control within teaching practices. Utilizing these concepts facilitated understanding of why and how professional identity appeared to play a central role in shaping teachers' attitudes toward AI.

This abductive theoretical redescription significantly extended beyond the initial functionalist interpretation by providing an explanatory framework that recognized teachers as active agents influenced by both personal and structural factors. For instance, where functionalist models primarily explained AI adoption in terms of technology characteristics or organizational efficiency, sociological theories of the professions

clarified why teachers frequently evaluated AI through their core professional values, ethics, and self-conception as educators. This shift provided a nuanced interpretation that educators were not simply passive recipients of technology, but active evaluators whose professional identities significantly mediated their technological decisions.

Step 3: Retroduction (Identifying Causal Mechanisms and Conditions)

The final analytical step employed retroductive analysis to explore deeper causal mechanisms behind the empirical trends observed. Guided by the CR methodology, the analysis moved iteratively between the concrete empirical observations and the underlying theoretical frameworks, aiming to identify the conditions necessary for certain causal mechanisms to become manifest in educators' attitudes towards AI.

The analysis concluded that professional identity served as a fundamental causal mechanism shaping teachers' attitudes toward AI integration. This professional identity mechanism operated primarily through the dimensions of autonomy, ethics, and perceived threats to professional jurisdiction. When teachers perceived AI as aligned with their sense of professional purpose and enhancing their autonomy, their attitudes toward AI were predominantly positive. Conversely, when AI was perceived as undermining professional autonomy or conflicting with deeply held professional ethics and pedagogical philosophies, negative attitudes emerged. Furthermore, broader institutional and societal contexts provided conditions that activated or inhibited these causal mechanisms.

Analytical Steps Using LLMs for Qualitative Coding and Analysis

Step 1: Initial Coding by Two Independent LLMs

The qualitative coding process began by submitting all 51 interview transcripts to two distinct LLMs: ChatGPT-4.5 and Google Gemini 2.5 Pro. These two LLMs independently conducted the initial coding based on an explicitly provided coding framework derived from theories and literature of functionalist models and teachers' professional identity, values, autonomy, and pedagogical philosophies (see Appendix A). Same instructions were provided to each LLM to ensure consistency in coding guidelines. Each model independently produced a set of provisional codes for every transcript.

Step 2: Consistency Check Using a Third LLM

The two independently derived coding outputs from ChatGPT-4.5 and Google Gemini 2.5 Pro were then submitted to a third LLM, ChatGPT-4o, for a systematic consistency check (see Appendix B for an example). This procedure was pioneered by Markowitz & Bailenson (2025). ChatGPT-4o's task was specifically defined in three aspects. First, identify and document agreements and disagreements between the two initial LLM coders. Second, summarize the extent and nature of the discrepancies, highlighting areas where the coding diverged significantly or areas with complete consensus. Last, provide a consistency report, marking the consistent coding themes and flagging notable inconsistencies for further review.

Step 3: Researcher-led Reconciliation and Final Coding Decisions

Following the consistency report generated by ChatGPT-4o, the researcher reviewed all identified agreements and discrepancies and critically evaluated them in relation to the coding framework, the original interview transcripts, and theoretical

insights from the sociology of professions literature. Drawing on expertise and judgment, divergent codes were reconciled by selecting the most contextually accurate interpretations from either ChatGPT-4.5 or Google Gemini 2.5 Pro, combining codes where appropriate to capture nuanced meanings in the data, and introducing new or refined codes when necessary. This process ensured both theoretical coherence and empirical rigor. The outcome was a finalized, reconciled coding dataset that reflects analytical accuracy and conceptual depth. Table 2 below demonstrated examples of the coding process.

Example Quotes	ChatGPT-4.5 Code	Google Gemini 2.5 Code	ChatGPT-4o Checking	Researcher Human Decisions
"I feel like at the level that I teach, [...] they're using, I feel like they need the fundamentals of what I am trying to teach them that they're trying to avoid by using the AI in order to eventually maybe use AI as an actual useful tool."	Code 1: Teaching Philosophy Code 2: Aspirations for Students' Development Code 3: Compatibility with Teaching (Fit & Value Alignment)	Code 1: Impact on Student Learning (Loss of Skills/Creativity) Code 2: Problematic Uses & Ethical Concerns	Both coders agree the quote is important, but they frame its significance differently. Gemini 2.5 Pro codes it as an observation of risk: AI misuse compromises student learning. GPT-4.5 codes it as a reflection of professional philosophy that the teacher resists AI because it threatens what they see as essential learning foundations.	Interpretation from GPT-4.5 offers a more aligned and theoretically generative coding of the quote. These codes directly tie into how professionals evaluate technologies not only for utility but for alignment with core values and professional norms. Therefore, the researcher decided to employ layered coding for this quotation, identifying the first-order code as "Student Misuse of AI", the second-order codes as "Teacher's Aspiration for Foundational Skills" and "AI as Misaligned with Pedagogical Vision", and the third-order theme as "Professional Identity Tension in the Age of AI."
"So like the other teachers who teach 10th grade English, you know, every now and then when we have our group meetings, somebody will bring up, oh, you know, I tried out this software that uses AI and we'll take a look at it and see, you know, could this be useful to us or not?"	Social Influence, Perceived Ease of Use	Social Influence (Peer/Community Influence)	Gemini treats this quote as a descriptive observation about the school's informal professional culture. GPT-4.5 also uses "Social Influence", but layers in "Perceived Ease of Use".	The coding from ChatGPT-4.5 aligns with the broader contextual realism of teachers' working environments, reflecting the sociology of professions (norm-building, peer control). Google Gemini 2.5's coding implicitly references constructs from UTAUT and DOI, reflecting technology adoption models. The researcher coded this instance as Social Influence, noting in the coding memo that it reflects insights from both theoretical perspectives.

Table 2. Examples of the LLM-assisted Coding Process.

Steps 4, 5, and 6 followed an iterative workflow: “two LLMs for coding → one LLM for consistency checking → researcher’s final adjudication.”

Step 4: Identification of Demi-Regularities via LLM-Assisted Analysis

The finalized coding dataset, reconciled in Step 3, was first independently analyzed by ChatGPT-4.5 and Google Gemini 2.5 Pro to identify recurring empirical demi-regularities across the 51 interviews. Each LLM independently generated summaries of the dominant themes, patterns, trends, and interrelationships among codes. These two sets of demi-regularity summaries were then input into ChatGPT-4o for a consistency check. ChatGPT-4o compared the summaries, documented areas of agreement and identified discrepancies. The researcher critically reviewed the consistency report provided by ChatGPT-4o, revisited original coded data and transcripts when needed, and applied my professional judgment to finalize the empirical demi-regularities.

Step 5: Abduction (Theoretical Redescription) with LLM Support

The demi-regularities from Step 4 were next submitted separately to ChatGPT-4.5 and Google Gemini 2.5 Pro for theoretical redescription using key concepts from sociology of professions literature, including professional identity, autonomy, ethics, and teaching philosophy. Each LLM independently articulated how theoretical concepts could reinterpret the empirical findings. The two independently produced theoretical redescriptions were then input into ChatGPT-4o to perform a consistency check. Following this, the researcher reviewed ChatGPT-4o's consistency summary and used your theoretical expertise and judgment to reconcile differences.

Step 6: Retroduction and Identification of Causal Mechanisms

The theoretically redescribed data from Step 5 underwent further analysis to uncover causal mechanisms via retroduction. Independently, ChatGPT-4.5 and Google Gemini 2.5 Pro generated propositions about causal mechanisms on how teachers' professional identity, autonomy, and ethics influence their attitudes toward AI under various contextual conditions. The outputs were then checked by ChatGPT-4o for consistency. Subsequently, the researcher reviewed this consistency summary, evaluated flagged discrepancies by referencing original empirical evidence and theoretical frameworks, and exercised my researcher judgment to finalize clearly articulated and empirically substantiated causal mechanisms.

Privacy

For privacy considerations, this study used the “Temporary Chat” mode in ChatGPT-4.5 and ChatGPT-4o. This mode ensures that chats do not appear in the user’s history, are not stored in or used to update ChatGPT’s memory, and are not used for model training (OpenAI Help Center, 2025). Similarly, for Google Gemini, this study disabled “Gemini Apps Activity.” When this setting is turned off, Gemini deletes conversations within 72 hours and does not use newly stored conversations to improve its generative machine learning technologies (Gemini Apps Help, 2025).

In writing up the results, all pronouns were changed to gender-neutral forms (“they/them/their”) to protect the interviewees’ privacy.

Validity

To further enhance the validity of the findings, the study incorporates member checking as a technique to confirm the accuracy of the interpretations. This study have invited 10% of the total participants to review the synthesized themes and the corresponding interpretations drawn from their interviews. This approach allows participants to verify whether the analysis accurately captures their experiences and perceptions, providing an additional layer of validation from the participants themselves. Any feedback from these participants will be integrated into the final analysis, ensuring that the results remain grounded in the authentic voices of the teachers.

Additionally, the study maintains an audit trail throughout the research process to provide transparency and replicability. Detailed records of the coding process, thematic development, and changes made in response to expert and participant feedback will be meticulously documented. This allows other researchers to trace the decision-making process and understand how the themes and conclusions were derived.

Chapter 6 Findings and Discussion

This chapter analyzes interview data from 51 K–12 teachers and administrators to explore what influences their attitudes toward, and usage of, AI in their work. Guided by the CR framework, the analysis is structured in three steps: (1) identifying demi-regularities—recurring patterns or "tendencies" in how participants discuss AI; (2) using abduction to interpret these patterns through existing theoretical models (such as technology acceptance theories and sociology of professions concepts); and (3) retroduction to infer underlying mechanisms that best explain the observed attitudes and behaviors. The goal is to not only describe common factors shaping AI attitudes, but also to examine whether conventional technology adoption models adequately explain this context or if additional professional and ethical considerations are at play.

Participant Demographics and Overall Attitudes

A total of 51 K–12 educators (teachers and administrators) were interviewed. The sample included 36 teachers (71%) from elementary, middle, and high schools, and 15 school leaders (29%) such as principals or district administrators. Teaching subjects ranged across English/language arts, mathematics, social studies, science, world languages, and special education/resource roles. Participants' years of experience spanned from first-year teachers to retired veterans with 35+ years in education. They represented both well-resourced suburban schools and high-poverty schools (including Title I institutions), providing a diverse context for perspectives on AI in education.

Table 3 summarized the participant characteristics.

Category	Subgroup	N
Role	Teachers (K–12 classroom and support)	34
	Administrators (superintendents, principals, etc.)	17
School Level (teachers)	Elementary (K–5)	12
	Middle (6–8)	11
	High (9–12)	7
	Multiple	4
Admin Level (administrators)	Superintendent & Assistant superintendents	3
	School board member	1
	Principles & Assistant principles	10
	Department chair	1
	Executive director	1
	Administrator at Department of Education	1
Subject Area (teachers)	English Language Arts	4
	Art	2
	Computer	2
	Math	6
	Science	2
	Social Studies	3
	World Languages	1
	Special Education/	6
	School psychologist	2
	Multiple Subjects	8
Years of Experience	0–5 years	10
	6–15 years	8
	16+ years	30
Age	< 40 years old	19
	40–60 years old	21
	>60 years old	11

Ethnicity	Asian or Asian American	3
	Black or African American	2
	Hispanic or Latinx	1
	Mixed	3
	White or Caucasian	42
Highest education level	Bachelor degree	10
	Graduate degree	41
Employment status	Employed full time (40 or more hours per week)	37
	Employed part time (up to 39 hours per week)	3
	Retired	9
	Self-employed	2
Political affiliation	Democrat	28
	Independent or no affiliation	18
	Other	4
	Republican	1
Gender	Female	30
	Male	19
	Non-binary / third gender	2
Marital statue	Divorced (including living common law)	4
	Married (and not separated)	28
	Single (including living common law)	17
	Widowed (including living common law)	2
Children	No	25
	Yes	26

Table 3. Participant Demographics (N=51).

Interviewees were asked about their general stance on using AI in their professional roles. Overall attitudes ranged from enthusiastic pro-AI to cautionary or anti-AI, with many falling in a neutral or mixed middle ground. When pressed to self-identify, a plurality of participants described their stance as "neutral," often expressing both an openness to AI's benefits and reservations about its risks. A substantial minority were strongly positive about AI, while a smaller group voiced predominantly negative views. Table 4 shows the distribution of stated attitudes.

Attitude Orientation	Number of Participants (% of 51)	
	Teachers (% of 34)	Administrators (% of 17)
Pro-AI (generally favorable)	10 (29%)	8 (47%)
Neutral or Ambivalent	19 (56%)	8 (47%)
Anti-AI (generally skeptical)	5 (15%)	1 (6%)

Table 4. Distribution of Attitudes toward AI.

Identifying Demi-Regularities in AI Attitudes and Use

In reviewing all 51 transcripts, several demi-regularities emerged regarding influences on educators' attitudes toward AI and their actual use of AI tools. Broadly, these influences can be grouped into: perceived benefits; perceived drawbacks; the importance of the "human element" and professional role; the need for support, training, and policy guidance; and social-organizational context factors. This study also notes where teachers and administrators share similar concerns or diverge in perspective.

Perceived Benefits: Efficiency and Instructional Support

A prominent theme was the potential for AI to enhance efficiency and assist with routine or labor-intensive tasks. Many educators, especially those who had experimented with AI, recognized that certain AI tools could save them time or generate useful ideas for teaching. For example, some teachers found AI helpful for lesson planning or creating instructional materials. One teacher described being "open to using it to get ideas on how to best teach to students' needs," such as asking an AI for strategies to support a student with dyslexia (Transcript 51). Notably, finding AI tools useful did not necessarily mean this teacher was fully pro-AI. In fact, this teacher described themselves as "neutral on AI"—neither strongly for nor against it—but saw value in using AI to generate ideas and access information, as long as it was used thoughtfully:

> *"I definitely think that there is room to use AI in the right ways… kind of just like using it to generate ideas, get information, but then using your own thinking and reasoning skills… not just always falling back on it"* (Transcript 51).

Similarly, another educator felt that whether one likes AI or not is almost beside the point, because

> *"it's here, and it's not going away." This participant explained, "If I were in the classroom, I would definitely be using it because it's an amazing tool and it's here… I guess that makes me pro, or at least accepting of it"* (Transcript 6).

Such comments underscore a pragmatic recognition that AI can be an "amazing tool" for certain tasks—a source of new ideas, saved time, or improved productivity—aligning with a belief that AI enhances job performance.

Administrators also noted efficiency benefits, particularly for their administrative or leadership tasks. One high school principal described using an AI writing assistant to polish mass emails to parents. They recounted drafting a message about a student game and then letting AI "clean it up," fixing grammar and tone: *"I had written a very quick email and I was like, this sounds terrible. So I just throw it in [the AI]… and then it just cleans it up… it just saves me time"* (Transcript 7). By using AI to refine the communication, the principal felt the end result was more professional: *"I want it to sound a little polished… So I sound a little more thoughtful than if I wrote a really quick email"* (Transcript 7). This administrator did muse humorously, *"Am I cheating? I guess I am a little bit… I write the thing first and then ask it to clean it up,"* but ultimately concluded that using AI for routine communication was acceptable and helpful (Transcript 7). They mentioned colleagues who use AI *"to help generate ideas for speeches"* or other leadership tasks, indicating that some school leaders see AI as a valuable assistant for creative brainstorming or editing in their workflow (Transcript 7). Notably, the same principal encouraged teachers' use of AI for lesson planning and idea generation, observing that *"more and more conversations [are happening] with teachers around how they're using AI to plan lessons or activities"* (Transcript 7). In their view, having AI suggest creative lesson ideas or analyze content (like artwork or primary sources) was *"all good… teachers don't own their lesson plans, so I think using it in those ways is really good"* (Transcript 7). This reflects an emerging demi-regularity: when educators perceive AI as genuinely useful for enhancing their work or saving them effort, their attitude tends to be positive or at least open. The perceived usefulness ranges

from instructional differentiation (e.g. simplifying reading materials to a lower grade level for a struggling student—a task one teacher accomplished by having AI rewrite texts at a 4th-grade reading level, which they described as *"great because [the student] was able to access the curriculum"* (Transcript 15)) to administrative efficiency (e.g. quicker, well-phrased parent communications, as in Transcript 7). In the language of technology adoption, many educators are looking for a clear relative advantage or performance gain from AI. When they find it, they become more favorable toward using the technology.

Perceived Drawbacks: Student Learning, Cheating, and "Doing the Work"

Balanced against the potential benefits, nearly all educators voiced significant concerns—especially about AI's impact on student learning and academic honesty. A strong demi-regularity is that teachers worry AI may encourage student cheating and shortcut-taking, thereby undermining learning. Multiple teachers reported instances of students using tools like ChatGPT to generate essays or answers instead of doing their own work. *"I've seen it a lot,"* said one high school English teacher about students turning in AI-written essays. *"Anytime I come across it, it's always students… 'I don't want to do this assignment, so I'm going to have ChatGPT do it for me.'"* (Transcript 1). This teacher estimated that in a major writing assignment, roughly *"three to five students"* per class of 30 had attempted to use AI to write their papers (Transcript 1). Far from saving the teacher time, this behavior created *new burdens*: *"I have to be vigilant… go back into their Google Doc revision history, see if they copy-pasted. There are so many more steps I have to take to verify did this student write this or not?"* (Transcript

1). In this case, AI's presence in the classroom was seen as adding work (detecting misconduct) rather than reducing it. The same teacher summarized their experience: at present,

> *"AI is not helping the students to learn the things they're supposed to learn, for example, essay writing or critical thinking, but [instead] causes more chances of cheating and academic dishonesty… [It] doesn't help me save time… it costs me a lot of trouble… having to take extra time to either learn the AI tools or to identify students' ethical use"* (Transcript 1).

This negative appraisal—that current AI tools offer little instructional benefit *"for any of my students… right now"* but do pose challenges to academic integrity—was echoed by several educators who consequently felt lukewarm or even opposed to classroom integration of AI (Transcript 1).

In addition to cheating, teachers worried that over-reliance on AI by students would stunt important skill development. As one teacher put it, *"I'm worried it will take away opportunities for people to develop skills"* (Transcript 6). This concern applied "mostly [to] students," in that if students can simply ask AI for answers, they might bypass learning core research and thinking skills (Transcript 6). *"Students need to learn how to research… learning how to do that with AI is really different,"* the teacher elaborated, adding that if educators aren't careful, students might *"just rely on the AI"* and *"learn really little because they just rely on the AI"* (Transcript 6). Several teachers argued that schools must *adapt assignments and expectations* in response—essentially to *outsmart the shortcut*. For instance, one teacher advocated shifting away from traditional

take-home essays toward more in-class writing and authentic tasks that AI can't easily do. They suggested incorporating more creative, project-based assessments:

> *"We need to change our expectations… If we keep looking for the same products we've always looked for, students aren't going to be learning, because now they can get us those same products [from AI] without a lot of their own intellectual input"* (Transcript 6).

This teacher imagined alternatives like performances or art-infused projects: *"Have them perform a play that demonstrates their understanding… they can use AI to help write the play, but AI can't do the play"* (Transcript 6). Such adaptive strategies indicate that *educators feel a responsibility to ensure students still engage their "own intellectual capacities"* despite AI's capabilities (Transcript 6).

Administrators are cognizant of these issues as well. One principal noted that their school had implemented an academic integrity policy treating AI-generated work *"the same as plagiarism"*—with graded penalties and parent conferences for violations (Transcript 7). They acknowledged the arms race aspect: *"We have a few different programs… AI detectors… and they're not accurate. But often you can tell"* by a sudden change in a student's writing voice or by checking the document's revision timestamps (Transcript 7). Ultimately, teachers and administrators alike expressed that uncritical use of AI by students is viewed very negatively, as it conflicts with educational goals and even creates new supervisory burdens. This greatly colors their attitudes: educators who see rampant misuse tend to be more *cautious, critical, or resistant* toward AI integration in the classroom.

Another drawback frequently mentioned was the fear that AI might encourage teachers themselves to abdicate effort or craftsmanship in their teaching practice. Some participants grappled with the idea of using AI for core teaching tasks like grading, lesson planning, or giving feedback—tasks traditionally considered part of a teacher's professional labor. On one hand, a few saw a tantalizing opportunity to reduce unpaid overtime. As one interviewee acknowledged,

> *"a lot of teachers are spending [an] extreme amount of hours doing… grading [and] planning… during times they're not paid. It could be a little bit more ethical, let's say, to [use AI to] scan a lot of student essays… then we can just double check certain things… it could save a lot of teachers a lot of time. That way they're a lot less burned out, they have more energy to spend in class, and… better mental health"* (Transcript 41).

However, even this individual—who understood the potential benefit of AI-assisted grading—was deeply uneasy with the idea. When asked if letting AI grade or comment on student work might *"violate your autonomy… replace your own labor or decision-making"*, the teacher admitted that *"I personally am not a huge fan"* of using AI in that way (Transcript 41). They explained that *"with reading the essays, you really get to know your students… AI doesn't know your students like you do"* (Transcript 41). The educator gave concrete examples: a human teacher can see the thought process in a student's work, catch a misconception or a near-miss, and respond with personalized guidance.

> *"For example, you could see a student make a mistake and say, 'I know exactly where they were going with this… now I can talk to them and we can fix this.'… I*

> *feel like part of the role of being a teacher is to really put in that effort to get to know your students, and using AI just doesn't really allow you to do that on the same level"* (Transcript 41).

Because of this, the teacher concluded, *"I'm very anti-AI, especially within education… I recognize [I'm] biased."* (Transcript 41). This quote exemplifies a broad sentiment: educators fear that over-using AI in teaching tasks could lead to a loss of the deep understanding and personal connection that comes from a teacher's direct effort. It's not simply a fear of "losing one's job" mechanically; rather, it's a concern that outsourcing the intellectual and relational labor of teaching to a machine would dilute the quality of education.

Administrators voiced similar qualms about AI taking over core teaching functions. A veteran school leader mused about a hypothetical scenario where teachers rely on AI to grade work or provide feedback:

> *"If that were possible… the AI doing the teacher's work… the role of teaching… may be more of a facilitation. Maybe the role of a teacher needs to change as AI comes along. Because I just think if teachers are going to be able to count on AI to do so much of the teacher's role, where does the teacher fit in?"* (Transcript 27).

This rhetorical question—*"where does the teacher fit in?"*—captures a deep uncertainty about the future of the profession if AI encroaches too far. The same administrator worried that such changes could

> *"… negatively impact the relationship between the teacher and the student… If students don't need to count on the teacher's take on something… or the creativity that a teacher can offer, we… as a society are going to lose… our counting on each other"* (Transcript 27).

They emphasized that empathy and human interaction are irreplaceable: *"If we're counting on AI to explain life to us… I don't see how empathy can be there… It's an easy way to understand things, but I don't think it'll be the full understanding"* (Transcript 27). Here again, the drawback is framed not just as an individual job threat, but as a societal loss of human connection and understanding if AI were to mediate too much of the teaching-learning process. In summary, a demi-regularity in the data is that even when educators acknowledge AI's possible benefits, many are wary of its drawbacks: encouraging academic dishonesty, impeding skill development, and potentially deskilling the teaching profession or eroding the human touch in education. These perceived drawbacks strongly influence attitudes—often tipping teachers toward a more skeptical or "wait and see" stance on AI use in K–12 settings.

The Human Element and Professional Identity

One of the most striking cross-cutting themes is the emphasis on the "human element" in teaching and how indispensable it is perceived to be. Teachers and administrators frequently invoked the idea that teaching is fundamentally a human, relational practice, and they doubted AI could ever replicate that quality. This is closely tied to educators' sense of professional identity and values—the belief that their role is not just to deliver content, but to connect with, believe in, and inspire students in a way

technology cannot. For instance, an experienced teacher explicitly addressed colleagues' fears about AI "replacing" teachers. *"I know a lot of teachers are afraid… that AI is going to, if not replace teachers, alter their value or alter their role,"* this teacher said. *"I don't believe that for one second. I don't."* (Transcript 21). When asked why, they passionately elaborated that AI will never be able to truly *know* students as individuals the way a teacher does. Drawing from decades of experience, they gave a powerful example:

> *"I can go into my drawer of all my fourth graders' writing from 1975, and without looking at the names, I can hear that voice… I know the voice of each one of these writers. I just don't think a machine is going to [recognize] that"* (Transcript 21).

For this teacher, every student's writing had a unique fingerprint that a caring teacher learns to recognize and nurture. More broadly, they argued that a teacher's belief in a student is irreplaceable:

> *"When I was talking about identity, connectedness, confidence, and engagement—the piece that has to be part of that is somebody believing in you. The key thing is a teacher believing in each kid… in a very individual and personal way… I don't see AI fulfilling that role… the personal belief system that happens between a teacher and a kid"* (Transcript 21).

They summed up that

> *"you've got to have, as a teacher, [to] demonstrate that you believe in each kid… that the kid knows it… I don't think AI is going to carry that vibe. No… Good*

> *teachers… believe in every kid in front of them… Can AI do that? I don't think so"* (Transcript 21).

This heartfelt testimony demonstrated how educators see their work as fundamentally relational and moral—about caring, believing in students, and shaping their identity and confidence. The "vibe" or emotional support a teacher provides is something these educators insist technology cannot replicate. This belief greatly influences their attitudes: those who prioritize the relational dimension of teaching tend to view AI as at best a limited supplement and at worst a threat to the teacher-student bond.

Younger or less experienced teachers also echoed the importance of the human element. One teacher worried that if schools "over-rely" on AI,

> *"it takes the human element out of it. Every single teacher in my life that I've had… has been a unique person… whether [their style was] good or bad, I learned a ton because of the way they did things… If everyone is just doing the exact same thing [relying on the same AI outputs], I don't like the sound of that"* (Transcript 12).

This comment suggests a fear that AI could homogenize teaching, stripping away the personal creativity and quirks that make each teacher's approach distinctive and impactful. The phrase *"the human element"* recurred in several interviews, underscoring a shared conviction that learning experiences need human variety, empathy, and presence.

Administrators likewise valued the human touch. One retired superintendent noted, *"the more AI would be used by a teacher, the more chance there is it might*

negatively impact the relationship… It's an easy way to get information, but… I don't see how empathy can be there" (Transcript 27). Thus, across roles, educators' professional self-concept—as creative experts, mentors, and supporters of children—forms a lens through which AI is evaluated. When AI is perceived to encroach on these core professional values (like caring for students or exercising creative judgment), educators' attitudes skew negative. Conversely, if AI can be kept in a subordinate role—a tool that frees up teachers to do more of the human-centered work—then it is viewed more favorably. Indeed, one way some teachers reconciled AI use was by positioning it firmly as a tool under teacher control. For example, a teacher who used AI to simplify texts for English learners emphasized that he used it to better support the student, not to replace their own interaction: the student *"was able to access the curriculum"* thanks to AI, but it was still the teacher's responsibility to ensure comprehension and engagement:

> *"So I would take a PDF or I would take a document that I was having my students read and I would put it into AI and have it rewrite it at the fourth-grade reading level. And that was great because he was able to access the curriculum and he was able to get the topics... I never just give him a document that's totally AI. It usually ends up being 80% with 20% teacher editing. So I'll check the word, check the facts, check everything"* (Transcript 15).

In sum, a demi-regularity is that educators' attitudes are profoundly shaped by whether AI is seen as aligning with or undermining the core identity of a teacher as a caring, autonomous professional. This is a nuanced influence that goes beyond simple cost-

benefit calculations—it touches on pride in craftsmanship, ethical duty, and personal connection.

Need for Training, Support, and Clear Guidelines

Another recurring influence on attitudes was the availability (or absence) of support, training, and policy guidance regarding AI. Many teachers expressed that their comfort with using AI, or willingness to try it, depended on having proper professional development and clarity on how to integrate AI effectively. Without guidance, some felt "lost" or even resistant. One teacher reflected on how new technologies are often introduced in schools:

> *"There's always something every year… like, 'oh, you should use this, it's really great.' And I almost feel like, okay, well, if it's really great, shouldn't we talk about it and explain it? Not just, like, 'oh, use it.'… If it has something to do with technology, [I'll get] very lost. So I'm like, baby-step me through it, please… A lot of times people are just like, 'oh, you'll just figure it out,' [and I get] turned off by that"* (Transcript 12).

This honest admission reveals that lack of structured training or mentorship can breed frustration and reluctance. For teachers who are not already tech-savvy, being told simply to adopt AI without scaffolded learning feels overwhelming. The quote *"baby-step me through it"* (Transcript 12) poignantly captures the need for incremental, practical training. Another teacher similarly stated that to feel comfortable using AI, they would want *"some basic training and then a chance to experiment and learn from other teachers who are also experimenting… kind of learn through experience"* (Transcript 6).

This suggests that educators value not only formal training sessions but also informal peer learning communities around AI. Indeed, the social aspect of learning—seeing colleagues try AI, sharing use cases, and troubleshooting together—was mentioned as a support mechanism. For example, *"learn from other teachers who are also experimenting [with AI]"* (Transcript 6) and hearing from *"colleagues who use it a lot"* (Transcript 7) both came up as ways to build confidence.

From the administrative side, it appears that as of these interviews, most schools had not yet provided extensive training or guidelines for teachers' use of AI—a gap that influenced teachers' attitudes. One school leader noted,

> *"No, there aren't [any policies regulating teachers' AI use]. And again, like I said, I think I'm seeing more and more conversations with teachers around how they're using AI to plan lessons or to plan activities that are interesting... But, yeah, we don't have any regulation on it right now"* (Transcript 7).

While this lack of restriction could be seen as granting teachers autonomy to explore, it also meant that teachers desiring guidance might feel on their own. The same administrator observed that some teachers were indeed taking initiative to use AI for lesson planning: *"Teachers use it for all kinds of things. Teachers use it to help them lesson plan or do creative activities... So I think our teachers have taken it, are doing two things right"* (Transcript 7). However, it is implied that this was due to their own resourcefulness rather than a coordinated school effort.

In terms of policies, the focus had been on student use (as discussed earlier, treating AI plagiarism like any other cheating). When asked about regulating teachers'

use, the principal responded,

> *"No, there aren't [policies]. And again, like I said, I think I'm seeing more and more conversations with teachers around how they're using AI… I think that's all good… using it in those ways is really good… we don't have any regulation on it right now"* (Transcript 7).

This laissez-faire stance indicates that at the time, administrators were in an exploratory phase themselves. They were generally encouraging positive uses and watching what emerged. However, from a teacher's perspective, this might translate into uncertainty: Am I allowed to use AI for X? How should I properly use it? One teacher asked a pertinent question during their interview: *"What kind of training support do teachers and staff need to effectively use AI tools in the classroom?"* and answered it by emphasizing a two-stage need: *"first the teachers need to be trained on how to use AI… that's the absolute first part. And the second part is understanding how to teach it [to students]"* (Transcript 25). They even reflected on how introducing students to AI might require a "new paradigm" of gradual release, implying that teachers themselves need a well-thought-out pedagogy for AI, which they currently lack:

> *"I'm not exactly sure what that looks like with AI because I don't want them to just jump straight across that learning curve... teachers would have to come up with like sort of a new paradigm for how to introduce these AI tools so that they're supporting the students in those sort of different phases"* (Transcript 25).

This underscores that educators feel a need for both technical training (how AI works, how to operate the tools) and pedagogical guidance (how to integrate AI into teaching in

a responsible, effective way). In environments where such support is lacking, many teachers adopt a cautious or minimal-use approach by default.

Social and Organizational Influences

Finally, educators' attitudes do not form in isolation—they are influenced by social and organizational context. Several transcripts indicate that peer influence and leadership stance can sway how AI is perceived. For instance, a principal mentioned hearing other principals talk about how frequently they used AI, they began to feel that they might not be taking full advantage of its potential (Transcript 7). In their case, knowing that colleagues were finding value in AI encouraged them to experiment a bit more (though they still used it sparingly, as they enjoyed writing themself):

> *"I have colleagues who use it a lot more than I do... when I talk to other principals, I'm like, oh, yeah, I use AI all the time. So I use it sometimes, but I wouldn't say I use it very much... I guess if I knew other ways I could use it in my position, I wouldn't be opposed to that. I just don't know of any"* (Transcript 7).

Among teachers, there were examples of collaboration and shared learning: one teacher suggested *"experimenting and learning from other teachers"* as a comfort-builder (Transcript 6): *"I think like with any technology, sort of some basic training and then a chance to experiment and learn from other teachers who are also experimenting and, yeah, kind of learn through experience"* (Transcript 6). The same teacher also described how a PhD student's presentation to their class helped them frame AI as a "research assistant," which eased their discomfort with using AI for tasks such as drafting emails or analyzing data:

> *"We had a PhD student present to our class recently that really helped me with this... She was talking about using it for research and data analysis... and she just said, you just have to think of it like a research assistant. Like, you know, there's nothing wrong with having a research assistant, but it's still on you to make sure the research is valid"* (Transcript 6).

Another kindergarten teacher described a collaborative approach to using AI, explaining, *"We gather together to discuss plans. We'll check out the AI and discuss whether the ideas it gave us worked. I see AI as a collaborator in that setting"* (Transcript 24). This indicates that when educators are exposed to positive norms or success stories about AI use from trusted peers or experts, they become more open to it. Conversely, if their immediate colleagues are skeptical or if the school culture is cautious, individuals may mirror that stance.

Organizational leadership also plays a role. In some transcripts, teachers mention district or school policies as important. For example, one teacher alluded to the numerous "new things" that get pushed every year (Transcript 12), implying perhaps some fatigue or skepticism toward top-down initiatives, including possibly AI. If AI is seen as another fad being foisted on teachers without support, attitudes sour. Administrators themselves are aware of this; as one said, *"there's always something… they encourage us, 'use it, it's great'… I guess I'm used to [needing clear instructions or else] I get lost"* (Transcript 12). Therefore, the way AI is introduced by leadership, whether through collaborative dialogue and training or by simple edict, can significantly influence teacher receptivity.

Another environmental factor is the broader educational climate and media narrative. A few educators noted that AI is *"out of the box and not going back in"* (Transcript 15), reflecting a broader awareness that this technology is a societal shift, not a passing trend. Some expressed a sense of inevitability that *"people are going to use it"* and thus education must adapt (Transcript 51). This recognition sometimes made teachers *more* receptive to learning about AI (to guide students responsibly in its use), but in other cases it simply added to their anxiety. One teacher pragmatically noted, *"I'm not against it because I think it's unavoidable at this point. So I think teaching students the best ways to use it is important"* (Transcript 51). In that case, an external reality that AI is ubiquitous in society pushes the teacher toward a middle-ground attitude: neither celebration nor rejection, but a resolve to educate students about AI.

In contrast, some teachers held off on embracing AI because they hadn't yet *"seen evidence that it's super useful"* in K–12 learning:

> *"I think at this point I don't see a lot of evidence that it's super useful. I do think that teachers and policymakers should continue to keep their eyes on it and see how it develops, but at this point, I don't see it as being something that we need big legislative pushes for or anything like that"* (Transcript 1).

This suggests that if/when concrete success examples become visible, for example, a neighboring school implements an AI tutor program with great results, such observability could influence attitudes. At the time of these interviews, the evidence base was still forming, so cautious teachers often said they would *"keep an eye on it as it develops"* (Transcript 1) but weren't ready to actively champion AI in the classroom.

Differences Between Teachers and Administrators

To address the question of whether administrators' attitudes and usage are influenced by the same factors or different ones, the data shows considerable overlap in core concerns, with some differences in emphasis. Both teachers and administrators are influenced by perceived usefulness, ethical considerations, and professional values. Both worry about student misuse and the importance of human relationships. However, administrators tend to view AI through the lens of organizational impact and policy, whereas teachers focus on day-to-day instructional impact and personal teaching practice. For example, administrators discussed the importance of establishing consistent rules and considering how AI might fit into the broader structure of teaching and learning. One administrator explained, *"So we've created a clear AI plagiarism policy. We have some tools that our teachers use that can find AI-generated work... it's progressive discipline. And it's the same for AI, it is listed under that as well"* (Transcript 27). The same administrator shared reflections on leadership and change management:

> *"My superintendent and my assistant superintendent, I took time, we debriefed it. We talked about what we should have done differently. And so any other change that we've made since then has gone better than that... If you want to make things better all the time, then you have to make sure that they're sustainable and that they make sense to everybody"* (Transcript 27).

Administrators were also concerned with supporting their staff. One principal, although not using AI extensively themself, paid close attention to how their teachers were using it and ensured that experimentation was not discouraged:

> *"No, there aren't. And again, like I said, I think I'm seeing more and more conversations with teachers around how they're using AI to plan lessons or to plan activities... So I think our teachers have taken it, are doing two things right... But, yeah, we don't have any regulation on it right now"* (Transcript 7).

They added,

> *"I have colleagues who use it a lot more than I do... when I talk to other principals, I'm like, oh, yeah, I use AI all the time. So I use it sometimes, but I wouldn't say I use it very much... I guess if I knew other ways I could use it in my position, I wouldn't be opposed to that. I just don't know of any"* (Transcript 7).

In contrast, teachers spoke more about how AI affects their individual classroom, their students, and their own workload. Teachers voiced more personal anxieties. For example, one teacher said,

> *"I would really need to see how somebody else used it before I would feel comfortable using it myself... Baby step me through it, please. And a lot of times, I think that people are just like, 'Oh, you'll just figure it out.' I'm turned off by that… If there was something where you could actually, like, take the time and somebody could walk you through the steps again, like, really, like, hold my hand, baby step me through it, I'd be all about that"* (Transcript 12)

Another expressed their worries:

> *"I worry that people with slim budgets are just gonna, you know, make larger class sizes where it's harder for teachers to do the work that they do. And then these, like, brilliant AI programs are gonna be used or put in there as if they*

could actually make up for that change. And I think they cannot" (Transcript 6).

The same teachers added:

> *"I'm worried that it will, like, take away opportunities for people to develop skills... Students aren't going to be learning because now they can get us those same products without a lot of their own intellectual input"* (Transcript 6).

Administrators, often having a bit more distance from the classroom, sometimes had a slightly more positive or exploratory tone about AI. This may be because they themselves were using it for administrative tasks effectively. For instance, an administrator may say

> "*I use it to help write emails or to, I'm not going to lie, I use it to help me polish my speeches. When I write a speech, I say, you know, make this cleaner, make it shorter. It's a great editing tool. It saves me time"* (Transcript 7),

whereas a teacher might say

> *"On the student side, I've run into a lot of students trying to use AI to avoid writing for themselves. They're not using it in a way that is helpful to them, really. They're not getting any of the critical thinking skills... they're just sort of, 'I don't want to do this assignment, so I'm going to have ChatGPT do it for me"* (Transcript 1).

That said, both groups ultimately converge on the idea that AI should *support, not replace* the human educator. No administrator in these interviews advocated replacing teachers with AI; rather, they shared teachers' reservations about maintaining relationships and creativity. If anything, administrators might be more poised to consider

structural changes (like rethinking the teacher's role or curriculum design in the age of AI), while teachers are more focused on immediate tactics (like altering assignments or teaching students how to use AI properly). But the fundamental influences—usefulness, ease of use, support, ethical fit, and professional norms—appear to be common, with differences in how they manifest given the person's role.

In summary, the demi-regularities identified include: (a) the allure of AI's usefulness for saving time and enhancing teaching (tempered by the need to ensure real pedagogical value); (b) significant concerns about negative impacts on student learning and integrity; (c) a strong attachment to the humanistic and moral dimensions of teaching that educators feel must be protected; (d) the importance of training, support, and clear policies in shaping comfort with AI; and (e) social/organizational context factors (peer usage, leadership approach, broader trends) that influence attitudes. These patterns set the stage for interpreting the findings with theoretical insight.

Abduction: Theoretical Interpretation of Findings

In the abductive step, this study related the above empirical patterns to existing theories and models, both to see how well these frameworks explain the data and to identify needed modifications or extensions. The analysis is initially guided by several prominent functionalist technology adoption models—TAM, UTAUT, DOI, and TOE—as these have commonly been used to explain educators' adoption of new technologies. I then consider concepts from the sociology of professions (professional autonomy, professional identity, ethical jurisdiction, and moral authority) to capture elements of

teacher and administrator attitudes that go beyond what the functionalist models typically encompass.

Insights from Technology Adoption Models

The findings show several points of alignment with classic technology acceptance factors. TAM, for instance, posits that two key beliefs—perceived usefulness and perceived ease of use—shape an individual's attitude toward using a technology and their intention to use it. In the data, perceived usefulness (PU) clearly plays a pivotal role. Educators who found concrete, job-enhancing uses for AI (e.g. saving time on emails or getting lesson ideas) developed more positive attitudes and in some cases routinized the use of AI (Transcripts 7, 51, 15). Several statements illustrated how AI enhanced their job performance. One teacher shared,

> *"I use it to help write emails or … polish my speeches. When I write a speech, I say, you know, make this cleaner, make it shorter. It's a great editing tool. [...] And it just saves me time"* (Transcript 7).

Another explained,

> *"I definitely found it helpful, especially because this school year I've been working with kids that I hadn't worked with grade-level-wise before... AI was able to give me just that extra support of just generating different ideas of what I could do... AI kind of just gives you that little extra ideas that others just haven't come up with before."* (Transcript 51)

These examples reflect the TAM definition of perceived usefulness (the degree to which using the system is believed to improve job outcomes). Conversely, when the perceived

usefulness was low or negative, as with teachers who said AI offers *"no evidence it's useful"* for learning or that it actually added to their burden, their attitude was correspondingly negative (Transcript 1). This aligns with TAM's prediction: if a teacher does not perceive meaningful benefits from AI, they will likely not favor using it.

Perceived ease of use (PEOU) also emerged, though less prominently. Several educators implicitly touched on ease or difficulty. For example, the teacher who needed "baby steps" and was easily "lost" with new tech (Transcript 12) illustrates that if AI tools are seen as complicated or if adequate instruction is absent, perceived ease-of-use is low, which discourages adoption. Another teacher's comment that *"with any technology, [we need] some basic training and then a chance to experiment"* (Transcript 6) underscores the importance of effort expectancy (in UTAUT terms) or ease of use. Teachers want to minimize the effort and uncertainty involved in learning a new tool, suggesting that without proper training and a user-friendly experience, their attitudes toward the technology may decline. In TAM, a technology that is not "free from effort" to use will not be positively embraced (Davis, 1989). This dynamic was evident; one educator noted being "turned off" when told to just figure a tool out (Transcript 12), implying the effort required was a deterrent:

> *"If there was something where you could actually, like, take the time and somebody could walk you through the steps again, like, really, like, hold my hand, baby step me through it, I'd be all about that... A lot of the times I feel like when we get professional development, they're just like, 'Oh, this thing's amazing here.' And we're like, 'Alright, how do you start?' And they're just like, 'We'll figure it*

> *out.' And I'm like, no. For somebody that's not tech savvy, it's the worst thing in the world. I'm turned off by that"* (Transcript 12).

On the other hand, an AI tool that functioned simply and effectively (like copying text into a prompt to simplify it, which one teacher did) likely was seen as easy enough, and thus more readily adopted, as noted earlier by Transcript 15 (p. 150).

UTAUT, an evolution of TAM, brings in additional factors—performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Performance expectancy in UTAUT is analogous to perceived usefulness, which as noted strongly appears in the data. Social influence—the degree to which individuals are influenced by others' opinions about the technology—can be seen in how some educators referenced colleagues and experts. For instance, the principal who heard other principals touting AI's usefulness (Transcript 7) or the teacher who learned from a PhD student presenter (Transcript 6) both demonstrate that peers and respected figures can shape one's attitude. If colleagues are enthusiastic and show success, a teacher might feel more pressure or motivation to try the tool. Conversely, if a school's teacher community is wary of AI, perhaps sharing horror stories of cheating, that social norm could reinforce individual reluctance. The interviews provided examples of positive social influence, such as collegial conversations that generated new ideas, rather than explicit negative peer pressure, although it is reasonable to expect that both can occur. Facilitating conditions in UTAUT, referring to the degree to which technical and organizational resources support use, are reflected in educators' calls for training and administrative support. Teachers explicitly asked for training and guidelines (Transcripts

6, 25), which are facilitating conditions that would enable use. The absence of formal guidelines (Transcript 7, where no policy exists for teacher AI use) places the onus on individual teachers to navigate AI's challenges, potentially hindering adoption for some. In short, UTAUT's multi-factor lens maps well onto this study's findings: performance expectancy/usefulness is a major driver (or inhibitor), effort expectancy/ease matters especially for less tech-confident teachers, social influence is present in the form of peer examples and leadership signals, and facilitating conditions (training, tools, policies) are either an enabler when present or a barrier when absent.

From a DOI perspective (Rogers, 2003), several attributes influencing adoption emerge clearly from the data, including relative advantage, compatibility, complexity, and observability. Relative advantage aligns closely with the TAM concept of usefulness. When teachers perceive that AI provides tangible benefits, such as quicker grading or more tailored instructional materials, they become more inclined to adopt it; conversely, without perceiving clear benefits, their motivation declines. Compatibility, referring to how well the innovation aligns with teachers' values, needs, and current practices, is particularly important for interpreting certain underlying forms of resistance observed in this study. Many teachers essentially argued that generative AI, as currently used (for cheating or automating human tasks), conflicts with their professional values and teaching philosophy. For example, a teacher who prides herself on intimately knowing each student's work (Transcript 21) finds the idea of AI-generated student work incompatible with the educational value they place on personal expression:

> *"I think if I'm expecting the student to write their own ideas and their own thoughts, they should get my own ideas and my own thoughts in feedback... If I want it to sound like me, it's going to come from me and I'm not going to use AI for that."*

Similarly, educators who value student struggle and skill-building see AI shortcuts as incompatible with learning goals, a concern expressed by Transcript 6 on page 159. Another teacher shared a similar perspective:

> *"On the student side, I've run into a lot of students trying to use AI to avoid writing for themselves. They're not using it in a way that is helpful to them, really. They're not getting any of the critical thinking skills... they're just sort of, 'I don't want to do this assignment, so I'm going to have ChatGPT do it for me"* (Transcripts 1).

On the flip side, one could argue AI was compatible with the needs of the teacher who had an English language learner reading at 4th-grade level—the AI tool fit neatly into their differentiation practice, earlier mentioned by Transcript 15 (p. 150). Compatibility also ties to the "human element" issue: teachers' ethos of personalized care is a value that AI must be compatible with (or at least not undermine) if it is to be embraced. Complexity, or perceived difficulty of use, was mentioned (those needing hand-holding or fearing tech)—when complexity is high, adoption lags. Trialability and observability also play roles: some teachers experimented in small ways (trialability) like using AI for one task (Transcript 15's text simplification started likely as a trial), and seeing outcomes. Observability refers to seeing results or others using the tech; we noted that

educators are watching each other and the broader discourse. However, in the data, direct evidence of AI improving student outcomes (observability of positive results) is still sparse, which might be slowing broader adoption. One teacher specifically said, *"I think [we should] keep our eyes on it and see how it develops"* and wasn't ready to push AI in low-income districts without evidence (Transcript 1). This attitude reflects a DOI mindset of waiting for more observable evidence of success before fully committing.

TOE framework provides a macro lens, highlighting that adoption is influenced by factors in three contexts: the technological (features and availability of AI tools), the organizational (internal support, culture, policies), and the environmental (external pressures like policy, competition, or societal trends; Tornatzky & Fleischer, 1990). This study's findings support this layered perspective. For the technological context, teachers commented on what current AI can or cannot do. For instance, one principle pointed out a technological limitation: *"We have some tools that our teachers use that can find AI-generated work... they're not accurate"* (Transcript 7). Another teacher noted AI's inability to understand students in the way a human can:

> *"The AI can't see my students, and so I know the needs of the group of students I have right now. The AI doesn't... AI is writing for a generic group of students that probably are at the same grade level and don't have different needs"* (Transcript 41).

Some educators expressed concerns about the quality and reliability of AI-generated outputs. For example, they described manually reviewing and editing AI-generated email drafts to ensure the tone and content aligned with their intent. One teacher explained, *"I*

never sent something without first reading it and making tweaks to it so that I felt like it sounded like me or was close enough, and it was what I wanted to say" (Transcript 6). Another added, *"I never just give him a document that's totally AI. It usually ends up being 80% with 20% teacher editing. So I'll check the word, check the facts, check everything"* (Transcript 7).

In terms of organizational context, school-level factors such as the presence of AI policies, principals' stances, the availability of training, and the overall culture of innovation among faculty all influenced attitudes. In one case, a school implemented a policy that treated AI use as plagiarism (Transcript 7), signaling that both students and potentially teachers are expected to approach AI carefully and uphold academic integrity. Regarding school culture, some educators described environments of either collaborative exploration or, alternatively, fear and confusion, which shaped how they personally responded.

In terms of environmental context, this includes broader educational mandates, district or state guidelines, parental expectations, and even media narratives about AI. A few participants touched on these. For example, one teacher mentioned policymakers, advising against any *"big legislative pushes"* for AI in classrooms until its value is proven:

> *"I think at this point I don't see a lot of evidence that it's super useful. I do think that teachers and policymakers should continue to keep their eyes on it and see how it develops, but at this point, I don't see it as being something that we need big legislative pushes for or anything like that"* (Transcript 1).

Another noted historical trends like No Child Left Behind, COVID-19, and the ubiquity of smartphones as part of a "perfect storm" changing education (Transcript 7), implicitly, AI could be seen as the next wave in that environment:

> *"I think that probably started with No Child Left Behind and it just built from that. Right. And that's where we are now. And then you had COVID and then you have phones and then you have all these things on top of it. It's almost like a perfect storm to really change what public education is facing."*

Additionally, the notion that *"this tool is out of the box and it's not going back in. So I think it's important that the world is different now"* (Transcript 15) indicates teachers feel an external pressure that the society is changing with AI, and schools must react. In summary, the TOE framework recognizes that teacher and administrator attitudes toward AI result from an interplay between the technology's attributes, the school's internal support structures, and the larger socio-educational environment. The findings support this view. For example, supportive school leadership combined with ample professional development at the organizational level can mitigate a teacher's personal hesitancy, while constant news about AI or directives from higher authorities at the environmental level can either encourage adoption or provoke pushback, depending on the alignment with professional values.

Overall, the functionalist models (TAM/UTAUT, DOI, TOE) do capture many core influences observed: utility, ease, peer influence, organizational facilitation, and external context all emerge as important. However, these models alone do not fully explain the depth of some teachers' resistance or ambivalence, especially when that

resistance stems not from a lack of utility or high effort per se (some resisters actually concede potential utility, as in Transcript 41 with time-saving, yet still oppose AI for deeper reasons). This suggests the need to extend my theoretical interpretation beyond generic adoption factors into the realm of teachers' professional norms and values. The sociology of professions offers constructs that help explain why certain perceived threats strongly shape attitudes here, perhaps even more so than in other technology adoption contexts.

Professional and Ethical Constructs: Beyond Functionalist Models

Teachers and administrators are not just technology users; they are members of a profession with a distinct ethos, responsibilities, and social contract. The interview data clearly show that professional constructs—autonomy, identity, ethical duty, and authority—are central to how these educators make sense of AI. These factors go "beyond" the typical scope of functionalist models, requiring a critical sociological lens.

Professional autonomy refers to educators' desire to exercise their own judgment and control in their work, without undue external interference (Abbott, 1988; Frostenson, 2015). In the context of AI, we saw concerns that adopting AI for certain tasks might undermine teacher autonomy or professional decision-making. For example, when asked whether using AI for grading or lesson planning might undermine their autonomy, one teacher agreed, saying they valued grading essays themselves because it gave them insights and a sense of control that delegating to AI would forfeit:

> *"Like anything else, when you send an email to someone, it has to have your tone and your voice in it... I don't know, it just doesn't ring true. I don't know why... So*

> *I think I would prefer to do it on my own. Maybe it's a sense of satisfaction... Like I've heard people say that they have these things create their quizzes, and I'm just like, seriously, you can't write your own quiz?... I'd rather write my own stuff... I like to put my own voice into stuff, you know, I like to do things that I'm excited about because I think that translates well to a student. I just think if it was all something that was done by a computer, it wouldn't have that personal touch to it"* (Transcript 41).

Similarly, the notion of yearly ed-tech initiatives being "pushed" on teachers (Transcript 12) touches on autonomy: teachers become wary if they feel a technology is being imposed without their input or without alignment to their professional judgment:

> *"There's always something every year that gets pushed on us is the wrong word. But, like, they encourage us. They're like, oh, you should use this. It's really great. And I almost feel like, okay, well, if it's really great, shouldn't we talk about it? And, like, explain it. Not just like, oh, use it. It's great... And a lot of times I think that people are just like, oh, you'll just figure it out. [I'm] turned off by them... Then it takes the human element out of it"* (Transcript 12).

Some teachers likely fear that AI tools could come packaged with administrative mandates or scripted usage that reduce their freedom to teach as they see best. Although none explicitly said *"I fear losing autonomy,"* the subtext is present in their defensive stance about keeping core tasks human (which is a way of protecting their domain of expertise). From the admin side, interestingly, there was a respect for teacher autonomy evident: *"we don't have a policy regulating teachers' use"* (Transcript 7), implying they

are leaving it to teacher judgment for now. This lack of policy can be interpreted positively (trusting teachers to decide how to use AI) or negatively (leadership hasn't given guidance). In any case, autonomy is a lens through which AI is evaluated: teachers want to remain the authors of their lesson plans, the evaluators of student work, and the drivers of how AI might be utilized, rather than ceding those prerogatives to an algorithm or a top-down decision.

Professional identity is the composite of beliefs and values that shape what it means to be a teacher or administrator. The findings indicate that many educators perceive an inherent tension between their professional identity and the use of AI in certain ways. Teachers often see themselves as mentors, motivators, role models, and experts in human development, roles that an AI cannot fulfill. When a teacher says *"part of the role of being a teacher is to put in that effort to get to know your students"* (Transcript 41) or *"you have to demonstrate that you believe in each kid"* (Transcript 21), they are articulating key aspects of teacher identity: dedication to students, personal engagement, and emotional labor. If using AI seems to diminish those aspects (for example, by automating tasks that the teacher feels are integral to knowing students or by reducing face-to-face interaction), then it clashes with their identity. This explains the visceral resistance some expressed that it's not just about efficiency, it's about *"this is not who I want to be as a teacher."* Conversely, some teachers incorporated AI into their identity in a way that supports their core mission. The teacher who used AI to differentiate texts for an English learner (Transcript 15) likely saw this as fulfilling their professional duty to reach every student—essentially extending their capacity, which

aligns with the identity of an inclusive educator. That positive integration is possible when the technology use is framed as enhancing one's professional practice, not detracting from it. The concept of moral authority also links here: traditionally, teachers hold authority in the classroom not just by position but by moral leadership, such as, guiding students in what is right, modeling learning behavior. Some educators worried that relying on AI could erode their moral authority. For instance, if a teacher uses AI to write student feedback or emails, would that be seen as less genuine or even "cheating" as one principal half-joked (Transcript 7)? That principal ultimately justified it (saving time on an email was not violating any moral duty in her view), but the fact they asked "Am I cheating?" shows awareness of a normative line:

> *"Yesterday I had an email that I needed to send out to all parents and students... and I had written a very quick email and I was like, this sounds terrible... I just throw it in [AI]. I say, 'AI, can you just clean this up? I'm a high school principal sending this note to parents and students'... It just cleans it up... saves me time... So am I cheating? I guess I am a little bit. I don't know. I don't think I am. I mean, it's an email. It's a communication. I don't know. Could somebody say, you AI generated that? I guess they could, yeah. But I mean, I write the thing first and then I ask it to clean it up and just make it a little more presentable"* (Transcript 7).

Teachers, as moral exemplars, hesitate to use AI in ways that might seem like they are not doing the work they expect of students (e.g. writing in one's own voice). Maintaining integrity and practicing what they preach about learning and effort is part of their

professional self-image. So, if using AI is seen as cutting corners, it may conflict with their sense of integrity or professionalism.

Ethical jurisdiction refers to the domain of ethical decision-making and responsibility that professionals claim (Abbott, 1988; Hordern, 2024). In the case of teaching, ensuring fairness, equity, and honesty in student learning is squarely in their jurisdiction. Teachers took very seriously the ethics of AI use. They expressed that allowing students to turn in AI-generated work unchallenged would be a "huge disservice" and even "dangerous" to students' development (Transcript 6). In other words, teachers feel it is their ethical responsibility to prevent misuse and to guide proper use of AI. This sense of duty influences their attitude that they might be more wary of AI because they foresee ethical pitfalls (plagiarism, bias, inequity between those who have access to AI and those who don't). Educators explicitly talked about equity, some noted that well-resourced vs. under-resourced schools might have differing access, and that until AI proves beneficial, pushing it could even widen gaps. For examples, one teacher said:

> *"I do think it's going to help the kids who are from the richer families more, just because I think they already know the foundation, if that makes sense. Like, they're not having to be pulled for Title I services, which is like small groups. They're not having to be pulled to learn their letters and their sounds because they know their letters and their sounds, and by default, they get to do more things than the other students who are struggling. And of course, there are poor kids that are the smartest in the class and vice versa, so. But as general, it just seems like*

> *those kids who don't have the support at home are the kids that are having to spend more time on the basics while the other kids who have those life experiences and who went to expensive preschools and their parents are, you know, they're not working third shift, they're able to sit down with them and teach them things at home. So I teach think it is more beneficial to those students"* (Transcript 6).

Another teacher agreed:

> *"I think it definitely can help the kids who are from the richer families more just because I think they already know the foundation, if that makes sense. Like they're not having to be pulled for Title I services, which is like small groups"* (Transcript 11).

However, a school principal held a different perspective:

> *"I think that it could help bridge the divide because it has a lot of, you know, it can do a lot, you know, but I think that those with more resources will be better positioned to know how to use it. [...] I mean, I just think like most resources, like those who already have a lot, tend to, you know, like take advantage of the resources that they have"* (Transcript 10).

The same person added:

> *"But it is, it can kind of, you know, I wouldn't say that that's a necessary outcome. I think it could kind of bridge the divide because now we have something that can, you know, I mean, it's very, it can like spit out things, but like you ask a question*

that can intelligent also, you know, it may not be fully reliable, but it can do quite a lot" (Transcript 10).

The study did see administrators focusing ethically on balancing innovation with caution. For example, not banning AI outright but enforcing honesty (plagiarism policy) and urging common-sense (the principal warning students about a dangerous water-gun game via an AI-polished email, Transcript 7, is a different context but shows the principal's sense of duty to communicate responsibly):

"I had an email that I needed to send out to all parents and students about—do you know this game that seniors play called Senior Assassin? So it's a silly game, but it can be very dangerous. So it's a thing that seniors do toward the end of school, and they have squirt guns, and they try to get each other out. But it can be very dangerous because if they use water guns that look like real guns. There was an issue in a school district in [state name] that the police came because they thought someone had a real gun. Anyway, so they were fine, but it scared everybody. So I was sending an email out to families and seniors saying, 'If you're going to do this, please, like, here's a news article about a school where the police had to come. We're not giving you permission to play this game, but if you play it off campus, please be careful for X, Y, and Z.' And I had written a very quick email, and I was like, 'This sounds terrible.' So I just threw it in [AI], I say, 'AI, can you just clean this up? I'm a high school principal sending this note to parents and students about a senior prank game.' And then I put the text of my

> *document in and then it just cleans it up, and it catches all the grammar and makes it sound [good]. And it just saves me time"* (Transcript 7).

In essence, educators' adoption of AI is mediated by whether they can uphold their ethical standards while using it. If they feel using AI would violate academic integrity, such as providing students with AI-generated comments without any personal input, they are likely to reject that use. A retired superintendent (Transcript 27) expressed this concern on page 146. Educators emphasized that AI should fit within the ethical boundaries of teaching practice, not stretch or break them.

Lastly, moral authority and trust. Teachers often occupy a role of trust—students and parents trust them to provide accurate knowledge and to act in the students' best interests. AI, being a new actor, raises questions of trust. Do teachers trust AI's information quality? A few hinted at this. One teacher said they always double-check AI outputs and edit them to sound like themselves (Transcript 6):

> *"I would always, like, I never sent something without first reading it and making tweaks to it so that I felt like it sounded like me or was close enough, and it, you know, it was what I wanted to say."*

Another worried AI might homogenize error (Transcripts 27): *"I'd be afraid of just trusting it entirely because sometimes I think it's wrong, or sometimes I think it might miss nuances or things like that. I don't want every student's response to sound the same."*

If teachers do not trust the AI to be accurate or aligned with curriculum, they won't use it for substantive tasks. Administrators similarly must trust that AI will not lead

the school astray; for instance, an admin might worry if a teacher relies on AI for feedback, could it give wrong advice to a student? None explicitly said this, but underlying some caution is the notion that the teacher is ultimately accountable for what happens in the classroom. Using AI does not remove that accountability; if anything, it requires the teacher to oversee the AI's contributions. This sense of ultimate responsibility can make educators slower to hand tasks over to AI unless they're confident in it.

In summary, applying sociology of professions concepts reveals that teachers and administrators filter AI through their professional value system. The functionalist models might predict a teacher who sees usefulness and has low effort barriers will eagerly adopt. Indeed, many did start using AI for certain tasks. But those same teachers might still limit their use or feel "neutral" rather than "very positive" because of concerns like preserving student creativity or maintaining their own role. Transcript 51 illustrates this balanced perspective: the teacher uses AI for idea generation, indicating both perceived usefulness and ease of use, yet remains cautious about over-reliance in order to protect creativity and problem-solving. As the teacher explained,

> *"I would say I'm a neutral AI person because I'm not so pro-AI that I think we should use it all the time in every situation. Because I think if you over-rely on AI, you're going to lose your own creativity, your own reasoning skills, your own problem-solving skills. But I'm not against it because I think it's unavoidable at this point, people are going to use it. So I think teaching students the best ways to*

> *use it is important. And I also think it can be helpful in certain situations. So I'm kind of in the middle—neutral on AI"* (Transcript 51).

Traditional adoption models don't fully capture that kind of value-based moderation of enthusiasm. By incorporating professional identity and ethics into the analysis, we see that educators' adoption of AI is not just a matter of efficiency or social norms, but of existential questions about their role and the purpose of education.

The abductive analysis suggests that functional technology adoption models are necessary but not sufficient to explain K–12 educators' attitudes toward AI. TAM, UTAUT, DOI, and TOE highlight the importance of perceived utility, ease, social influence, organizational support, and external context—all of which were evident in the data and do influence attitudes in expected ways. However, these educators' responses were also significantly shaped by sociocultural factors related to their professional role: concerns about autonomy, identity, ethical practice, and the preservation of the teacher-student relationship. These latter factors sometimes support the conventional models (e.g. if AI aligns with professional values, it enhances the perceived compatibility or facilitating conditions), but other times they lead educators to modify or even reject what a purely functional cost-benefit analysis would suggest. In other words, a teacher might rationally see an AI tool as useful, but choose not to use it in certain ways because it conflicts with their sense of what good teaching entails. Any comprehensive explanation of AI adoption in K–12 education must therefore blend the insights of acceptance models with an understanding of teacher professionalism.

Retroduction: Underlying Mechanisms and Refined Explanations

In the final step, retroduction, this study stepped back to theorize about the underlying mechanisms and structures that give rise to the observed patterns. The goal is to propose a refined model or explanation that accounts for the demi-regularities identified, consistent with the CR aim of uncovering deeper causal forces.

A Dual-Factor Mechanism: Functional Benefits vs. Professional Values

One emergent explanation for what influences teachers' (and administrators') attitudes toward AI is the tension or balance between two sets of forces: on one side, the functional benefits and pressures to adopt AI (pragmatic factors like efficiency, external expectations, and keeping up with innovation), and on the other side, the professional norms and values of the education field (the commitment to human-centric pedagogy, autonomy, and ethical practice). The interviews suggest that an educator's stance on AI results from how these two forces interplay in their context. If the functional benefits can be realized without violating professional values, then positive adoption is likely. This was the case when, for example, a teacher used AI to differentiate a reading without sacrificing personal connection—the tool was employed to better serve the student, fitting the teacher's values, thus the teacher embraced that use (Transcript 15):

> *"I had a student who, he was from China. His English was at... about a fourth-grade reading level... So I had to take articles and translate [them] into a fourth-grade level... I would start creating documents... I would put it into AI and have it rewrite it at the fourth-grade reading level. And that was great because he was able to access the curriculum... Those documents that AI were creating just don't exist... It was nice because it was taking the actual document that my students,*

without accommodations, were reading and getting the key points. I also like it because I could edit it... It usually ends up being 80% with 20% teacher editing... It was employed to better serve the student, fitting the teacher's values."

Similarly, a principal using AI to polish an email did not feel it undermined their professional integrity. Instead, it was seen as a way to communicate more clearly with the community, aligning with the responsibilities of the role, as noted earlier by Transcript 7 (p. 172. In such scenarios, the mechanism enabling adoption is that AI as a value-congruent enhancer of professional practice. Teachers frame the technology as an assistant to their professional judgment, such as a modern equivalent of a spell-checker or a library resource, something that they control to better achieve their goals (like helping students or saving time for more important tasks).

However, if functional pressures to adopt AI clash with professional values, the likely outcome is resistance or very cautious use. Many demi-regularities I saw (e.g., rejecting AI grading because it conflicts with the teacher's pedagogical values, or resisting AI-driven instruction because it threatens teacher creativity) point to an underlying mechanism of professional self-defense. Educators act to protect the core of their profession when they perceive it to be challenged by an innovation. This could be theorized as a form of "professional boundary-keeping". The sociology of professions literature (Abbott, 1988; Freidson, 2001) often describes how professions fight to retain control over their domain of work and maintain their social significance. In this study's context, that translates to teachers and administrators instinctively pushing back against uses of AI that might de-skill teaching, commodify it, or reduce the direct teacher-student

interaction. So, deeper than individual attitudes, there is a structural force: the professional culture of education which highly values personal engagement, teacher autonomy, and moral stewardship of youth. This cultural backdrop generates a mechanism wherein any technology is scrutinized for its impact on those values. AI, being a particularly powerful and potentially disruptive technology, triggers a strong activation of this mechanism. That's why even absent explicit external opposition, many teachers themselves voice critical notes that the profession's collective ethos speaks through individual practitioners.

Thus, one can retroductively infer that the conjunction of a technological change with the entrenched culture of the teaching profession produces a unique pattern of cautious, value-mediated adoption. Neither the technology nor the culture alone can explain the outcome: it is their interaction. In a profession with different values, say finance or manufacturing, a useful technology might be adopted more quickly with less concern about human relational factors. But in education, the social function of the profession (to nurture human development) acts as a gatekeeper for technology use.

Risk and Trust

From a critical realist perspective, it is important to consider the unseen factors that cause teachers to hesitate even when benefits are apparent. A plausible mechanism is accountability risk, as teachers operate under heavy accountability to student learning outcomes, to parents, to administrators, and to their own conscience. Introducing AI adds a layer of uncertainty—will using it inadvertently harm student learning or lead to backlash if misused? Several teachers implied worries about future consequences: *"I*

think that would be really dangerous [if we let students present AI work as their own]" (Transcript 6), or *"What do we become if AI takes over tasks… everyone would just be the same"* (Transcript 12). These statements reflect a projection of risk to the fundamental mission of schooling. The underlying dynamic is that teachers, in their role as guardians of learning, tend to err on the side of caution, which could be an example of the precautionary principle in action. Until they trust that AI will not jeopardize critical aspects of learning (critical thinking, creativity, honesty) and until they have strategies to manage those risks, their adoption will remain guarded. This mechanism is less about the technology per se and more about the educational system's responsibility to children: teachers feel the weight of not "messing up" a generation by rushing into an unproven approach.

From the administrators' viewpoint, a mechanism at play is institutional cautious optimism. Administrators see the potential strategic advantages of AI (e.g. improving operations, modernizing education to keep it relevant) but are simultaneously custodians of policy, equity, and public trust. The underlying cause for their attitude seems to be a drive to innovate tempered by a duty of care. We heard administrators neither demonizing AI nor rushing to mandate it. Instead, they are carefully feeling out how AI can be included: e.g., *"I wouldn't be opposed to using it more, I just don't know of any [other uses yet]"* (Transcript 7). They are also the ones who must think systemically: one principal mentioned the possibility that *"the role of a teacher needs to change as AI comes along"* (Transcript 27), indicating that at a structural level, they foresee adaptations (perhaps teachers becoming more facilitators than lecturers, etc.). This

reflects an organizational adaptation process that schools as institutions will gradually adapt roles and policies to integrate AI in a way that preserves the institution's legitimacy and effectiveness. Administrators can influence teachers by framing AI in alignment with educational values. For example, a principal might encourage AI use for routine tasks to allow teachers more time with students—flipping the narrative to a supportive one. If that alignment is communicated, it could modify the teachers' internal valuation mechanism from defensive to embracing, as long as teachers believe their core role is only enhanced, not eroded.

Underlying Generative Mechanism

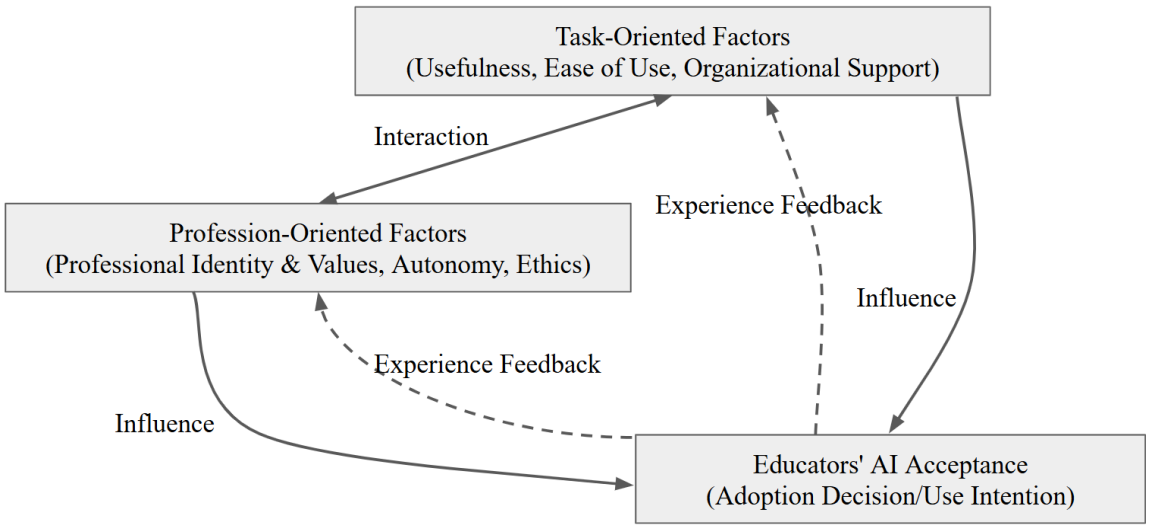
At the deepest level, the nature of the teaching profession can be seen as the generative mechanism shaping these attitudes and behaviors. Teaching is fundamentally a human-centric, ethically grounded profession, and any new technology is filtered through that nature. AI, as a technology capable of encroaching on cognitive and relational tasks, unlike a simple tool such as a new whiteboard, prompts fundamental questions about the essence of teaching. The profession's collective response, reflected in the individual voices captured in the transcripts, is to ensure that the technology serves human educational aims rather than subverting them. The professional ethos of education acts as a causal power that moderates technology adoption, ensuring that human relationships and professional agency remain central. This mechanism can produce the demi-regularities observed: cautious adoption, selective use-cases (only those that align with

educational values), and strong negative reaction to use-cases that threaten teacher-student connection or integrity.

Another layer is the multi-level causation between individual agency and structure. Teachers (agents) make choices about AI, but their choices are enabled or constrained by structures: the school policies, the availability of AI tools, societal narratives, and the profession's norms. For example, if a district banned AI entirely for students, a teacher might have a negative attitude not because of personal belief but because structurally they are told it's harmful. Conversely, if the structure provided ample training and a clear ethical framework, a hesitant teacher might be empowered to try AI in safe ways. This study found that currently structures are still catching up—many teachers felt structural support was insufficient (no policies for teachers, little training), so they relied on their personal and professional judgment in the meantime. A retroductive insight is that for AI integration to progress, structural changes (like professional development programs, ethical guidelines co-created with teachers, and demonstration of successful use cases) will be needed to change the context in which individual teachers operate. To activate the positive causal potential of AI (e.g., improved teaching and learning), one must also activate supporting mechanisms in the social system (professional learning communities, revised curriculum standards that incorporate AI literacy, etc.) while damping the opposing mechanisms (like fear of the unknown or legitimate concerns unchecked by guidance).

Refined Theoretical Model

Bringing together the study's insights, this study proposed a refined conceptual model for K–12 educators' acceptance of AI. This model is a distinct theoretical contribution of the research: it bridges the well-known, task-oriented factors from technology adoption models with profession-oriented factors unique to teaching. In other words, it recognizes that a teacher's decision to embrace or reject AI hinges not only on practical considerations (like whether the tool is useful or easy to use) but also on the teacher's professional identity, values, and ethics. By integrating these two domains, the model offers a holistic framework that reflects the reality of educators' experiences. It acknowledges that adopting AI in a classroom is not a value-neutral technical decision; rather, it is deeply intertwined with what it means to be a teacher. This framework therefore expands on traditional technology acceptance functionalist models (e.g. TAM or UTAUT) by adding the moral and professional dimensions of teaching, which emerged as crucial in interviews with 51 educators. The refined model is illustrated in a conceptual diagram (Figure 2) and explained in detail below.



Note. Refined model of AI acceptance for K–12 educators, integrating task-oriented and profession-oriented factors. Solid arrows indicate direct influences on a teacher's AI acceptance decision, while the dashed arrows indicate feedback loops where experience can reshape perceptions over time. A two-headed arrow between the factor groups signifies their dynamic interplay.

Figure 2. Refined Model of AI Acceptance for K–12 Educators.

Task-oriented factors—utility, usability, and support. On the technical or task side, teachers consider several practical factors when evaluating an AI tool. Perceived usefulness is paramount, as educators assess whether the tool helps them teach more effectively or saves time on essential tasks. If a system can reduce workloads, such as by automating routine grading or generating lesson ideas, and thereby free up more time for students, it is often seen as valuable. Many interviewees emphasized this potential, with some noting that AI could handle tedious tasks and reduce burnout by reclaiming hours, a benefit they valued highly. One teacher described the appeal of *"saving unpaid hours"* through AI support.

Alongside usefulness, perceived ease of use also plays a significant role. Teachers prefer tools that are user-friendly and relatively free of technical difficulties or errors.

Busy schedules and limited time make educators less inclined to adopt tools that require excessive effort to learn or operate. In the study, several teachers with lower confidence in technology admitted feeling discouraged by AI tools that were not straightforward, particularly when support was lacking. One teacher expressed frustration at being told to figure it out without guidance, which led to disengagement: *"People just say, oh, you'll figure it out, and I get turned off by that."*

A third practical consideration is organizational support and social influence. Teachers often observe the practices of their colleagues and leaders, gaining confidence when they see peers using AI successfully. When a principal provides time, training, and clear policies for implementation, educators feel more prepared and justified in experimenting with the technology. In contrast, if the school environment is skeptical or no guidance exists (a *"figure it out yourself"* climate), teachers may hesitate. In summary, these task-oriented factors—usefulness, ease of use, and organizational support—set the stage by addressing whether using AI is practically advantageous and feasible for a teacher. These mirror the classic drivers identified in technology adoption research (teachers, like other users, want tools that improve their work and are easy to use), but they are only one side of the equation.

Profession-oriented factors—values, identity, and ethics. Equally crucial are factors rooted in the professional domain of teaching. K–12 education is fundamentally a human-centered, values-driven profession. Educators naturally consider whether the use of AI aligns with their professional values and identity as teachers. This compatibility with professional values emerged as a key theme. Teachers in our study often spoke

about maintaining their core teaching values—such as fostering student creativity, critical thinking, equity, and authentic teacher-student relationships—when deciding on AI. If an AI tool complements their role (for instance, by helping differentiate instruction for diverse learners or giving them more time to mentor students), it is seen as aligning with what they believe "good teaching" entails. Those teachers view AI as an aide that supports their professional purpose of educating and caring for students. On the other hand, if a tool seems to undermine the teacher's role or pedagogy, it clashes with their professional identity.

Several educators voiced concern that using AI for certain tasks (like writing feedback comments or lesson plans wholesale) might erode their autonomy or unique professional touch. One teacher worried that if AI handles too much, *"the role of a teacher needs to change"* and they could be seen less as experts and more as mere facilitators. This reflects a fear of deprofessionalization—the concern that indiscriminate AI use could deskill teachers or reduce the craftsmanship in teaching. Thus, a strong sense of professional identity can make educators selective: they are willing to use AI in ways that reinforce their values and professional standards, but not in ways that violate them.

Finally, ethical considerations and perceived risk form the other major professional factor. Teachers consistently reflected on whether they could trust an AI tool to be safe and fair for their students. If a system threatens student privacy, equity, or academic integrity, teachers hesitate or refuse to use it. For example, some interviewees described an almost visceral discomfort with AI that might enable "cheating" or shortcut

learning—they felt using it inappropriately would violate the ethical duty to cultivate honest student work. Even administrative tasks raised ethical questions, as one principal admitted half-jokingly that they wondered whether they were cheating when considering using AI to write emails to parents. This humorous remark belies a normative concern that educators do not want AI to cross moral lines or compromise trust. Additionally, teachers expressed a sense of accountability, recognizing that even if an AI suggests an answer or grades an essay, they are ultimately responsible for what happens in the classroom. Therefore, many exercise caution that they might try AI in low-risk areas (lesson brainstorming, administrative help) but avoid it in high-stakes areas (like directly giving feedback to students) until they are sure it's pedagogically sound and fair. In essence, these profession-oriented factors —compatibility with teaching values/identity, and ethical acceptability—act as a moral and ideological filter. Even a very handy tool will be rejected if it "doesn't feel right" as a teacher. Conversely, if an AI strongly supports what teachers see as good teaching, they are willing to work past some inconveniences to adopt it. This mirrors the pattern we found: educators will embrace AI to the extent that it reinforces, rather than diminishes, their professional purpose of educating students.

Dynamic interaction between task and professional factors. A core insight of this refined model is that these two sets of factors are not isolated silos but continuously interact and balance each other in shaping AI acceptance. Teachers navigate the interplay between assessing what the technology can offer and determining whether its use aligns with their professional identity. Rather than one set of factors dominating outright, the

findings suggest a compensatory dynamic in which a strongly positive factor in one domain can sometimes offset a weaker factor in the other, within certain limits. For example, if an AI tool provides substantial practical benefits such as dramatically reducing grading time, a teacher may be willing to overcome moderate usability challenges or initial discomfort, particularly if the tool helps reduce burnout or allows more time for direct student interaction. Several educators described pushing through a steep learning curve because the payoff was worthwhile. One teacher learned to use an initially confusing AI tool solely because it saved hours of work, which could then be reinvested in lesson planning and rest—an exchange they viewed as consistent with their values of being an effective and energized teacher. Conversely, a red flag in the professional domain can veto an otherwise promising technology. There were several examples where, even if a tool was seen as useful, teachers would reject or severely limit it if it raised ethical concerns or conflicted with their teaching ethos. For example, a teacher might acknowledge that an AI-driven grading program could save time, but if they believe it is unfair or diminishes their understanding of students' work, they will not adopt it in core practice. In this way, the professional "brake" can override the technical "accelerator." Ultimately, all factors must be sufficiently positive for wholehearted adoption, which is a significant shortfall in any one area that can hold an educator back. This interplay explains why two teachers with similar classroom contexts might differ in AI use: each is internally weighting these factors based on personal values and experiences. It also reflects a harmony (or tension) between the innovation's task appeal and the profession's normative boundaries. The refined model deliberately portrays this

as a dynamic equilibrium rather than a one-way chain: teachers seek a balance where the technology's advantages align with their professional conscience.

Feedback loops and ongoing adaptation. Importantly, the model also acknowledges that acceptance is not a single event but rather an ongoing process involving feedback loops over time. As shown by the dashed arrows in Figure 2, teachers' experiences with AI can circle back and alter their perceptions in both domains. In practice, this means initial use (or non-use) of AI often leads to learning and readjustment. For instance, an educator who cautiously experiments with an AI tool might, after some positive outcomes, revise their opinion on its usefulness or come to trust it more. One interviewee, initially neutral about AI, became more favorable after seeing it "actually help differentiate lessons for a struggling student"—the success reinforced the tool's perceived usefulness and eased some ethical worry. Such positive feedback can create a virtuous cycle: useful, value-aligned experiences encourage more use, which further normalizes the tool as part of the teacher's practice. Conversely, negative experiences can feed a caution loop. If a teacher tries an AI recommendation that turns out poor or problematic (for example, an automated feedback tool that gave incorrect advice), their trust may erode and they'll become more skeptical about similar tools, strengthening their professional reservations. This study's data contained hints of this cautious learning process—teachers often started small with AI and expanded use only when it consistently proved safe and beneficial. This iterative aspect aligns with broader research suggesting technology adoption is a gradual, reflective process for educators, not a single moment of decision. Traditional models like TAM are largely

static snapshots and might overlook how experience reshapes beliefs (for example, how using AI for a while can increase its perceived usefulness as teachers discover more benefits). By contrast, the refined model implies a more cyclical flow: beliefs influence initial behavior, but outcomes of that behavior feed back into beliefs, either reinforcing or adjusting them. Additionally, there can be feedback at the community level—as some teachers adopt and report success, their colleagues might shift attitudes (strengthening the social influence factor), and if many teachers find alignment with professional values, this can slowly shift professional norms about AI. In short, the model captures AI acceptance as an evolving interplay: teachers and their environments learn and adapt. Over time, the task-oriented and profession-oriented elements may come into greater alignment as schools develop guidelines (addressing ethical risks) and teachers refine how they use AI in pedagogically sound ways. The model's inclusion of feedback loops underscores that achieving acceptance is an ongoing process of sense-making, not simply a checklist of factors.

Paradigm pluralism and multi-layered insights. Apart from the discussion on functionalist models mentioned above, the CR framework combined with a sociology of professions lens enabled this study to capture nuances at multiple levels of analysis that a purely interpretive or critical study would likely overlook. This study illustrated how this approach captured unique insights in three ways. First, professional identity and boundary-keeping. The CR + professions lens revealed that teachers' resistance to certain AI uses often stems from their instinct to protect core professional values and autonomy when they perceive technology as encroaching on their domain. For example, many

educators rejected AI-driven instruction or grading tools that seemed to de-skill teaching or undermine their expert judgment, effectively acting in "professional self-defense" of their role. This insight aligns with classic sociology of professions theory that occupations strive to retain control over their work and status (e.g., defending autonomy and expertise). A purely interpretive approach might well document individual teachers' feelings of unease or anecdotes of resistance, but without a professions lens it may not recognize these as part of a larger structural pattern of the teaching profession guarding its jurisdiction. The behavior could remain interpreted as personal attitudes or localized stories rather than evidence of an underlying professional norm across participants. Conversely, a purely critical theory approach would certainly acknowledge resistance as a form of teacher agency against imposed change, but might cast it chiefly in terms of opposition to external power or management mandates. Such a view could miss the affirmative role of teachers' internalized professional ethos (their sense of duty, ethics, and pride in skilled teaching) in motivating that resistance. CR contextualized individual accounts within a broader professional culture. This study showed that teachers' pushback is not only a reaction to top-down power, but also a principled stand rooted in professional identity, which is a nuance that neither an interpretive narrative alone nor a broad critical critique might fully surface.

Second, value alignment as a key to adoption. This study also uncovered that teachers are willing to embrace AI when it is perceived as congruent with their professional values and goals. Many participants described using AI as an assistant that streamlines tedious tasks (like lesson formatting or administrative paperwork) in order to

better fulfill their core teaching mission. In these cases, educators framed AI as a tool under their control that enhances their professional practice (for instance, freeing up time to focus on students or creative lesson planning) rather than replacing their expertise. This finding led to a nuanced insight: alignment with professional purpose is a critical condition for teacher buy-in. A critical perspective might downplay such positive engagements, perhaps viewing adoption of AI as coerced compliance with institutional or market pressures. A critical-theory analysis focused on power could overlook the professional agency and creativity teachers exercise when they integrate AI on their own terms (e.g. "co-opting" the technology to serve educational values rather than simply to serve administrators' mandates). Meanwhile, an interpretive-only study would certainly capture teachers' positive testimonies about AI (their stories of success or excitement with a new tool), but it might treat each case as an idiosyncratic anecdote. Without a theoretical framework to connect them, an interpretivist might not generalize that these anecdotes collectively point to a pattern, namely, that teachers adopt AI only when it meshes with their professional identity and ethics. In my CR-guided analysis, however, such patterns were not only noted but explained as we identified "value-congruence" as a causal mechanism driving acceptance or rejection of AI.

Third, integrating multiple levels of analysis. Under a CR paradigm, the study explicitly examined the phenomenon at multiple ontological layers—individual experiences, the school/profession context, and broader structural forces—rather than privileging a single level. This multi-layered analytic focus is a distinctive strength of the chosen approach. CR posits a stratified reality (empirical, actual, real) and encourages

researchers to seek out the often unseen generative mechanisms behind observable events. In practical terms, this meant my interpretation of teachers' AI adoption drew connections between micro-level subjective meanings and macro-level structures. For example, researchers could link a teacher's personal hesitation about AI to institutional norms and professional cultural values acting in the background, and then further to systemic issues like policy or labor concerns. This approach resulted in a synthesized explanation that teachers' attitudes were shown to arise from an interaction of individual and structural factors, not reducible to either alone. Neither a purely interpretive approach nor a purely critical one typically achieves this integration. An interpretivist study might excel at richly describing teachers' lived experiences and sense-making processes, but it generally would stop at the empirical level of what participants say or believe, hesitating to infer broader causal structures beyond participants' own accounts. On the other hand, a critical study might focus on structural and political-economic factors (e.g. how tech adoption is driven by administrative power or ed-tech companies), thus operating at a high level of abstraction and critique, but it might pay less attention to the actual lived nuances and varied perceptions among practitioners on the ground. By contrast, this study's CR-informed approach allowed the researchers to both respect and analyze teachers' subjective viewpoints (an interpretive element), while also examining how those viewpoints were shaped by and reacted to objective structures like professional norms, technological affordances, and power dynamics (a critical/structural element). This fusion of insights embodies paradigm pluralism—the idea that leveraging multiple paradigmatic perspectives together provides a more complete understanding. Indeed, as

scholars like Gioia and Pitre (1990) and Mingers (2001) argue, complex social phenomena are often best understood through such theoretical pluralism, because each paradigm illuminates different facets of reality. In this study, paradigm pluralism translated into a more nuanced and actionable picture of AI adoption in education that one could see how standard functional factors (e.g. perceived usefulness, ease of use) interweave with interpretive factors (teachers' meanings and narratives) and critical factors (issues of professional power and control) in shaping outcomes. This multi-layered insight is a result of the chosen CR and sociology of professions lens. It demonstrates the value of stepping outside any single "comfort zone" of methodology and instead integrating frameworks to capture the full complexity of teachers' engagement with AI.

Chapter 7 Conclusion and Implications

Through a CR-guided analysis, this study found that K–12 teachers' and administrators' attitudes toward AI are shaped by a blend of traditional technology adoption factors and deeper professional considerations. In line with classic technology acceptance models, educators did consider practical factors such as an AI tool's perceived usefulness and ease of use. Social and organizational influences also played a role, as suggested by models like TAM and UTAUT. Indeed, the interview data confirmed that if teachers find an AI application helpful for teaching and reasonably easy to implement, and if their colleagues or leaders support its use, they are more inclined to consider adopting it. However, technology adoption in schools clearly does not occur in a value-neutral vacuum. Beyond utility and usability, educators' decisions were strongly shaped by professional values and ethics—what it means to be a "good" teacher or school leader. Teachers spoke about concerns like student cheating, the preservation of academic integrity, and whether using AI might undermine essential aspects of their role. Administrators similarly weighed whether AI aligns with the core mission of schooling and the values of their institution. Thus, a key finding is that AI acceptance in K–12 education is tightly interwoven with the professional identity and moral purpose of educators, not just with technical considerations.

There were some nuanced differences between teachers and administrators in how these factors manifest. Administrators generally shared the same set of considerations as teachers but tended to think at the organizational level. Many school leaders expressed a cautious optimism about AI. They were interested in its potential benefits (for example,

to streamline administrative tasks or personalize learning) yet felt responsible for ensuring that any AI use aligns with educational goals and policies. Administrators often talked about creating supportive conditions (professional development opportunities, guidelines, resource allocation) to help teachers use AI effectively and ethically. Teachers, on the other hand, were more directly focused on classroom-level impacts and their personal role. Teachers frequently voiced worries about how AI might affect their daily teaching practices, student engagement, and the teacher-student relationship. For instance, some were concerned that over-reliance on AI tools could diminish their autonomy or even threaten their job relevance, while others worried about students misusing AI (e.g. to cheat or avoid learning basic skills). Despite these concerns, both groups—teachers and administrators—shared a common underlying goal: they seek to harness AI's benefits without compromising the fundamentally human-centered nature of education. In essence, educators at all levels want AI to serve as a tool that enhances teaching and learning, not as a replacement for the human relationships and ethical responsibilities at the heart of the educational process.

Importantly, while this study's findings supported elements of existing models such as TAM, UTAUT, DOI, and TOE, they also point to the need for extending beyond these functionalist models. Classic adoption theories provided a useful starting point by highlighting factors like perceived usefulness, ease of use, social influence, and organizational facilitators. Participants acknowledged these factors, for example, teachers noted whether AI could save them time or whether their peers were supportive, echoing core constructs of TAM/UTAUT. However, those models traditionally treat context,

values, and professional norms as external or secondary variables. In the context of K–12 schooling, we found that these so-called "external" factors are in fact central. Technology adoption in education is not merely a matter of an individual's cost-benefit calculation; it is profoundly contextual and value-laden. What it means to "accept" AI in the classroom is intertwined with what it means to be a teacher or a school leader committed to an educational mission. Therefore, models of technology acceptance must be broadened to fully understand educational settings—taking into account that teaching is not only technical work but also ethical and relational work. By recognizing this dual character of teaching, this study gains a more comprehensive view of why certain technologies are embraced, cautiously tried, or resisted in schools. In summary, this study concludes that the key to understanding and ultimately improving AI adoption in K–12 education lies in recognizing that educators will embrace AI to the extent that it reinforces, rather than diminishes, their professional purpose of educating and caring for students. This overarching conclusion sets the stage for translating the findings into concrete recommendations for equitable and constructive AI integration in schools.

A Refined Theoretical Model of AI Adoption in Education

One of the key contributions of this study is the development of a refined conceptual model that frames K–12 AI adoption dualistically—both as a technological uptake decision and as a professional judgment. By synthesizing our empirical insights with existing theories, this study constructed a model that illustrates how teachers' intentions to use AI arise from the interplay of two intertwined sources of influence. On one side are the task-oriented imperatives familiar from traditional technology acceptance

models, which emphasize improving teaching practice through enhanced efficiency, effectiveness, or student outcomes. These imperatives rest on the promise that the technology will be useful and relatively easy to use in the classroom setting. On the other side are the profession-oriented imperatives identified through a critical, sociological lens, which highlight the need to honor the educational mission, uphold ethical standards, and maintain the teacher's identity and responsibilities. The data suggest that neither set of factors alone can explain teachers' attitudes toward AI; rather, it is the combination and tension between these two domains that produces the observed outcomes, such as cautious trial of an AI tool, selective and limited use, or in some cases enthusiastic embrace accompanied by safeguards.

In building this model, this study started with the foundations laid by existing technology acceptance frameworks. The TAM and related theories emphasize that users evaluate new technologies in terms of perceived usefulness ("Will this help me teach or manage my class better?") and perceived ease of use ("How hard will this be to learn and implement?"). Consistent with TAM and UTAUT predictions, the interviewees did take into account these practical considerations. For example, several teachers mentioned that they would be more likely to use an AI-based software if it saved them time on grading or provided clear instructional benefits, and only if it was not too difficult or cumbersome to use during class. Social influence and organizational support also emerged in the findings, as teachers were encouraged by positive experiences from colleagues and emphasized the role of support or directives from school leadership in legitimizing AI use. In these respects, the findings affirm the relevance of established models. However,

as I delved deeper, it became evident that traditional models alone are insufficient to fully explain AI acceptance in the K–12 context. Teachers' talk of "cheating," "values," and "what it means to be a teacher" pointed to dimensions that TAM, UTAUT, and similar frameworks might regard as external contextual factors or even as noise. In practice, participants revealed that these professional and ethical considerations were central determinants of their willingness to adopt AI. A purely utilitarian model of decision-making could not account for why a teacher might reject a tool that is objectively useful and user-friendly. The missing piece was whether using that tool would conflict with or support their professional ethos and the norms of good teaching.

To capture these insights, this study integrated professional identity, values, and ethics directly into our model of technology acceptance for educators. Drawing on the sociology of professions literature, this study considered how teachers view their role (for instance, as mentors, caregivers, and moral exemplars for students, not just deliverers of content) and how that professional self-conception impacts their openness to new technologies. The refined model thus extends beyond the functional benefits of AI to include what we might call "profession-compatibility"—the degree to which using AI is compatible with teachers' sense of what good teaching entails. From a theoretical standpoint, this integration aligns with the CR perspective because it acknowledges multiple layers of causation and influence. This study recognize that individual cognition (e.g., a teacher's belief that an AI tool is useful) is operating within a larger social context (e.g., peer influences, institutional pressures) and an institutional/ideological context (e.g., normative ideas about the teacher's role and responsibilities). These layers interact

in complex ways to shape behavior. By accounting for this, this study's model provides a more nuanced explanation of educators' technology adoption decisions than any single-paradigm model could offer.

In essence, the refined model proposes that a teacher's intention to use AI emerges from the dynamic interplay between practical utility and professional-ethical alignment. Adoption is most likely when a technology is perceived as both beneficial for teaching and consistent with professional values and identity. This corresponds to scenarios observed in the study in which some educators enthusiastically embraced AI while maintaining safeguards, such as using it to assist with lesson planning but not to autonomously grade students in order to preserve human oversight. When a tool is viewed as useful but misaligned with values, for instance if it is perceived to undermine authentic learning or professional ethics, educators often respond with hesitation or selective use, applying it only in limited ways or under strict conditions. Tools that are neither useful nor value-aligned are typically rejected outright. Even when a tool aligns with professional values but offers no clear usefulness, it is often regarded as irrelevant and left unused. The combination of practical utility and professional-ethical fit therefore appears to be the determining factor in adoption outcomes. This theoretical insight emerged from analysis of the 51 interviews and serves as a conceptual bridge between mainstream technology adoption theory and the sociology of the teaching profession.

By framing the findings in this dualistic model, this study contributes to a theoretical lens that future research and practice can utilize. For researchers, this model suggests new variables and relationships to examine. For instance, measures of

professional identity or value congruence could be incorporated into technology acceptance studies in education to see how they affect adoption behavior. This work encourages scholars to move beyond viewing technology acceptance as a purely individual and rational choice, and instead to study it as a situated, culturally informed decision that engages both head and heart, so to speak. For practitioners and policymakers, the model underscores that efforts to increase AI adoption in schools should not focus only on making better technology (i.e. improving functionality and user-friendliness) nor only on trying to change teachers' attitudes through training or mandates. Successful integration of AI will require attention to both domains, ensuring that stakeholders demonstrate clear educational benefits while aligning the technology's use with educators' core values and ethical standards. In practical terms, this may involve including teachers in the design and implementation of AI tools to address their professional concerns and providing evidence of how AI can enhance student learning or well-being to meet the test of utility. This refined model, therefore, stands as a framework that others can build upon to understand and support educational innovation. It bridges the gap between technology adoption theory and the moral-professional realities of the teaching vocation. In conclusion of this theoretical discussion, the model captures an idea that educators are most likely to embrace AI when it supports their teaching and respects their role as professionals, and they will reject it when it fails either test. By recognizing this, this study encourages a new way of thinking about technology acceptance in K–12 education—one that sees it not as a purely technical decision, but as a profoundly human and professional judgment.

Implications for Practice and Policy

The insights from this study carry several important implications for educational practice and policy, especially regarding how school systems might approach the integration of AI in a constructive, educator-aligned way. First and foremost, the finding that teachers and administrators prioritize the human-centered nature of education implies that any AI initiative must be framed as enhancing human teaching, not replacing or devaluing it. Teachers need to view AI as a tool that empowers them in their professional mission, such as by automating routine tasks to free up time for creative lesson planning or individual student support, rather than as a tool that mechanizes or monitors their work in ways that undermine their autonomy or expertise. Similarly, administrators should approach AI adoption with the clear message that the role of the teacher remains fundamental and irreplaceable. Communicating this vision can help alleviate fears that often accompany new technology in schools, such as the fear of teachers becoming obsolete or the learning process becoming overly automated.

Another practical implication revolves around professional development and support structures. Since both usefulness and value alignment are critical, training for teachers on AI should go beyond technical how-to workshops. It should create spaces for educators to discuss and confront the ethical and pedagogical questions that AI raises. For example, workshops could include scenarios about academic honesty (to address concerns about “cheating” with AI assistance), discussions on equity and bias in AI systems, and collaborative planning on how to incorporate AI in ways that uphold inclusive, student-centered teaching. By engaging teachers in these conversations, school

leaders acknowledge the professional and moral dimensions of technology use. This approach respects teachers' professional agency and can increase their comfort and willingness to experiment with AI in their practice. Administrators, who were found to be cautiously optimistic in the study's findings, are well positioned to facilitate such dialogue and learning opportunities. They can model an organizational culture that is critically optimistic about AI, encouraging innovation and exploration of its benefits while also establishing clear guidelines and boundaries to ensure the technology is used ethically and in alignment with school values. For instance, a district might allow teachers to use an AI-driven tutoring app but establish policies on data privacy and require parental consent, thus balancing innovation with responsibility.

The difference in perspective between teachers, with their classroom focus, and administrators, with their organizational focus, also indicates the need to align goals and expectations in AI initiatives. Policymakers and school leaders should actively seek teacher input when selecting or implementing AI tools in curricula. Teachers' on-the-ground insights can inform whether a purportedly useful AI tool will actually be practical in a real classroom setting and whether it fits the developmental and emotional needs of students. Additionally, teachers' concerns, such as maintaining meaningful teacher-student interactions and ensuring that AI does not widen achievement gaps, should be considered in policy decisions. Involving teachers in decision-making processes demonstrates trust in their professional judgment and increases the likelihood of securing their support. This collaborative approach resonates with the finding that social/organizational context matters—when educators feel that adopting AI is a

collective effort supported by their peers and leaders, and not something imposed that conflicts with their values, they are more open to it.

Ethical guidelines and accountability frameworks will be crucial in practice as AI tools become more common in schools. Given that teachers in this study frequently raised ethical issues, school districts should be proactive in establishing what "responsible AI use" looks like in education. This could include creating codes of practice that outline how AI can be used to personalize learning without infringing on student privacy and how AI assistants, such as automated graders or recommendation systems, should be implemented in ways that complement teacher assessment rather than replace the teacher's judgment. Clear ethical guidelines help reassure educators that there are boundaries protecting the integrity of teaching and learning. They also provide teachers and administrators with a shared language to discuss AI's role, aligning with the professional norms of accountability and care.

Another implication for practice is the need to address the issue of professional identity in change management. The findings indicate that teachers take pride in their role as educators and caregivers, and they may consciously or subconsciously resist changes that seem to encroach on that role. Therefore, when introducing AI, school leaders and policymakers should highlight how the technology can strengthen the teacher's role. For example, if an AI system can help differentiate instruction, it should be presented as a way to help teachers better meet individual student needs and augment the teacher's ability to care for and educate each student, rather than as an expert system that knows more than the teacher. This framing aligns the innovation with teachers' professional

purpose, making it less threatening and more appealing. In addition, recognizing and validating teachers' concerns publicly (in staff meetings, policy documents, etc.) can go a long way. When teachers hear their leaders acknowledge the importance of maintaining human connection in education or protecting teacher autonomy, it builds trust that those in charge are not blindly adopting technology for technology's sake, but are mindful of preserving what matters in education.

From a policy perspective, an equitable and constructive integration of AI in schools will require attention to resource disparities and training gaps. Not all schools or teachers will have equal access to high-quality AI tools or the time to learn to use them effectively. Administrators expressed an organizational-level awareness of such issues in our interviews. Policymakers should heed this by ensuring that initiatives around AI come with adequate funding for infrastructure, ongoing support, and perhaps even incentives for schools serving disadvantaged communities to pilot beneficial AI interventions. Equitable integration also ties back to the professional ethics of educators that many teachers in this study were concerned about AI's impact on equity. For instance, if only some students benefit from AI-driven tutoring or if AI inadvertently carries biases against certain groups. Thus, practical guidelines should include provisions for monitoring and mitigating bias in AI, and for ensuring all students have fair access to AI-augmented learning opportunities.

In summary, the practical and policy implications of this study emphasize a balanced approach to AI in education, one that integrates technological possibilities with professional wisdom. Efforts to introduce AI should demonstrate clear educational

benefits, such as effectiveness, efficiency, and improved learning outcomes, while upholding the values and identity of the teaching profession, including human connection, ethics, and equity. Schools that manage this balance are likely to find teachers and administrators becoming partners in innovation, leading to more sustainable and meaningful uses of AI in the classroom. On the other hand, initiatives that focus narrowly on the technical side while ignoring educators' professional perspectives are likely to encounter resistance or superficial compliance at best. The findings of this research encourage school leaders, teacher educators, and policymakers to approach AI not merely as a new gadget to adopt, but as a catalyst for deeper conversations about the values we hold in education. It emphasizes the importance of preserving the human essence of teaching even as we continue to innovate. The findings from this research encourage school leaders, teacher educators, and policymakers to view AI as more than a novel technology to adopt. Instead, AI should serve as a catalyst for discussions about educational values, ensuring that innovation occurs while preserving the human essence of teaching.

Methodological Reflections and Research Contributions

Beyond the substantive findings on AI adoption, this study's methodological approach offers insights for educational technology research. The study employed the CR paradigm in conjunction with concepts from the sociology of professions, which enabled a multi-layered investigation into the phenomenon of AI adoption. This approach proved fruitful in uncovering how individual educators' actions and interpretations are simultaneously influenced by personal beliefs and values, the professional culture of

teaching, and broader institutional and social structures. By employing abductive and retroductive reasoning, key strategies in CR research, the study moved iteratively between concrete data from teachers and administrators and abstract theoretical concepts, ultimately identifying underlying explanations that account for the observed patterns. This approach extends beyond purely descriptive or interpretive analyses by exploring the underlying reasons behind educators' attitudes, such as why teachers expressed unease toward certain beneficial AI tools or why administrators showed cautious optimism. Additionally, it surpasses purely critical analyses, as it does more than critique existing theories for their limitations. Instead, it systematically develops a more comprehensive theoretical framework to address these gaps.

A significant contribution of this dissertation’s research design is its use of multiple theoretical lenses, described here as paradigm pluralism. Rather than restricting itself to a single theoretical perspective, the study integrates functionalist models such as TAM and UTAUT, which originate from a positivist tradition aimed at predicting behavior, along with interpretive and critical models including sociology of professions and CR, which emphasize meaning, power, and context. This pluralistic strategy enabled the study to capture nuances that might otherwise remain unnoticed if examined through a single paradigm alone. For example, a traditional study based on TAM might only measure teachers' perceptions of usefulness and ease of use to identify predictors of AI adoption. However, such an approach might overlook subtler themes, such as professional boundary-keeping, where teachers distinguish clearly between tasks and decisions they believe should remain under human control and those they are comfortable

delegating to AI. Similarly, a purely interpretive case study might richly describe teachers' feelings about AI but might not connect those feelings to broader theoretical constructs of technology adoption. By integrating multiple perspectives, this study was able to critically examine and expand upon existing theoretical models. The research concretely demonstrated how phenomena reflect underlying professional values that shape adoption decisions. Such insights might be dismissed as anomalies or overlooked entirely within a purely functionalist framework.

This multi-paradigm approach revealed several important nuances and underlying mechanisms. The research highlighted the interaction between structure and agency within AI adoption in educational contexts. Structural factors such as school policies, assessment standards, and technology infrastructure provide the conditions under which teachers exercise agency to accept or reject AI. Using retroductive reasoning, the study identified how teachers' agency is simultaneously constrained and supported by these structural conditions. For instance, a school policy explicitly prohibiting AI-generated student work could discourage teachers from exploring AI tools, whereas an institutional culture encouraging innovation might motivate teachers to experiment with AI despite uncertainties. Moreover, educators collectively shape institutional norms and policies concerning AI by expressing their concerns or advocating specific practices. This reciprocal relationship between teachers' agency and structural conditions would be challenging to explore without incorporating CR's emphasis on generative mechanisms and the sociology of professions' perspective on how professional groups respond to change. By elucidating these dynamics, the research underscores the practical benefits of

using multiple theoretical frameworks. Specifically, the study identified patterns such as teachers' tendency to adopt AI innovations that closely align with their educational values, and further traced how these adoption patterns emerge from individual judgments as well as institutional narratives about the teaching profession.

Reflecting on this methodological approach highlights how integral these choices were to the substantial contributions of the research. The decision to employ multiple theoretical frameworks was not merely a methodological preference; rather, it directly responded to the inherent complexity of the research topic. AI adoption in education intersects technical, personal, and social domains, making it challenging to capture through a singular theoretical lens. Conversely, the paradigm pluralist strategy adopted in this study, which combined the predictive capabilities of technology adoption models with the contextual insights from sociological perspectives, resulted in a more comprehensive understanding. This methodological approach serves as a model for future research addressing similarly complex phenomena. Although employing multiple paradigms presents certain challenges, the insights gained can be significantly deeper. In this study, the pluralistic approach enabled a critical evaluation of functionalist models by highlighting their limitations within educational contexts and facilitated the development of an integrated framework capable of addressing both quantifiable adoption factors and the underlying professional values guiding educator decisions.

For the field of educational technology research, this approach emphasizes the value of methodological openness and innovation. As emerging technologies such as AI increasingly intersect with established social systems, researchers may need to integrate

multiple theoretical perspectives to fully understand these phenomena. This study demonstrates that such theoretical blending is both achievable and valuable. Additionally, it contributes practically to the literature on CR methodologies by providing an explicit example of how abductive and retroductive reasoning can be systematically employed to bridge empirical observations with theoretical insights. Overall, the key methodological insight from this study is that adopting multiple paradigms along with CR analysis can uncover deeper layers of understanding that single-paradigm approaches might overlook. This enhances both the rigor and comprehensiveness of the findings regarding AI adoption in education and enriches broader methodological discussions by illustrating the process of conducting multi-paradigm research in educational contexts.

A second significant methodological contribution of this research is its demonstration of a clear and practical way to incorporate LLMs into qualitative data analysis using a critical realist framework. This method integrates LLM-assisted coding with abductive and retroductive reasoning, both of which are fundamental to CR. In this study, the LLM functioned as a collaborative analytical partner by initially identifying codes and suggesting thematic insights from the qualitative data. Researchers then refined these insights through abductive reasoning to investigate unexpected patterns and develop new explanations, and retroductive reasoning to identify underlying mechanisms and structures responsible for observed phenomena. Instead of replacing human interpretation, the LLM complemented it by offering analytical suggestions, which researchers critically evaluated and integrated into the emerging theoretical framework. Treating the LLM as a collaborative analytical partner allowed the analysis to benefit

from the model's capacity to swiftly identify patterns while maintaining the critical realist focus on contextual and explanatory depth. This innovative integration of AI tools and critical realist reasoning demonstrates how advanced technologies can be effectively leveraged without diminishing methodological and philosophical rigor.

Equally important was the transparency and rigor with which LLM assistance was implemented. The study utilized a cross-validation strategy involving multiple LLMs alongside human oversight, mirroring the reliability gained through multiple independent coders. Multiple LLMs or repeated analyses using the same LLM with varied prompts were applied concurrently to code the dataset. The outputs from these analyses were systematically compared, allowing the researcher to identify areas of agreement and disagreement. In cases of disagreement or uncertainty, the human researcher reviewed the raw data segments alongside the competing LLM-generated codes to determine the most appropriate coding based on context and the study's analytic framework. A clearly defined codebook, grounded in literature, theory, and initial human analysis, guided this process. This codebook was provided to the LLMs through instructional prompts or illustrative examples, ensuring that AI-generated suggestions aligned closely with the established conceptual definitions of each code. This alignment prevented LLM outputs from diverging into unrelated or overly subjective interpretations. Furthermore, each stage of the analytical process, including LLM prompts, their outputs, and researcher adjudication decisions, was thoroughly documented, producing an audit trail. This documentation exemplifies the methodological transparency essential for fostering trust in AI-assisted qualitative research. Collectively, these practices involving multi-LLM

validation, careful human adjudication, and systematic adherence to a codebook establish a rigorous and reliable protocol for integrating LLMs into qualitative data analysis.

Adopting LLMs in this way markedly enhanced efficiency in the analytical process while upholding interpretive depth. Tasks that typically demand extensive manual effort were accelerated by the LLM's capacity to process large volumes of text quickly. This efficiency gain allowed the researcher to focus more time on higher-order analysis and critical interpretation, rather than getting bogged down in the mechanics of data handling. Notably, the time saved did not come at the cost of interpretive rigor. By employing the safeguards described above, the study maintained a human-centered analysis where the quality criteria of qualitative research, such as credibility, consistency, and reflexivity, were continuously applied. The researcher maintained active engagement throughout the analysis by critically reviewing and refining the outputs produced by the LLM. This active involvement ensured that nuanced meanings, subtle contextual elements, and contradictions within the data were thoroughly considered and analyzed, rather than passively accepting the AI-generated results. Effectively, the LLM managed the more laborious tasks involved in coding, while the interpretive process and deeper analytical sense-making remained firmly under human control. This division of labor created a workflow that was both efficient and interpretively rigorous. Early findings from related research reinforce this balanced approach, demonstrating that careful integration of LLMs can enhance efficiency and reduce resource demands, all while maintaining the integrity and quality of qualitative research outcomes.

Positioning this approach as a methodological innovation, the dissertation speaks to broader implications for qualitative research in education and other fields grappling with complex sociotechnical change. Educational research frequently addresses multifaceted social phenomena and extensive qualitative data, such as longitudinal interviews, classroom observations, and open-ended survey responses. Thus, the capability to leverage LLMs as analytical tools can significantly advance the field. Researchers exploring socio-technical changes, such as the introduction of new technologies in educational settings, often encounter complex interactions and unexpected outcomes. This AI-supported approach provides a practical method for managing this complexity. LLMs can efficiently analyze extensive data, identify emerging patterns, and present initial thematic suggestions. Researchers then apply their theoretical and contextual understanding to interpret these findings. In the current study, for example, the use of LLMs facilitated the initial identification of themes across diverse stakeholder accounts, which were subsequently analyzed by the researcher through critical realist theory to uncover potential underlying causes influencing technology adoption. This combination of human insight and AI-driven analysis offers new opportunities for conducting qualitative research. Recent methodological discussions have emphasized the importance of balancing the efficiency and breadth enabled by AI tools with the depth, care, and reflective practice associated with traditional qualitative approaches. The contribution of this dissertation is thus not limited to the specific application of LLMs within one research context. Instead, it serves as a methodological

blueprint for researchers seeking responsible ways to integrate advanced AI tools into qualitative inquiry, addressing substantial research questions in education and beyond.

Reflecting on the strengths and limitations of using LLMs for qualitative data analysis, this study presents a balanced perspective. Among the primary strengths, the study demonstrated that LLMs reliably generated consistent codes for clearly defined constructs and efficiently managed routine coding tasks. For instance, in coding straightforward and explicitly stated phenomena, the model's outputs often closely matched human judgment. The consistency of these outputs improved further when retrieval augmentation or explicit examples guided the coding process. Additionally, the LLM served effectively as an additional analytical resource, identifying overarching patterns and insights that might otherwise have gone unnoticed by human analysts alone. Employing multiple LLMs simultaneously enhanced confidence that critical themes were comprehensively identified, reducing the risks of oversight or fatigue-related errors. Moreover, the cross-validation approach provided further credibility; when independent LLM analyses and human interpretation agreed, it strengthened the validity of the findings, suggesting that conclusions were robust rather than dependent on any single analyst, human or machine.

Despite these advantages, the study also noticed limitations of using LLMs in qualitative research. Foremost among these limitations was the difficulty in interpreting nuanced, context-dependent data. The LLM often struggled to accurately capture subtle meanings, implicit assumptions, or contextual complexities, areas in which human expertise and judgment are essential. Consequently, the model sometimes generated

codes that appeared linguistically appropriate yet overlooked the deeper, context-specific meanings recognized by human researchers. Consistent with other recent findings, the LLM encountered the greatest challenges when dealing with data segments that were also difficult for human analysts, including emotionally complex situations or contradictory statements by participants. This indicates that LLMs do not remove interpretive complexities but instead mirror some of the same interpretive challenges faced by human analysts.

Another significant limitation was variability among different LLM models and versions. The study observed noticeable performance differences among various LLMs, with some requiring more extensive corrections and newer versions occasionally providing interpretations that diverged from previous iterations. This variability highlighted the importance of rigorous cross-validation and cautioned that analytical outcomes might depend significantly on the choice of specific AI models.

Furthermore, the research emphasized the continuing necessity for active human oversight and ethical vigilance when using LLMs. Researchers needed to remain attentive to potential biases inherent in AI-generated outputs and carefully avoided becoming overly dependent on model suggestions. Additionally, ethical considerations surrounding data security and participant privacy were acknowledged as essential, particularly given the sensitivity of qualitative data and the implications of using cloud-based AI tools. Although a full exploration of these ethical aspects was beyond the immediate scope of the study, they remain critical to any responsible use of AI.

In conclusion, experiences drawn from this research underscore that while LLMs offer considerable value in qualitative analysis, they do not replace the necessity of human interpretation. Their strengths, including efficiency, breadth, and consistency, provide clear advantages, yet their limitations in context comprehension, susceptibility to biases, and the imperative for human oversight necessitate careful and thoughtful integration into qualitative research practices.

Conclusion

In summary, this research provides an in-depth exploration of how K–12 educators perceive and navigate the introduction of AI into their professional lives. The attitudes held by teachers and administrators toward AI adoption result from multiple intersecting considerations, ranging from highly practical concerns to profound philosophical reflections. Educators evaluated AI from a practical standpoint, questioning its effectiveness, efficiency, reliability, and usability. Concurrently, they assessed the technology against core professional values, considering whether it genuinely benefits their students, aligns with high-quality teaching practices, and influences their roles as educators. By examining these practical and value-oriented dimensions simultaneously, the study enriches traditional technology acceptance theories by anchoring them in the concrete experiences and realities of educational settings. It demonstrates that although factors like usefulness and ease of use are essential for AI adoption, they alone are inadequate, especially in education, a field inherently embedded with ethical and social responsibilities. Educators approach technology adoption as a blend of technical evaluation and moral decision-making, underscoring that any theoretical model or

implementation strategy that ignores ethical considerations remains fundamentally incomplete.

The conceptual model introduced in this research captures this dual process of decision-making, bridging existing theoretical perspectives with novel insights. The model emphasizes that educators are more likely to adopt AI positively when they believe it supports their instructional objectives and aligns with the ethical and professional standards of their field. When these conditions are satisfied, teachers and administrators are typically open to exploring and advocating for AI innovations, facilitating their thoughtful and productive integration into practice. In contrast, if educators perceive an AI tool as incompatible with educational values or as potentially undermining their professional role, even clear practical benefits may be insufficient to encourage full adoption. This dynamic clarifies why schools frequently demonstrate cautious or conditional acceptance of AI technologies. Educators actively evaluate AI tools against both practical effectiveness and core educational values, embracing adoption only when both criteria are adequately fulfilled.

From a practical perspective, this study emphasizes a key point for those who support AI integration in educational settings, including school leaders, policymakers, and technology designers. Effective integration requires active engagement with the human and professional dimensions involved, rather than focusing solely on technical capabilities. Initiatives that view educators merely as technology consumers, rather than as professional collaborators, are unlikely to succeed. Conversely, efforts that value and support educators' professional judgment are more likely to be positively received. The

findings indicate that educators are neither opposed to technology nor resistant to innovation by default. Instead, they adopt a carefully selective approach, embracing technologies that align clearly with education's core mission and maintaining skepticism toward those that do not. This cautious and reflective stance prioritizes students' best interests, setting a high standard that any new innovation, including AI, must satisfy.

Finally, the study's multilayered analytical approach contributes meaningfully to broader conversations about researching and understanding complex phenomena in education. By integrating functionalist models and the sociology of professions, the analysis captures both the practical functions of AI, including its applications and outcomes, and the deeper meanings it holds within the context of educational norms and professional values. This viewpoint represents a significant strength of the dissertation, demonstrating how combining multiple theoretical perspectives can yield a richer and more nuanced understanding than relying solely on any single perspective. This research aims to illuminate not only the specific dynamics of AI adoption in K–12 settings but also encourages educators, researchers, and technology developers to adopt a more holistic mindset when exploring educational innovations. Technology in education should not be pursued simply for novelty or technological advancement alone. Rather, it should always serve the purpose of enhancing human teaching and learning, addressing simultaneously technical, social, and moral dimensions.

In closing, this chapter has presented the study's key conclusions and implications. The central insight is that successful AI adoption in education requires thoughtfully balancing innovation with tradition, integrating cutting-edge tools and

practices within a deeply human-centered and value-oriented educational framework. When balanced carefully, AI offers significant opportunities to enhance K–12 education by expanding the capabilities of teachers and students. However, if AI integration neglects educational values or lacks clear evidence of meaningful benefits, educators will justifiably resist its implementation. By recognizing and acting upon these insights, educational stakeholders can ensure that AI integration is not only technologically sophisticated but also equitable, meaningful, and aligned with education's fundamental mission.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4.5 to improve the readability and language of the manuscript. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the article.

Appendix A Provisional Codebook

1. Perceived Usefulness (Performance Expectancy): The degree to which the educator believes AI will improve teaching or learning outcomes. This captures any mentions of benefits or value of AI, for example, references to AI saving time, enhancing student engagement, personalizing learning, or otherwise enhancing job performance for teachers.
2. Perceived Ease of Use (Effort Expectancy): How easy or difficult the educator finds (or expects) AI tools to use in practice. This code covers comments about usability and complexity, for example, an interviewee describing AI as user-friendly and straightforward, or conversely noting steep learning curves, technical difficulties, or effort required to integrate AI into their workflow.
3. Social Influence (Peer/Community Influence): The role of colleagues, administrators, or community opinions in shaping the educator's view of AI. Include any references to peer pressure, trends, or norms. For example, a teacher mentioning that other teachers' enthusiasm or parent expectations encourage (or discourage) their own AI use. This also covers perceptions of support (or skepticism) from school leadership and the broader education community regarding AI.
4. Facilitating Conditions (Support & Resources): Perceived availability of organizational support, technical infrastructure, and resources to enable AI use. Code here mentions of having (or lacking) the necessary infrastructure (devices, internet, software) and institutional support (IT help, admin backing) for using AI. For example, if an administrator notes the school has adequate devices and an AI training

program (a facilitator), or if a teacher laments insufficient technology or no IT support (a hindrance), those would be captured under this category.

5. General Attitude Toward AI: The educator's overall disposition or sentiment about AI in education. This code captures broad statements of enthusiasm, optimism, caution, or skepticism. For example, a teacher expressing excitement about AI's potential or, conversely, voicing a distrust or fear of AI would fall under this category. (This code gives an overarching sense of their attitude, which in theoretical models is influenced by the above factors and in turn shapes adoption intent.)
6. Self-Efficacy (Confidence in Using AI): The educator's confidence in their own ability to learn and use AI tools effectively. Look for references to feeling competent or empowered to use AI versus feeling unsure or unskilled. For example, if a teacher mentions they feel comfortable experimenting with AI, or conversely says they lack the tech skills to use AI, those statements reflect AI-related self-efficacy. This factor often influences willingness to adopt new technology.
7. Compatibility with Teaching (Fit & Value Alignment): How well the use of AI aligns with the teacher's existing practices, pedagogical beliefs, or curriculum. This code captures any mention of AI fitting (or not fitting) into their teaching style or subject requirements. For example, a participant might say AI complements their project-based learning approach, or instead argue that using AI conflicts with their philosophy of hands-on learning. Such statements reflect perceived compatibility or incompatibility, a known factor in tech adoption (analogous to "relative advantage" and compatibility in diffusion of innovations theory).

8. Intended Use or Actual Usage Behavior: Mentions of whether and how the educator is currently using AI, or their stated intentions to use (or avoid) AI in the future. This code flags any description of current integration (e.g. “I’ve started using ChatGPT to help draft quizzes”) or explicit plans and willingness (“I plan to try an AI tool next semester” or “I don’t intend to use AI at all”). It helps identify patterns of actual adoption versus just attitudes.
9. Prior Experience & Exposure: The educator’s personal experience with AI tools in an educational context so far. This includes any anecdotes of tools tried, duration/frequency of use, or lack of exposure. For example, a teacher describing that they experimented with an AI tutoring app last year, or an administrator noting they’ve never used AI before, would be coded here. This helps gauge each person’s baseline familiarity with AI technology in education.
10. Conceptualization of AI (Definition): How the participant defines or understands “AI” in their own words. Code any explicit definitions or descriptions of what they believe AI is. This might reveal misconceptions or varying scope. For example, some might consider only robots or advanced systems as “AI,” while others include simple automation. Capturing their definitions provides context for their perspectives (since understanding of AI can shape their attitudes and comfort level).
11. Acceptable Uses of AI (Perceived Appropriate Applications): The kinds of AI use-cases in education that the educator views as beneficial, acceptable, or appropriate. This code covers any endorsed or positive application mentioned, for example, using AI for lesson planning, generating teaching materials, providing adaptive feedback to

students, automating administrative tasks, or other uses they find helpful. These are effectively the "green-light" scenarios where the interviewee sees AI adding value or at least doing no harm. For example, "It's fine if AI helps me differentiate instruction for diverse learners" would be coded here.

12. Problematic Uses & Ethical Concerns: AI applications or outcomes that the educator finds troubling, unacceptable, or risky. This includes a range of concerns, such as students cheating or becoming overly reliant on AI, issues of academic integrity, data privacy worries, algorithmic bias or fairness issues, loss of teacher roles, or any negative impacts on learning. Essentially, any mention of misuses or feared consequences of AI in schools belongs here. For example, a teacher expressing concern that AI-generated feedback might be misleading, or an administrator worried about equity gaps due to AI, would fall in this category.
13. Equity and Inclusivity Considerations: References to how AI in education might advantage or disadvantage certain groups of students, and concerns about fair access. Code instances where interviewees discuss issues related to the digital divide, bias, or inclusion, such as observations that not all students have access to AI outside of school or concerns that AI tools may contain inherent biases affecting minority groups. Positive mentions might include hopes that AI could close gaps (by providing personalized support to those who need it), whereas concerns might include AI exacerbating disparities or not being culturally responsive.
14. Policy & Governance: Mentions of any school, district, or governmental policies (or lack thereof) guiding AI use. This code captures references to rules, guidelines, or

administrative stances on AI. For instance, if a teacher notes there is no clear policy yet and that uncertainty affects their usage, or an administrator mentions their district is drafting an AI policy, use this code. This category also covers any suggestions for needed policies or governance concerns raised by participants.

15. Training & Professional Development: Any discussion of teacher training, workshops, or support for learning to use AI. This includes whether they have received (or wish to receive) professional development on AI tools. For example, a teacher might say they've had no training and feel unprepared, or an administrator might describe providing personal development sessions on AI. Such mentions are critical since comprehensive teacher training is needed to realize AI's potential. This code helps identify if lack of training is a common issue or if training programs are enabling adoption.
16. Hopes for the Future (AI Potential): Expressions of optimism or aspirations about the future role of AI in teaching and learning. Code here any forward-looking statements about what they hope AI will achieve. This could include hopes for more personalized learning through AI, reduced teacher workload, improved student outcomes, or other opportunities they envision. For example, an interviewee may say they're excited that AI could take over routine tasks so teachers can focus on mentorship, reflecting a positive future vision.
17. Fears for the Future: Any anxieties or worst-case scenarios the educator imagines regarding AI in education moving forward. This captures their long-term concerns, such as fear that AI might replace teachers, diminish human interaction in learning,

erode critical thinking, or otherwise harm the educational landscape. For example, a teacher might worry that in a decade AI could take over their job, or an administrator might fear AI could intensify inequalities if unchecked.

18. Teaching Role & Context: Captures the participant's role (teacher vs. administrator), grade level, subject area, and school context. These factors provide background for understanding attitudes. This code logs context that may influence perspectives on AI (e.g. subject taught or district policies).
19. Teaching Philosophy: Indicates the educator's teaching philosophy—whether they favor student-centered, constructivist approaches or more traditional, teacher-directed methods. Literature shows that teachers with constructivist, student-centered beliefs are more inclined to adopt AI in education. This code will capture references to teaching philosophy or beliefs about how students learn best, as these beliefs can shape openness to AI integration.
20. Aspirations for Students' Development: Codes statements about what skills or qualities teachers/administrators want to cultivate in students. This includes goals like critical thinking, creativity, digital literacy, or preparation for the future. For example, many educators emphasize preparing students for a future where AI is ubiquitous. Any mention of fostering "21st-century skills," AI literacy, or similar future-ready competencies would fall under this code.

Appendix B Example of ChatGPT 4o Consistency Check for Transcript 11

The coding results from the two documents — one generated by Gemini 2.5 Pro and the other by GPT-4.5 — are generally consistent in terms of high-level themes, but there are notable differences in depth, structure, and interpretation. Here's a comparative analysis:

✅ Areas of Consistency

1. Major Code Categories:

   Both coders identified similar high-level themes such as:

   - Teaching Role & Context
   - Teaching Philosophy
   - Aspirations for Students
   - AI Usage Behavior
   - Attitudes Toward AI
   - Ethical Concerns
   - Policy and Governance
   - Training and Support
   - Student Misuse of AI

2. Core Interpretive Alignment:

   - Both highlighted the teacher's cautious openness to AI.
   - Both acknowledged ethical dilemmas, especially the "hypocrisy" concern.
   - Both recognized institutional gaps in training and policy.

- Both captured the teacher's emphasis on civic engagement and critical thinking.

⚠️ Areas of Difference

Aspect	Gemini 2.5 Output	GPT-4.5 Output
Organization	Organized strictly by codes, mostly thematic.	Also organized by codes but includes more line-by-line quoting, resulting in a more exhaustive capture of utterances.
Subcoding Depth	More segmented — e.g., "Policy & Governance: Lack of Policy" and "Policy & Governance: Call for Policy" are separated.	Uses broader categories like "Policy & Governance" and keeps quotes nested under them.
Granularity	Sometimes splits similar content into multiple codes (e.g., separates "Actual Usage" from "Perceived Usefulness").	Groups multiple related sentiments into one code, possibly under-representing some nuanced distinctions.
Interpretive Framing	Leans toward interpretive summaries with quotes.	Prioritizes verbatim excerpts, often allowing data to "speak for itself."
Quote Attribution	More paraphrasing and partial quoting.	More full, verbatim excerpts and timestamps (when available).

🧠 Implications for Inter-Coder Reliability

- Substantive Agreement: High. Both coders agree on the major themes and how the participant thinks about AI.
- Interpretive & Structural Agreement: Moderate. Coding categories are compatible but not standardized, which affects comparison precision.

- Unitization Differences: GPT-4.5 sometimes codes longer segments as a unit, while Gemini 2.5 breaks down into smaller sub-themes — impacting how many codes a passage gets tagged with.

BIBLIOGRAPHY

Abbott, A. (1988). *The system of professions: An essay on the division of expert labor*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226189666.001.0001

Achinstein, B., & Ogawa, R. (2006). (In) fidelity: What the resistance of new teachers reveals about professional principles and prescriptive educational policies. *Harvard Educational Review*, *76*(1), 30–63. https://doi.org/10.17763/haer.76.1.e14543458r811864

Aguilar, S. J., & Wang, C. (2024). Duty vs. consequence: Exploring teachers' assessment of the ethical dimensions of generative AI technologies. *Proceedings of the 39th ACM/SIGAPP Symposium on Applied Computing*, 106–108. https://doi.org/10.1145/3605098.3636180

AI for Education. (2025, July 1). *State AI Guidance for K12 Schools*. AI for Education. https://www.aiforeducation.io/ai-resources/state-ai-guidance

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Akdeniz, R. K., & Konakli, T. (2022). The emergence, reasons and results of resistance to change in teachers. *International Journal on Lifelong Education and Leadership*, *8*(1), 49–67. https://doi.org/10.25233/ijlel.1107137

Al Darayseh, A., & Mersin, N. (2025). Integrating generative AI into STEM education: Insights from science and mathematics teachers. *International Electronic Journal of Mathematics Education*, *20*(3), em0832. https://doi.org/10.29333/iejme/16232

Al-Emran, M., & Granić, A. (2021). Is it still valid or outdated? A bibliometric analysis of the technology acceptance model and its applications from 2010 to 2020. In M. Al-Emran & K. Shaalan (Eds.), *Recent Advances in Technology Acceptance Models and Theories* (Vol. 335, pp. 1–12). Springer International Publishing. https://doi.org/10.1007/978-3-030-64987-6_1

Almulla, A. A., & Adam, U. A. (2025). Perceived effectiveness of artificial intelligent for special-needs students in Saudi Arabian primary schools: A model study. *International Journal of Innovative Research and Scientific Studies*, *8*(2), 630–641. https://doi.org/10.53894/ijirss.v8i2.5255

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use E-learning systems. *IEEE Access*, *7*, 26797–26809. https://doi.org/10.1109/ACCESS.2019.2899368

Alsolami, A. S. (2025). The effectiveness of using artificial intelligence in improving academic skills of school-aged students with mild intellectual disabilities in Saudi Arabia. *Research in Developmental Disabilities*, *156*, 104884. https://doi.org/10.1016/j.ridd.2024.104884

Alsup, J. (2006). *Teacher identity discourses: Negotiating personal and professional spaces*. Routledge. https://doi.org/10.4324/9781410617286

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies*, *28*(5), 5187–5208. https://doi.org/10.1007/s10639-022-11286-z

Archer, M. S., Bhaskar, R., Collier, A., Lawson, T., & Norrie, A. (2013). *Critical realism: Essential readings*. Taylor and Francis.

Ashwin, J., Chhabra, A., & Rao, V. (2025). Using large language models for qualitative analysis can introduce serious bias. *Sociological Methods & Research*, *0*(0), 1–45. https://doi.org/10.1177/00491241251338246

Awa, H. O., Ojiabo, O. U., & Orokor, L. E. (2017). Integrated technology-organization-environment (T-O-E) taxonomies for technology adoption. *Journal of Enterprise Information Management*, *30*(6), 893–921. https://doi.org/10.1108/JEIM-03-2016-0079

Awofala, A. O. A., Bazza, M. B., Ojo, O. T., Oladipo, A. J., Olabiyi, O. S., & Arigbabu, A. A. (2025). Structural equation modeling of Nigerian science, technology and mathematics teachers' adoption of educational artificial intelligence tools. *Digital Education Review*, *46*, 51–64. https://doi.org/10.1344/der.2025.46.51-64

Ayer, L., Boudreaux, B., Paige, J. W., Holmes, P., Blagg, T. L., & Mendon-Plasek, S. J. (2023). *Artificial intelligence–based student activity monitoring for suicide risk:*

Considerations for K–12 schools, caregivers, government, and technology developers. https://www.rand.org/pubs/research_reports/RRA2910-1.html

Bagozzi, R. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, *8*(4), 244–254. https://doi.org/10.17705/1jais.00122

Baker, L. R., Phelan, S., Woods, N. N., Boyd, V. A., Rowland, P., & Ng, S. L. (2021). Re-envisioning paradigms of education: towards awareness, alignment, and pluralism. *Advances in Health Sciences Education*, *26*(3), 1045–1058. https://doi.org/10.1007/s10459-021-10036-z

Ballenas, E. B., & Lasco, M. T. (2024). Exploring mathematics teachers' behavioral intentions to use artificial intelligence through structural equation modeling. *2024 International Conference on TVET Excellence & Development (ICTeD)*, 195–200. https://doi.org/10.1109/ICTeD62334.2024.10844599

Banks, D. C. (2023, May 18). *ChatGPT caught NYC schools off guard. Now, we're determined to embrace its potential.* Chalkbeat. https://www.chalkbeat.org/newyork/2023/5/18/23727942/chatgpt-nyc-schools-david-banks/

Baydas, O., Kucuk, S., Yilmaz, R. M., Aydemir, M., & Goktas, Y. (2015). Educational technology research trends from 2002 to 2014. *Scientometrics*, *105*(1), 709–725. https://doi.org/10.1007/s11192-015-1693-4

Becher, A. (2024). Holding our ground in the face of public mistrust: The future of professionalism in teaching and teacher education. *Journal of Teacher Education*, *75*(5), 476–487. https://doi.org/10.1177/00224871241268552

Becher, A., & Lefstein, A. (2021). Teaching as a clinical profession: Adapting the medical model. *Journal of Teacher Education*, *72*(4), 477–488. https://doi.org/10.1177/0022487120972633

Beijaard, D., Meijer, P. C., & Verloop, N. (2004). Reconsidering research on teachers' professional identity. *Teaching and Teacher Education*, *20*(2), 107–128. https://doi.org/10.1016/j.tate.2003.07.001

Beijaard, D., Verloop, N., & Vermunt, J. D. (2000). Teachers' perceptions of professional identity: An exploratory study from a personal knowledge perspective. *Teaching and Teacher Education*, *16*(7), 749–764. https://doi.org/10.1016/S0742-051X(00)00023-8

Bekkering, E., Johnston, A. C., Warkentin, M., & Schmidt, M. B. (2009). An empirical assessment of technology adoption as a choice between alternatives. *Information Resources Management Journal*, *22*(4), 23–44. https://doi.org/10.4018/irmj.2009061902

Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems*, *8*(4), 211–218. https://doi.org/10.17705/1jais.00126

Bhaskar, R. (1975). Forms of realism. *Philosophica*, *15*(1), 99–127. https://doi.org/10.21825/philosophica.82713

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, *25*(3), 351. https://doi.org/10.2307/3250921

Blose, A. (2023, April 12). As ChatGPT enters the classroom, teachers weigh pros and cons. *NeaToday*. https://www.nea.org/nea-today/all-news-articles/chatgpt-enters-classroom-teachers-weigh-pros-and-cons

Brass, J., & Holloway, J. (2019). Re-professionalizing teaching: The new professionalism in the United States. *Critical Studies in Education*, *62*(4), 519–536. https://doi.org/10.1080/17508487.2019.1579743

Breazu, P., Schirmer, M., Hu, S., & Katsos, N. (2024). Large Language Models and the challenge of analyzing discriminatory discourse: human-AI synergy in researching hate speech on social media. *Journal of Multicultural Discourses*, *19*(3), 157–175. https://doi.org/10.1080/17447143.2025.2476967

Burrell, G., & Morgan, G. (1979). *Sociological paradigms and organisational analysis: Elements of the sociology of corporate life*. Heinemann.

Campbell, S. (2008). Mobile technology and the body: Apparatgeist, fashion, and function. In J. E. Katz (Ed.), *Handbook of Mobile Communication Studies* (pp. 153–164). The MIT Press. https://doi.org/10.7551/mitpress/7445.003.0015

Chambers, C., Crumb, L., & Harris, C. (2019). A call for dreamkeepers in rural United States: Considering the postsecondary aspirations of rural ninth graders. *Theory & Practice in Rural Education*, *9*(1), 7–22. https://doi.org/10.3776/tpre.2019.v9n1p7-22

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology*, *10*, 1652. https://doi.org/10.3389/fpsyg.2019.01652

Chew, R., Bollenbacher, J., Wenger, M., Speer, J., & Kim, A. (2023). *LLM-assisted content analysis: Using large language models to support deductive coding*. arXiv. https://doi.org/10.48550/ARXIV.2306.14924

Chocarro, R., Cortiñas, M., & Marcos-Matás, G. (2023). Teachers' attitudes towards chatbots in education: a technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics. *Educational Studies*, *49*(2), 295–313. https://doi.org/10.1080/03055698.2020.1850426

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction*, *39*(4), 910–922. https://doi.org/10.1080/10447318.2022.2049145

Cobing, L. (2024, November 23). *AI-powered assessments in eLearning*. Mindsmith. https://www.mindsmith.ai/blog/ai-powered-assessments-in-elearning

CO-EDP, V. (2025, June 23). *Educators opting out of AI over fears of creativity erosion and academic dishonesty*. Devdiscourse. https://www.devdiscourse.com/article/education/3466006-educators-opting-out-of-ai-over-fears-of-creativity-erosion-and-academic-dishonesty

Dai, S.-C., Xiong, A., & Ku, L.-W. (2023). LLM-in-the-loop: Leveraging large language model for thematic analysis. *Findings of the Association for Computational Linguistics: EMNLP 2023*, 9993–10001. https://doi.org/10.18653/v1/2023.findings-emnlp.669

Daliri-Ngametua, R., Hardy, I., & Creagh, S. (2022). Data, performativity and the erosion of trust in teachers. *Cambridge Journal of Education*, *52*(3), 391–407. https://doi.org/10.1080/0305764X.2021.2002811

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Day, C., Kington, A., Stobart, G., & Sammons, P. (2006). The personal and professional selves of teachers: stable and unstable identities. *British Educational Research Journal*, *32*(4), 601–616. https://doi.org/10.1080/01411920600775316

De Paoli, S. (2023). Performing an inductive thematic analysis of semi-structured interviews with a large language model: An exploration and provocation on the limits of the approach. *Social Science Computer Review*, *42*(4), 997–1019. https://doi.org/10.1177/08944393231220483

DeCarlo, M., Cummings, C., Agnelli, K., & Laitsch, D. (2022). *Graduate research methods in education (leadership): A project-based approach*. BC Campus. https://pressbooks.bccampus.ca/dlaitsch/

Dele-Ajayi, O., Strachan, R., Anderson, E. V., & Victor, A. M. (2019). Technology-enhanced teaching: A technology acceptance model to study teachers' intentions

to use digital games in the classroom. *2019 IEEE Frontiers in Education Conference (FIE)*, 1–8. https://doi.org/10.1109/FIE43999.2019.9028527

Duer, B. (2023, April 21). *Alliance City Schools embraces artificial intelligence, ChatGPT platform*. Canton Repository. https://www.cantonrep.com/story/news/education/2023/04/21/alliance-schools-ohio-embrace-chatgpt-ai-artificial-intelligence/70128841007/

Dunivin, Z. O. (2025). Scaling hermeneutics: A guide to qualitative coding with LLMs for reflexive content analysis. *EPJ Data Science*, *14*(1), 28. https://doi.org/10.1140/epjds/s13688-025-00548-8

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Evetts, J. (2009). New professionalism and new public management: Changes, continuities and consequences. *Comparative Sociology*, *8*(2), 247–266. https://doi.org/10.1163/156913309X421655

Evetts, J. (2011a). A new professionalism? Challenges and opportunities. *Current Sociology*, *59*(4), 406–422. https://doi.org/10.1177/0011392111402585

Evetts, J. (2011b). Sociological analysis of professionalism: Past, present and future. *Comparative Sociology*, *10*(1), 1–37. https://doi.org/10.1163/156913310X522633

Fathema, N., Shannon, D., & Ross, M. (2015). Expanding the technology acceptance model (TAM) to examine faculty use of learning management systems (LMSs) in

higher education institutions. *Journal of Online Learning & Teaching*, *11*(2), 210–232.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Feng, G. C., Su, X., Lin, Z., He, Y., Luo, N., & Zhang, Y. (2021). Determinants of technology acceptance: Two model-based meta-analytic reviews. *Journalism & Mass Communication Quarterly*, *98*(1), 83–104. https://doi.org/10.1177/1077699020952400

Fichman, R. (1992). Information technology diffusion: A review of empirical research. *ICIS 1992 Proceedings*, *39*. https://aisel.aisnet.org/icis1992/39

Fish, M., & Turner, J. (1995). Understanding the process of information technology implementation. *AMCIS 1995 Proceedings*, 187. https://aisel.aisnet.org/amcis1995/187

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: an introduction to theory and research*. Addison-Wesley.

Fletcher, A. J. (2017). Applying critical realism in qualitative research: methodology meets method. *International Journal of Social Research Methodology*, *20*(2), 181–194. https://doi.org/10.1080/13645579.2016.1144401

Flores, M. A., & Day, C. (2006). Contexts which shape and reshape new teachers' identities: A multi-perspective study. *Teaching and Teacher Education*, *22*(2), 219–232. https://doi.org/10.1016/j.tate.2005.09.002

Forrester, G., Hudson, R., Rowley, J., & Pugh, J. (2022). Mind the aspiration gap: How primary school pupils perceive their future adult selves and the perspectives and expectations of parents and teachers. *Educational Review*, *76*(4), 732–752. https://doi.org/10.1080/00131911.2022.2134845

Freidson, E. (2001). *Professionalism: The third logic*. University of Chicago Press.

Frostenson, M. (2015). Three forms of professional autonomy: De-professionalisation of teachers in a new light. *Nordic Journal of Studies in Educational Policy*, *2015*(2), 28464. https://doi.org/10.3402/nstep.v1.28464

Funck, E. (2012). Professional archetype change: The effects of restricted professional autonomy. *Professions and Professionalism*, *2*(2). https://doi.org/10.7577/pp.334

Garg, R., Han, J., Cheng, Y., Fang, Z., & Swiecki, Z. (2024). Automated discourse analysis via generative artificial intelligence. *Proceedings of the 14th Learning Analytics and Knowledge Conference*, 814–820. https://doi.org/10.1145/3636555.3636879

Gemini Apps Help. (2025, June). *Manage & delete your Gemini Apps activity*. Google Help. https://support.google.com/gemini/answer/13278892?hl=en&co=GENIE.Platform%3DAndroid#zippy=%2Cin-the-gemini-mobile-app

Ghimire, A., & Edwards, J. (2024). Generative AI adoption in the classroom: A contextual exploration using the technology acceptance model (tam) and the innovation diffusion theory (IDT). *2024 Intermountain Engineering, Technology*

and Computing (IETC), 129–134. https://doi.org/10.1109/IETC61393.2024.10564292

Gioia, D. A., & Pitre, E. (1990). Multiparadigm perspectives on theory building. *The Academy of Management Review*, *15*(4), 584. https://doi.org/10.2307/258683

Glaser, B. G., & Strauss, A. L. (1967). *Discovery of grounded theory: Strategies for qualitative research* (1st ed.). Aldine de Gruyter. https://doi.org/10.4324/9780203793206

Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning acceptance among university students: An integrated model of TPB and TAM. *The International Review of Research in Open and Distributed Learning*, *20*(3). https://doi.org/10.19173/irrodl.v20i4.4061

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213. https://doi.org/10.2307/249689

Granić, A. (2022). Educational technology adoption: A systematic review. *Education and Information Technologies*, *27*(7), 9725–9744. https://doi.org/10.1007/s10639-022-10951-7

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Guerrero Puerta, L., & Lorente García, R. (2024). Illuminating the path: A methodological exploration of grounded theory in doctoral theses. *Qualitative Research Journal*, *24*(4), 384–393. https://doi.org/10.1108/QRJ-07-2023-0119

Hanna, F., Oostdam, R., Severiens, S. E., & Zijlstra, B. J. H. (2019). Domains of teacher identity: A review of quantitative measurement instruments. *Educational Research Review*, *27*, 15–27. https://doi.org/10.1016/j.edurev.2019.01.003

Hanna, F., Oostdam, R., Severiens, S. E., & Zijlstra, B. J. H. (2020). Assessing the professional identity of primary student teachers: Design and validation of the Teacher Identity Measurement Scale. *Studies in Educational Evaluation*, *64*, 100822. https://doi.org/10.1016/j.stueduc.2019.100822

Henry, C. T. (2023, March 16). Peninsula School District embracing potential of ChatGPT. *Gig Harbor Now*. https://www.gigharbornow.org/news/education/peninsula-school-district-embracing-potential-of-chatgpt/

Herzallah, A. M., & Makaldy, R. (2025). Technological self-efficacy and sense of coherence: Key drivers in teachers' AI acceptance and adoption. *Computers and Education: Artificial Intelligence*, *8*, Article 100377. https://doi.org/10.1016/j.caeai.2025.100377

Holden, R. J., & Karsh, B.-T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Holloway, S. L., & Pimlott-Wilson, H. (2011). The politics of aspiration: Neo-liberal education policy, 'low' parental aspirations, and primary school Extended Services in disadvantaged communities. *Children's Geographies*, *9*(1), 79–94. https://doi.org/10.1080/14733285.2011.540441

Holmes, D. (2005). *Communication theory: Media, technology, society*. SAGE Publications Ltd. https://doi.org/10.4135/9781446220733

Homburg, V. M. F. (2013). Diffusion of personalized e-government services among Dutch municipalities. *Tékhne*, *11*(2), 83–91. https://doi.org/10.1016/j.tekhne.2013.10.003

Hordern, J. (2024). Teacher professionalism, expertise and the jurisdictional struggle. *Education Inquiry*, 1–16. https://doi.org/10.1080/20004508.2024.2308945

Hu, P. J., Chau, P. Y. K., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of Management Information Systems*, *16*(2), 91–112. https://doi.org/10.1080/07421222.1999.11518247

Huang, D., Hash, N., Cummings, J. J., & Prena, K. (2025). Academic cheating with generative AI: Exploring a moral extension of the theory of planned behavior. *Computers and Education: Artificial Intelligence*, *8*, 100424. https://doi.org/10.1016/j.caeai.2025.100424

Huang, D., Huang, Y., & Cummings, J. J. (2024). Exploring the integration and utilisation of generative AI in formative e-assessments: A case study in higher education. *Australasian Journal of Educational Technology, 40*(4), 1–19. https://doi.org/10.14742/ajet.9467

Huang, D., & Katz, J. E. (2025). GenAI learning for game design: Both prior self-transcendent pursuit and material desire contribute to a positive experience. *Big Data and Cognitive Computing*, *9*(4), 78. https://doi.org/10.3390/bdcc9040078

Islam, A. K. M. N., Azad, N., Mäntymäki, M., & Islam, S. M. S. (2014). TAM and e-learning adoption: A philosophical scrutiny of TAM, its limitations, and prescriptions for e-learning adoption research. In H. Li, M. Mäntymäki, & X. Zhang (Eds.), *Digital Services and Information Intelligence* (Vol. 445, pp. 164–175). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-45526-5_16

Izadinia, M. (2013). A review of research on student teachers' professional identity. *British Educational Research Journal*, *39*(4), 694–713. https://doi.org/10.1080/01411926.2012.679614

Jiang, L., Wei, B., Qiu, N., & Huang, L. (2025). What influences ChatGPT's adoption and diffusion in Chinese higher education? A study based on Technology-Organization-Environment framework. *Interactive Learning Environments*, 1–22. https://doi.org/10.1080/10494820.2025.2479166

Jiang, Y., Ko-Wong, L., & Valdovinos Gutierrez, I. (2025). The feasibility and comparability of using artificial intelligence for qualitative data analysis in equity-focused research. *Educational Researcher*, *54*(3), 153–163. https://doi.org/10.3102/0013189X251314821

Katz, J. E., & Aakhus, M. (2002). *Perpetual contact: Mobile communication, private talk, public performance*. Cambridge University Press.

Katz, J. E., & Sugiyama, S. (2006). Mobile phones as fashion statements: evidence from student surveys in the US and Japan. *New Media & Society*, *8*(2), 321–337. https://doi.org/10.1177/1461444806061950

Kennedy, G., Dalgarno, B., Bennett, S., Judd, T., Gray, K., & Chang, R. (2008). Immigrants and natives: Investigating differences between staff and students' use of technology. In R. Atkinson & C. McBeath (Eds.), *Hello! Where are you in the landscape of educational technology?* (pp. 484–492).

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kirsten, E., Buckmann, A., Mhaidli, A., & Becker, S. (2024). *Decoding complexity: Exploring human-AI concordance in qualitative coding*. arXiv. https://doi.org/10.48550/ARXIV.2403.06607

Kittinger, L. I., & Law, V. (2024). A systematic review of the UTAUT and UTAUT2 among K–12 educators. *Journal of Information Technology Education: Research*, *23*, 017. https://doi.org/10.28945/5246

Klein, A. (2024, June 27). *AI's potential for bias puts onus on educators, developers*. GovTech. https://www.govtech.com/education/k-12/ais-potential-for-bias-puts-onus-on-educators-developers

Kong, S. C., Yang, Y., & Hou, C. (2024). Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model. *Computers and Education: Artificial Intelligence*, *7*, 100328. https://doi.org/10.1016/j.caeai.2024.100328

Lai, C., & Jin, T. (2021). Teacher professional identity and the nature of technology integration. *Computers & Education*, *175*, Article 104314. https://doi.org/10.1016/j.compedu.2021.104314

Lamote, C., & Engels, N. (2010). The development of student teachers' professional identity. *European Journal of Teacher Education*, *33*(1), 3–18. https://doi.org/10.1080/02619760903457735

Larson, M. S. (1977). *The rise of professionalism*. University of California Press. https://doi.org/10.1525/9780520323070

Larson, M. S. (2014). Looking back and a little forward: Reflections on professionalism and teaching as a profession. *Radical Teacher*, *99*, 7–18. https://doi.org/10.5195/rt.2014.112

Lauridsen, P. S. (2024, August 15). *Professional grief: When artificial intelligence challenges the teacher's professional identity*. Viden.AI. https://viden.ai/en/professional-grief-when-artificial-intelligence-challenges-the-teachers-professional-identity/

Lee, J., Alonzo, D., Beswick, K., Abril, J. M. V., Chew, A. W., & Oo, C. Z. (2024). Dimensions of teachers' data literacy: A systematic review of literature from 1990 to 2021. *Educational Assessment, Evaluation and Accountability*, *36*(2), 145–200. https://doi.org/10.1007/s11092-024-09435-8

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management*, *40*(3), 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4

Li, Y., Qi, J., & Shu, H. (2008). Review of relationships among variables in TAM. *Tsinghua Science and Technology*, *13*(3), 273–278. https://doi.org/10.1016/S1007-0214(08)70044-0

Lin, T., Zhang, J., & Xiong, B. (2025). Effects of technology perceptions, teacher beliefs, and AI literacy on AI technology adoption in sustainable mathematics education. *Sustainability*, *17*(8), 3698. https://doi.org/10.3390/su17083698

Liu, Q., & Geertshuis, S. (2016). Professional identity and teachers' learning technology adoption: A review of adopter-related antecedents. In S. Barker, S. Dawson, A. Pardo, & C. Colvin (Eds.), *Show me the learning: Proceedings of the 33rd International Conference of the Australasian Society for Computers in Learning in Tertiary Education (ASCILITE 2016, Adelaide)* (pp. 365–374).

Long, Y., Luo, H., & Zhang, Y. (2024). Evaluating large language models in analysing classroom dialogue. *Npj Science of Learning*, *9*(1), 60. https://doi.org/10.1038/s41539-024-00273-3

Lu, H., He, L., Yu, H., Pan, T., & Fu, K. (2024). A study on teachers' willingness to use generative AI technology and its influencing factors: Based on an integrated model. *Sustainability*, *16*(16), 7216. https://doi.org/10.3390/su16167216

Luckin, R., & Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. *British Journal of Educational Technology*, *50*(6), 2824–2838. https://doi.org/10.1111/bjet.12861

Lurye, S., & Bryan, C. (2025, March 12). *Takeaways from our investigation on AI-powered school surveillance*. AP News. https://apnews.com/article/ai-school-

chromebook-surveillance-gaggle-investigation-takeaways-381fa82978f27eb85f20d03236820711

MacDonald, K. (2023). Social justice leadership practice in unjust times: Leading in highly disadvantaged contexts. *International Journal of Leadership in Education*, *26*(1), 1–17. https://doi.org/10.1080/13603124.2020.1770866

Mack, B. (2025, April 30). *AI in early education: How AI may undermine the early childhood workforce*. Teaching Strategies. https://teachingstrategies.com/blog/how-ai-may-undermine-the-early-childhood-workforce/

Malatji, W. R., Eck, R. V., & Zuva, T. (2020). Understanding the usage, modifications, limitations and criticisms of technology acceptance model (TAM). *Advances in Science, Technology and Engineering Systems Journal*, *5*(6), 113–117. https://doi.org/10.25046/aj050612

Mandinach, E. B., & Gummer, E. S. (2016). *Data literacy for educators: Making it count in teacher preparation and practice*. Teachers College Press.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Martinez, M. A., Enyioha, J. C., Marquez, J. G., & Baker, A. M. (2022). "I get emotional about it": Teachers' (com)passion in college-going efforts at three urban high schools. *Urban Education*, *59*(6), 1905–1934. https://doi.org/10.1177/00420859221089544

Martino, A., Iannelli, M., & Truong, C. (2023). Knowledge injection to counter large language model (LLM) hallucination. In C. Pesquita, H. Skaf-Molli, V. Efthymiou, S. Kirrane, A. Ngonga, D. Collarana, R. Cerqueira, M. Alam, C. Trojahn, & S. Hertling (Eds.), *The Semantic Web: ESWC 2023 Satellite Events* (Vol. 13998, pp. 182–185). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-43458-7_34

Massey, E., Biesbroek, R., Huitema, D., & Jordan, A. (2014). Climate policy innovation: The adoption and diffusion of adaptation policies across Europe. *Global Environmental Change*, *29*, 434–443. https://doi.org/10.1016/j.gloenvcha.2014.09.002

Maxwell, J. A. (2012). *A realist approach for qualitative research*. SAGE Publications.

McFadden, M. G. (1995). Resistance to schooling and educational outcomes: questions of structure and agency. *British Journal of Sociology of Education*, *16*(3), 293–308. https://doi.org/10.1080/0142569950160302

McGehee, N. (2024). *Breaking barriers: A meta-analysis of educator acceptance of AI technology in education*. Michigan Virtual Learning Research Institute. https://michiganvirtual.org/research/publications/breaking-barriers-a-meta-analysis-of-educator-acceptance-of-ai-technology-in-education/

Mearian, L. (2023, April 25). *Schools look to ban ChatGPT, students use it anyway*. Computerworld. https://www.computerworld.com/article/1623825/schools-look-to-ban-chatgpt-students-use-it-anyway.html

Mingers, J. (2001). Combining IS research methods: Towards a pluralist methodology. *Information Systems Research*, *12*(3), 240–259. https://doi.org/10.1287/isre.12.3.240.9709

Natasia, S. R., Wiranti, Y. T., & Parastika, A. (2022). Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach. *Procedia Computer Science*, *197*, 512–520. https://doi.org/10.1016/j.procs.2021.12.168

Ndukwe, I. G., & Daniel, B. K. (2020). Teaching analytics, value and tools for teacher data literacy: A systematic and tripartite approach. *International Journal of Educational Technology in Higher Education*, *17*(1), 22. https://doi.org/10.1186/s41239-020-00201-6

Nguyen, V. K. L., Le, T. M. H., Duong, T. N. M., Nguyen, T. S., Le, T. T. H., & Nguyen, T. T. H. (2022). Assessing student's adoption of e-learning: An integration of TAM and TPB framework. *Journal of Information Technology Education: Research*, *21*, 297–335. https://doi.org/10.28945/5000

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, *14*(1), 110–121.

Oliver, C. (2012). Critical realist grounded theory: A new approach for social work research. *British Journal of Social Work*, *42*(2), 371–387. https://doi.org/10.1093/bjsw/bcr064

OpenAI Help Center. (2025, June). *Temporary Chat FAQ*. OpenAI. https://help.openai.com/en/articles/8914046-temporary-chat-faq

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, *3*(3), 398–427. https://doi.org/10.1287/orsc.3.3.398

Park, S.-H. "Sunny," Lee, L., & Yi, M. Y. (2011). Group-level effects of facilitating conditions on individual acceptance of information systems. *Information Technology and Management*, *12*(4), 315–334. https://doi.org/10.1007/s10799-011-0097-2

Prescott, M. R., Yeager, S., Ham, L., Rivera Saldana, C. D., Serrano, V., Narez, J., Paltin, D., Delgado, J., Moore, D. J., & Montoya, J. (2024). Comparing the efficacy and efficiency of human and generative AI: Qualitative thematic analyses. *JMIR AI*, *3*, e54482. https://doi.org/10.2196/54482

Puja, T., Digar, S. F., Anjana, B., & Rakhi, T. (2025). AI in classrooms: Impact on teacher identity and autonomy. *I-Manager's Journal on School Educational Technology*, *20*(4), 39. https://doi.org/10.26634/jsch.20.4.21964

Qiao, S., Fang, X., Wang, J., Zhang, R., Li, X., & Kang, Y. (2025). Generative AI for thematic analysis in a maternal health study: Coding semistructured interviews using large language models. *Applied Psychology: Health and Well-Being*, *17*(3), e70038. https://doi.org/10.1111/aphw.70038

Rasheed, Z., Waseem, M., Ahmad, A., Kemell, K.-K., Xiaofeng, W., Duc, A. N., & Abrahamsson, P. (2024). *Can large language models serve as data analysts? A*

multi-agent assisted approach for qualitative data analysis. arXiv. https://doi.org/10.48550/ARXIV.2402.01386

Raza, M. Z., Xu, J., Lim, T., Boddy, L., Mery, C. M., Well, A., & Ding, Y. (2025). *LLM-TA: An LLM-enhanced thematic analysis pipeline for transcripts from parents of children with congenital heart disease*. arXiv. https://doi.org/10.48550/ARXIV.2502.01620

Redman-MacLaren, M., & Mills, J. (2015). Transformational grounded theory: Theory, voice, and action. *International Journal of Qualitative Methods*, *14*(3), 1–12. https://doi.org/10.1177/160940691501400301

Rogers, E. M. (1962). *Diffusion of innovations* (First Edition). The Free Press of Glencoe.

Rosdi, A. M., Khalid, F., & Rasul, M. S. (2020). Factors influencing the formation of teacher professional identity in technology integration. *Journal of Educational and Social Research*, *10*(5), 1. https://doi.org/10.36941/jesr-2020-0082

Sachs, J. (2001). Teacher professional identity: Competing discourses, competing outcomes. *Journal of Education Policy*, *16*(2), 149–161. https://doi.org/10.1080/02680930116819

Sadeck, O. (2022). Technology adoption model: is use/non-use a case of technological affordances or psychological disposition or pedagogical reasoning in the context of teaching during the Covid-19 pandemic period? *Frontiers in Education*, *7*, 906195. https://doi.org/10.3389/feduc.2022.906195

SAIS. (2024, September 4). *Maintain teacher autonomy while adopting AI schoolwide*.

SAIS. https://sais.org/resource/maintain-teacher-autonomy-while-adopting-ai-schoolwide/

Sakaguchi, K., Sakama, R., & Watari, T. (2025). Evaluating ChatGPT in qualitative thematic analysis with human researchers in the Japanese clinical context and its cultural interpretation challenges: Comparative study. *Journal of Medical Internet Research*, *27*, Article 71521. https://doi.org/10.2196/71521

Sannino, A. (2010). Teachers' talk of experiencing: Conflict, resistance and agency. *Teaching and Teacher Education*, *26*(4), 838–844. https://doi.org/10.1016/j.tate.2009.10.021

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Selwyn, N. (2010a). Looking beyond learning: Notes towards the critical study of educational technology. *Journal of Computer Assisted Learning*, *26*(1), 65–73. https://doi.org/10.1111/j.1365-2729.2009.00338.x

Selwyn, N. (2010b). *Schools and schooling in the digital age: a critical analysis*. Routledge. https://doi.org/10.4324/9780203840795

Semenova, V. (2020). Technology adoption theories in examining the uptake of blockchain technology in the framework of functionalist and interpretive paradigms. *Vezetéstudomány / Budapest Management Review*, *51*(11), 26–38. https://doi.org/10.14267/VEZTUD.2020.11.03

Seshadri, M. (2024, August 19). *LAUSD's AI chatbot fail*. LAist. https://laist.com/brief/news/education/communities-demand-transparency-after-ed-lausds-ai-chatbot-fails

Shata, A. (2025). "Opting out of AI": Exploring perceptions, reasons, and concerns behind faculty resistance to generative AI. *Frontiers in Communication*, *10*, 1614804. https://doi.org/10.3389/fcomm.2025.1614804

Shelton, C. (2018). "You have to teach to your personality": Caring, sharing and teaching with technology. *Australasian Journal of Educational Technology*, *34*(4). https://doi.org/10.14742/ajet.3557

Shulman, L. (1987). Knowledge and teaching: Foundations of the new reform. *Harvard Educational Review*, *57*(1), 1–23. https://doi.org/10.17763/haer.57.1.j463w79r56455411

Silverstone, R., & Haddon, L. (1996). Design and the domestication of information and communication technologies: Technical change and everyday life. In R. Mansell & R. Silverstone (Eds.), *Communication by design: the politics of information and communication technologies* (pp. 44–74). Oxford University Press.

Silverstone, R., & Hirsch, E. (Eds.). (1992). *Consuming technologies: Media and information in domestic spaces*. Routledge.

Smakman, M. H. J., Konijn, E. A., Vogt, P., & Pankowska, P. (2021). Attitudes towards social robots in education: Enthusiast, practical, troubled, sceptic, and mindfully positive. *Robotics*, *10*(1), 24. https://doi.org/10.3390/robotics10010024

Soares, W. (2024, December 13). *AI tools and student data: Teachers can endanger kids' privacy without robust training*. Chalkbeat. https://www.chalkbeat.org/2024/12/13/ai-tools-used-by-teachers-can-put-student-privacy-and-data-at-risk/

Šumak, B., & Šorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behavior*, *64*, 602–620. https://doi.org/10.1016/j.chb.2016.07.037

Ta, R., & West, D. M. (2023, August 7). *Should schools ban or integrate generative AI in the classroom?* Brookings. https://www.brookings.edu/articles/should-schools-ban-or-integrate-generative-ai-in-the-classroom/

Tai, R. H., Bentley, L. R., Xia, X., Sitt, J. M., Fankhauser, S. C., Chicas-Mosier, A. M., & Monteith, B. G. (2024). An examination of the use of large language models to aid analysis of textual data. *International Journal of Qualitative Methods*, *23*, 16094069241231168. https://doi.org/10.1177/16094069241231168

Tarhini, A., Arachchilage, N. A. G., Masa'deh, R., & Abbasi, M. S. (2015). A critical review of theories and models of technology adoption and acceptance in information system research. *International Journal of Technology Diffusion*, *6*(4), 58–77. https://doi.org/10.4018/IJTD.2015100104

Tarhini, A., Hone, K., & Liu, X. (2013). User acceptance towards web-based learning systems: Investigating the role of social, organizational and individual factors in

European higher education. *Procedia Computer Science*, *17*, 189–197. https://doi.org/10.1016/j.procs.2013.05.026

Tarhini, A., Hone, K., & Liu, X. (2014). The effects of individual differences on e-learning users' behaviour in developing countries: A structural equation model. *Computers in Human Behavior*, *41*, 153–163. https://doi.org/10.1016/j.chb.2014.09.020

Taylor, P. C., Taylor, E., & Luitel, B. C. (2012). Multi-paradigmatic transformative research as/for teacher education: An integral perspective. In B. J. Fraser, K. Tobin, & C. J. McRobbie (Eds.), *Second International Handbook of Science Education* (pp. 373–387). Springer Netherlands. https://doi.org/10.1007/978-1-4020-9041-7_26

Tekin, Ö. G. (2024). Factors affecting teachers' acceptance of artificial intelligence technologies: Analyzing teacher perspectives with structural equation modeling. *Instructional Technology and Lifelong Learning*, *5*(2), 399–420. https://doi.org/10.52911/itall.1532218

Theelen, H., Vreuls, J., & Rutten, J. (2024). Doing research with help from ChatGPT: Promising examples for coding and inter-rater reliability. *International Journal of Technology in Education*, *7*(1), 1–18. https://doi.org/10.46328/ijte.537

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation* (4. print). Lexington Books.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on*

Engineering Management, *EM-29*(1), 28–45. https://doi.org/10.1109/TEM.1982.6447463

Tram, N. H. M. (2025). Unveiling the drivers of AI integration among language teachers: Integrating UTAUT and AI-TPACK. *Computers in the Schools*, *42*(2), 100–120. https://doi.org/10.1080/07380569.2024.2441155

Übellacker, T. (2024). *AcademiaOS: Automating grounded theory development in qualitative research with large language models.* arXiv. https://doi.org/10.48550/ARXIV.2403.08844

University of Illinois College of Education. (2024, October 24). *AI in schools: Pros and cons*. University of Illinois Urbana-Champaign. https://education.illinois.edu/about/news-events/news/2024/10/24/ai-in-schools--pros-and-cons

Van Ewijk, G., Smakman, M., & Konijn, E. A. (2020). Teachers' perspectives on social robots in education: an exploratory case study. *Proceedings of the Interaction Design and Children Conference*, 273–280. https://doi.org/10.1145/3392063.3394397

Vanassche, E., & Kelchtermans, G. (2014). Teacher educators' professionalism in practice: Positioning theory and personal interpretative framework. *Teaching and Teacher Education*, *44*, 117–127. https://doi.org/10.1016/j.tate.2014.08.006

Varghese, M., Morgan, B., Johnston, B., & Johnson, K. A. (2005). Theorizing language teacher identity: Three perspectives and beyond. *Journal of Language, Identity & Education*, *4*(1), 21–44. https://doi.org/10.1207/s15327701jlie0401_2

Vargo, S. L., Akaka, M. A., & Wieland, H. (2020). Rethinking the process of diffusion in innovation: A service-ecosystems and institutional perspective. *Journal of Business Research*, *116*, 526–534. https://doi.org/10.1016/j.jbusres.2020.01.038

Velli, K., & Zafiropoulos, K. (2024). Factors that affect the acceptance of educational AI tools by Greek teachers—a structural equation modelling study. *European Journal of Investigation in Health, Psychology and Education*, *14*(9), 2560–2579. https://doi.org/10.3390/ejihpe14090169

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, *24*(1), 115. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Wachinger, J., Bärnighausen, K., Schäfer, L. N., Scott, K., & McMahon, S. A. (2024). Prompts, pearls, imperfections: Comparing ChatGPT and a human researcher in

qualitative data analysis. *Qualitative Health Research*, *35*(9), 951–966. https://doi.org/10.1177/10497323241244669

Waite, R. (2025, June 4). *AI tutors vs. human teachers: Enhancing education or replacing it*. Robin Waite. https://www.robinwaite.com/blog/ai-tutors-vs-human-teachers-enhancing-education-or-replacing-it

Walter, Z., & Lopez, M. S. (2008). Physician acceptance of information technologies: Role of perceived threat to professional autonomy. *Decision Support Systems*, *46*(1), 206–215. https://doi.org/10.1016/j.dss.2008.06.004

Wang, C.-S., Jeng, Y.-L., & Huang, Y.-M. (2017). What influences teachers to continue using cloud services? The role of facilitating conditions and social influence. *The Electronic Library*, *35*(3), 520–533. https://doi.org/10.1108/EL-02-2016-0046

Wang, M., Chen, Z., Liu, Q., Peng, X., Long, T., & Shi, Y. (2024). Understanding teachers' willingness to use artificial intelligence-based teaching analysis system: Extending TAM model with teaching efficacy, goal orientation, anxiety, and trust. *Interactive Learning Environments*, *33*(2), 1–18. https://doi.org/10.1080/10494820.2024.2365345

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society*, *24*(3), 116–129. JSTOR. https://www.jstor.org/stable/27032860

Watty, K., McKay, J., & Ngo, L. (2016). Innovators or inhibitors? Accounting faculty resistance to new educational technologies in higher education. *Journal of Accounting Education*, *36*, 1–15. https://doi.org/10.1016/j.jaccedu.2016.03.003

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q., & Zhou, D. (2022). *Chain-of-thought prompting elicits reasoning in large language models*. arXiv. https://doi.org/10.48550/ARXIV.2201.11903

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science*, *16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Westberry, N., McNaughton, S., Billot, J., & Gaeta, H. (2015). Resituation or resistance? Higher education teachers' adaptations to technological change. *Technology, Pedagogy and Education*, *24*(1), 101–116. https://doi.org/10.1080/1475939X.2013.869509

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, *28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088

Williamson, B., Bayne, S., & Shay, S. (2020). The datafication of teaching in Higher Education: critical issues and perspectives. *Teaching in Higher Education*, *25*(4), 351–365. https://doi.org/10.1080/13562517.2020.1748811

Winch, C. (2010). *Dimensions of expertise: A conceptual exploration of vocational knowledge*. Continuum.

Wosny, M., & Hastings, J. (2024). Applying large language models to interpret qualitative interviews in healthcare. In J. Mantas, A. Hasman, G. Demiris, K. Saranto, M. Marschollek, T. N. Arvanitis, I. Ognjanović, A. Benis, P. Gallos, E.

Zoulias, & E. Andrikopoulou (Eds.), *Studies in Health Technology and Informatics*. IOS Press. https://doi.org/10.3233/SHTI240530

Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: An empirical investigation based on the UTAUT model and perceived risk theory. *Frontiers in Psychology*, *13*, 870777. https://doi.org/10.3389/fpsyg.2022.870777

Xiao, Z., Yuan, X., Liao, Q. V., Abdelghani, R., & Oudeyer, P.-Y. (2023). Supporting qualitative analysis with large language models: Combining codebook with GPT-3 for deductive coding. *28th International Conference on Intelligent User Interfaces*, 75–78. https://doi.org/10.1145/3581754.3584136

Xu, H., Yi, S., Lim, T., Xu, J., Well, A., Mery, C., Zhang, A., Zhang, Y., Ji, H., Pingali, K., Leng, Y., & Ding, Y. (2025). *Tama: A human-AI collaborative thematic analysis framework using multi-agent LLMs for clinical interviews*. arXiv. https://doi.org/10.48550/ARXIV.2503.20666

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: a systematic review. *Sage Open*, *14*(1), 21582440241229570. https://doi.org/10.1177/21582440241229570

Yao, N., & Abd Halim, N. D. (2023). Analyzing factors influencing primary school teachers' acceptance willingness of artificial intelligence technology. *Proceedings of the 2023 6th International Conference on Educational Technology Management*, 35–41. https://doi.org/10.1145/3637907.3637951

Yeung, H. W. (1997). Critical realism and realist research in human geography: A method or a philosophy in search of a method? *Progress in Human Geography*, *21*(1), 51–74. https://doi.org/10.1191/030913297668207944

Yi, M. Y., Jackson, J. D., Park, J. S., & Probst, J. C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management*, *43*(3), 350–363. https://doi.org/10.1016/j.im.2005.08.006

Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2007). Technology acceptance: A meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2*(3), 251–280. https://doi.org/10.1108/17465660710834453

Yuan, Z., Liu, J., Deng, X., Ding, T., & Wijaya, T. T. (2023). Facilitating conditions as the biggest factor influencing elementary school teachers' usage behavior of dynamic mathematics software in China. *Mathematics*, *11*(6), 1536. https://doi.org/10.3390/math11061536

Zaineldeen, S., Hongbo, L., Koffi, A. L., & Hassan, B. M. A. (2020). Technology acceptance model' concepts, contribution, limitation, and adoption in education. *Universal Journal of Educational Research*, *8*(11), 5061–5071. https://doi.org/10.13189/ujer.2020.081106

Zalaznick, M. (2023, January 31). A war on ChatGPT is raging. But some K12 leaders are making peace with AI. *District Administration*. https://districtadministration.com/briefing/chatgpt-bans-k12-school-districts-ai-chatbot-artificial-intelligence/

Zanello, G., Fu, X., Mohnen, P., & Ventresca, M. (2016). The creation and diffusion of innovation in developing countries: A systematic literature review. *Journal of Economic Surveys*, *30*(5), 884–912. https://doi.org/10.1111/joes.12126

Zhang, H., Wu, C., Xie, J., Kim, C., & Carroll, J. M. (2023). *QualiGPT: GPT as an easy-to-use tool for qualitative coding*. arXiv. https://doi.org/10.48550/ARXIV.2310.07061

Zhang, X., & Wareewanich, T. (2024). A study of the factors influencing teachers' willingness to use generative artificial intelligence based on the UTAUT model. *International Journal of Interactive Mobile Technologies*, *18*(06), 126–142. https://doi.org/10.3991/ijim.v18i06.47991

Zhao, J., Li, S., & Zhang, J. (2025). Understanding teachers' adoption of AI technologies: an empirical study from Chinese middle schools. *Systems*, *13*(4), 302. https://doi.org/10.3390/systems13040302

Zhou, J., & Zhang, H. (2025). Transforming education in the AI era: A Technology–Organization–Environment framework inquiry into public discourse. *Applied Sciences*, *15*(7), 3886. https://doi.org/10.3390/app15073886

Zhou, Y., Yuan, Y., Huang, K., & Hu, X. (2024). Can ChatGPT perform a grounded theory approach to do risk analysis? An empirical study. *Journal of Management Information Systems*, *41*(4), 982–1015. https://doi.org/10.1080/07421222.2024.2415772

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry.

Information Systems Research, *16*(1), 61–84. https://doi.org/10.1287/isre.1050.0045

Zipin, L., Sellar, S., Brennan, M., & Gale, T. (2015). Educating for futures in marginalized regions: A sociological framework for rethinking and researching aspirations. *Educational Philosophy and Theory*, *47*(3), 227–246. https://doi.org/10.1080/00131857.2013.839376

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