

Understanding the Multilevel Aspects of Resistance to AI Adoption in Higher Education

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Abstract: This study aims to examine how resistance to artificial intelligence adoption in higher education is shaped by current research directions. By employing a systematic approach combined with bibliometric co-citation analysis authors seek to understand the multilevel phenomena of resistance to AI adoption and uncover possible research gaps in the existing scientific field. The analysis, performed in accordance with PRISMA statement and mixed-method approach, included 2121 peer-reviewed publications from Scopus with manual qualitative interpretation of thematic clusters. The results reveal four interconnected dimensions of resistance. First, behavioral traits were uncovered, capturing how such factors as perceived usefulness, perceived ease of use, self-efficacy, and expected performance outcomes influence educators' desire to engage with AI tools. Secondly, organizational readiness for change including such parameters as institutional capacity, culture, and change management was highlighted as highly important in understanding the phenomena and nature of teachers and students resistance to adopt AI. Thirdly, ethical considerations were found to be crucial for current AI adoption management understanding. This research direction included variables such as data privacy, algorithmic bias, transparency, accountability, and broaden debates about the legitimacy of AI in knowledge production, assessment, and teaching practice. Finally, understanding psychological factors such as trust in AI, AI anxiety and perceived loss were also identified as promising research stream. These clusters combined demonstrated that resistance to AI adoption in higher education is a multi-layered phenomenon that can be observed complexly by scientists, combining different analysis levels rather than focusing solely on technological or attitudinal aspects. The findings contribute to organizational behavior theory research by clarifying how emotional, cultural, and institutional mechanisms interact in shaping AI resistance. The study provides a structured basis for integrating resistance factors into a broader model of organizational readiness for AI adoption in higher education, including institutional determinants in addition to psychological and organizational ones.

Keywords: Artificial Intelligence, Higher Education, Resistance to Change, Readiness for Change

1. Introduction

Artificial intelligence is one of the most significant drivers of transformation in contemporary educational organizations (Sohn & Kwon, 2020). AI-based systems are increasingly used for personalized learning, assessment, student support, administrative decision-making, learning analytics, and research assistance (Saragih, 2024). These technologies promise efficiency, scalability, and new forms of educational insight (Yan et al., 2020). However, despite the growing interest in AI, its adoption in higher education remains uneven and contested (Adiguzel et al., 2023).

Existing studies on AI adoption often rely on established technology acceptance frameworks, especially the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. These models emphasize perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence, and behavioral intention as key predictors of technology adoption (Davis, 1989; Venkatesh et al., 2003). While these approaches remain important, they are insufficient for fully explaining resistance to AI in universities. Resistance is not only an individual reaction to a new digital tool. It may also reflect organizational inertia, ethical uncertainty, professional identity concerns, lack of institutional readiness, or distrust toward algorithmic systems (Zawacki-Richter et al., 2019).

This issue is especially important in higher education because universities differ from ordinary business organizations. In companies, AI adoption is often framed through efficiency, productivity, competitive advantage, and managerial control (Kemp, 2024). In universities, however, adoption is embedded in academic autonomy, disciplinary cultures, collegial governance, pedagogical traditions, and public responsibility for knowledge production (Allam et al., 2025; Dotan et al., 2025). Universities are often described as loosely coupled systems, where formal strategies do not automatically translate into uniform practice across departments, faculties, and individual academics (Lutz, 1982). They can also be understood as professional bureaucracies, where the core work is performed by highly trained professionals whose autonomy is central to organizational functioning (Kallio et al., 2020). Therefore, AI adoption in higher education requires not only technological implementation but also organizational, ethical, pedagogical, and emotional alignment (Acosta-Enriquez et al., 2024).

The problem addressed in this study is the fragmentation of research on AI adoption and resistance in educational contexts. Existing literature covers technology acceptance, organizational change, ethical AI, trust, algorithm aversion, and digital transformation, but these streams are often analyzed separately. As a result, there is a need for a systematic synthesis that maps the intellectual landscape of resistance to AI adoption and connects it with the broader concept of organizational readiness.

The research question guiding this study is:

What dominant research streams on resistance to AI adoption can be identified in the educational context, and how can they inform a resistance-based framework for AI adoption in higher education?

The aim of the study is to map and synthesize the dominant research streams on resistance to AI adoption in higher education and to reinterpret resistance as a diagnostic component of readiness formation.

The article contributes to literature in three ways. First, it systematizes a fragmented body of research by identifying four thematic clusters of AI resistance. Second, it extends technology acceptance perspectives by integrating organizational readiness, ethical legitimacy, and emotional responses. Third, it highlights the specificity of universities as organizations and argues that AI adoption in higher education should not be approached through generic corporate adoption logic.

2. Methodology

To address questions, a mixed approach including qualitative and quantitative methods was adopted. The study used a systematic review combined with bibliometric co-citation analysis and qualitative thematic synthesis. This mixed-method design was selected because it allows the research field to be examined both quantitatively and interpretively.

Bibliometric analysis makes it possible to identify the intellectual structure of the field, while qualitative synthesis helps interpret the meaning of the detected clusters.

The review procedure was aligned with the general logic of the PRISMA approach for systematic reviews (Moher et al., 2009). The research process included the following stages: formulation of the research question, selection of the database, development of the search string, definition of inclusion criteria, extraction of bibliographic data, bibliometric mapping, cluster interpretation, and thematic synthesis.

Bibliographic data were collected from the Scopus database in February 2025. Scopus was selected because it provides broad coverage of peer-reviewed international literature and includes detailed citation metadata suitable for bibliometric analysis. The search strategy focused on artificial intelligence, higher education, resistance, and adoption-related concepts. The search included English-language journal articles indexed in relevant subject areas, including business, social sciences, economics, and psychology. Only peer-reviewed journal articles were included in the final dataset. The final sample consisted of 2,121 peer-reviewed articles published between 1989 and 2025. The dataset was exported from Scopus and prepared for bibliometric analysis.

The bibliometric stage was conducted using VOSviewer. Reference co-citation analysis was selected because it helps identify foundational intellectual traditions and research streams within a field. Co-citation analysis is based on the assumption that publications frequently cited together are intellectually related.

The analysis generated a co-citation network in which nodes represent cited references, links represent co-citation relationships, node size reflects citation frequency, and link strength indicates the intensity of intellectual association between references. The clustering procedure identified four major clusters. These clusters were then interpreted through expert inspection and qualitative synthesis.

After the bibliometric clusters were identified, the articles and references associated with each cluster were analyzed thematically. The synthesis focused on theoretical foundations, empirical findings, and conceptual gaps within each cluster. The coding logic followed the principles of thematic analysis proposed by Braun and Clarke (2006), including familiarization with the literature, identification of recurrent themes, refinement of themes, and interpretation of thematic patterns.

The purpose of the qualitative stage was not only to describe the clusters but also to connect them with the broader research problem of organizational readiness for AI adoption in higher education.

3. Results

The reference co-citation analysis identified four major thematic clusters that structure the research landscape on AI adoption and resistance in educational and organizational contexts. These clusters represent different but interconnected dimensions of resistance: user experience and behavioral intentions, organizational transformation and readiness, ethical and epistemic concerns, and emotional-psychological factors (Picture 1).

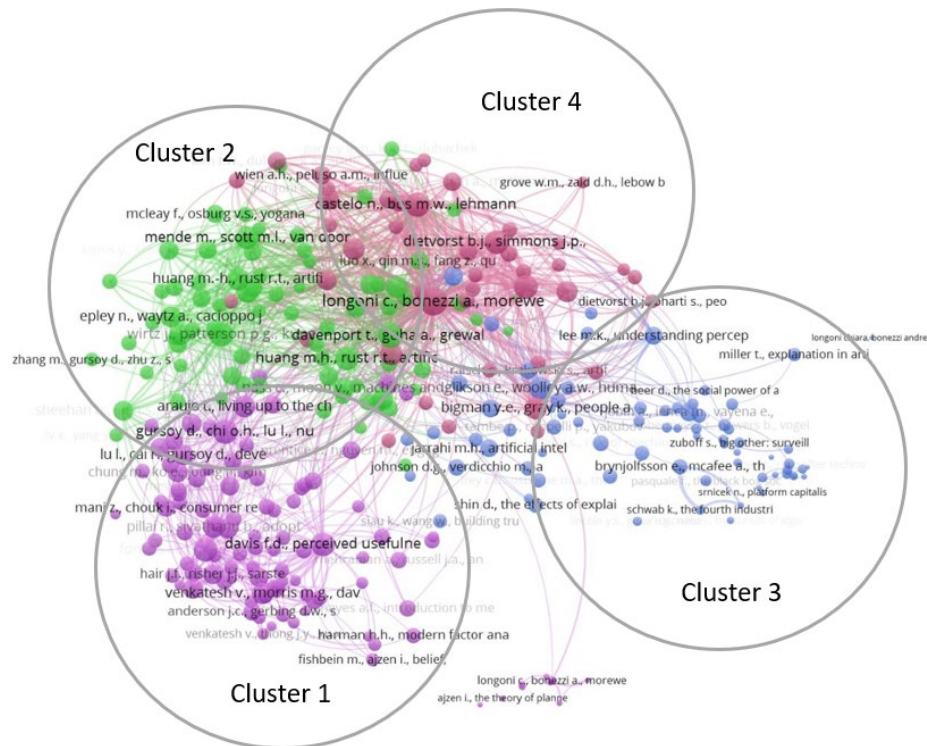


Figure 1: Results of co-citation analysis

3.1 Cluster 1: User Experience and Behavioral Intentions

The first cluster focuses on individual-level perceptions of AI systems and their influence on behavioral intention to use AI. This stream is strongly connected with technology acceptance research, particularly TAM and UTAUT. Studies in this cluster show that perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy remain important predictors of AI adoption (Davis, 1989; Venkatesh et al., 2003).

In higher education, these constructs acquire a specific meaning. Educators are more likely to accept AI when they perceive that it improves teaching quality, supports student learning (Ma & Lei 2024), reduces administrative burden, or enhances research productivity (Zhang & Zhang, 2024). Conversely, resistance emerges when AI tools are perceived as difficult to use, pedagogically irrelevant, or misaligned with classroom realities (Hutson, 2025).

The cluster also includes social and cultural influences on AI acceptance. Social influence, peer endorsement, leadership support, and professional norms may encourage or inhibit AI adoption. In educational organizations, this is particularly important because educators often rely on disciplinary communities and collegial validation when evaluating new technologies (Gill & Nair, 2025).

This cluster suggests that readiness for AI adoption begins at the level of user experience. However, readiness cannot be reduced to positive behavioral intention. A university may have technically available AI tools, but if educators do not perceive them as meaningful, legitimate, and compatible with their work, adoption remains superficial.

3.2 Cluster 2: Organizational Transformation and Readiness

The second cluster shifts attention from individual users to organizational conditions of AI implementation. It includes research on organizational culture, leadership support, infrastructure, resources, IT readiness, strategic

vision, and change management. Studies of this cluster show that AI adoption depends not only on whether individual users are willing to use AI, but also on whether the organization is prepared to support implementation (Davenport & 2018; Wang, 2021)

This cluster is directly relevant to the concept of organizational readiness. Organizational readiness refers to the extent to which an institution has the resources, capabilities, shared commitment, and implementation capacity necessary for change (Lokuge et al., 2019). In the context of AI adoption, readiness includes technological infrastructure, staff training, governance mechanisms, data management practices, leadership support, and a culture of experimentation (Felemban et al., 2024).

Therefore, resistance to AI in universities may reflect not only lack of resources or insufficient training, but also weak alignment between institutional strategy and academic practice. A central AI policy may exist, but its implementation may vary across disciplines and units. This makes resistance a distributed and multi-level condition rather than a single organizational attribute.

3.3 Cluster 3: Ethical and Epistemic Concerns

The third cluster focuses on ethical, societal, and epistemic issues related to AI implementation. Key themes include algorithmic opacity, accountability, surveillance, data privacy, explainability, and the changing nature of knowledge production (Logg et al., 2019; Castelo, 2019) .

This cluster is especially important for higher education because universities are not only users of AI technologies but also institutions responsible for producing, validating, and transmitting knowledge. AI adoption in universities raises questions about academic integrity, authorship, assessment fairness, student surveillance, data governance, and the role of human judgment in education (Gbadago et al., 2025).

Concerns about algorithmic opacity are central to this stream. When AI systems operate as black boxes, educators and students may not understand how decisions are produced, how recommendations are generated, or how data are used (Burrell, 2016). This creates accountability problems and may weaken trust. Similarly, algorithmic bias may reproduce social inequalities, while AI-based monitoring systems may intensify surveillance and threaten privacy (Barocas & Selbst, 2016)

The findings suggest that ethical resistance should not be dismissed as irrational. In many cases, it represents a legitimate concern about the normative foundations of education. For universities, responsible AI adoption requires ethical governance, transparent rules, participatory decision-making, and clear boundaries regarding the use of AI in teaching, assessment, and administration.

3.4 Cluster 4: Emotional and Psychological Factors

The fourth cluster highlights the emotional and psychological dimensions of AI resistance. Key themes include trust, anxiety, perceived loss of control, algorithm aversion, fear of replacement, and professional insecurity. This cluster shows that AI adoption cannot be explained only through rational evaluation of usefulness and effort.

Algorithm aversion is especially relevant. Research shows that users may avoid algorithmic recommendations even when algorithms perform well, especially after observing algorithmic errors (Dietvorst et al., 2015). In educational contexts, such aversion may be intensified by the fact that teaching involves relational, interpretive, and value-laden judgment. Educators may question whether AI can adequately understand students' needs, evaluate complex learning outcomes, or support meaningful pedagogical interaction.

This cluster also connects with organizational change theory. Piderit's multidimensional view of resistance emphasizes that resistance includes cognitive, emotional, and intentional components (Piderit, 2000). Applied to AI adoption in higher education, this means that educators may cognitively recognize AI's usefulness while emotionally distrusting it or behaviorally avoiding it.

The emotional dimension of resistance indicates the importance of psychological safety. Educators need space to experiment, express doubts, discuss ethical concerns, and learn from mistakes without fear of punishment or professional devaluation. Therefore, readiness for AI adoption includes not only skills and infrastructure, but also effective and relational conditions.

4. Discussion

In universities, organizational resistance has a distinctive structure. Unlike firms where authority may be concentrated in executive management, universities are characterized by distributed authority and multiple centers of decision-making (Hardy, 1991). Faculty members, departments, administrative units, IT services, quality assurance offices, ethics committees, and external regulators all influence whether AI adoption becomes accepted, resisted, fragmented, or symbolically adopted.

This specificity can be explained through higher education organization theory. Weick's concept of loosely coupled systems suggests that educational organizations often combine formal coordination with substantial autonomy of local units (Weick, 1982). In such systems, a central policy on AI adoption does not automatically translate into uniform classroom practice. A university may formally declare an AI strategy, while actual adoption varies significantly across faculties, disciplines, and individual educators. Similarly, Mintzberg's notion of professional bureaucracy helps explain why academic professionals resist direct standardization of their core work: teaching and research are governed not only by administrative rules, but also by professional expertise and disciplinary judgment (Mintzberg, 1979). Thus, resistance to AI may arise when educators interpret AI implementation as a threat to professional discretion, academic autonomy, or the quality of educational judgment.

Recent literature indicates that generative AI has already entered university life, while institutional capacity to guide, regulate, and pedagogically integrate it remains uneven. Studies published in 2025–2026 show that higher education institutions are moving from initial experimentation toward formal policy development, yet this transition is accompanied by persistent gaps in AI literacy, governance, assessment design, transparency, and trust (An et al., 2025; Jin et al., 2025). Therefore, resistance should be conceptualized not as the opposite of adoption, but as a diagnostic signal of incomplete readiness.

At the individual level, resistance is shaped by educators' AI literacy, perceived usefulness, perceived ease of use, self-efficacy, trust, and perceived compatibility of AI with teaching practice. However, recent research shows that these factors should be interpreted more broadly than in classical technology acceptance models. Ayyoub et al. (2025) emphasize that AI literacy is now a critical competence for educators, while Caspari-Sadeghi (2026) argues that the core question is no longer whether educators should use generative AI, but what knowledge, skills, and mindset they need to use it effectively and responsibly. This means that educators' resistance may not reflect unwillingness to innovate; it may reflect insufficient confidence, unclear pedagogical scripts, weak understanding of AI limitations, or uncertainty about responsible use.

Recent empirical work also confirms that trust and distrust are central to AI adoption in higher education. Lyu et al. (2025), based on a survey of university instructors, explicitly examine current practices, perceptions, trust, and distrust of generative AI in teaching and learning. This is important because trust is not reducible to general optimism about technology. Educators may trust AI for lesson preparation, summarization, brainstorming, or administrative support, while distrusting it for assessment, feedback, grading, or student evaluation. Thus, resistance is domain-specific: the same educator may be an AI adopter in one area and an AI resistor in another.

At the organizational level, resistance reflects whether the university has created conditions for meaningful and responsible AI use. These conditions include infrastructure, professional development, leadership support, training systems, data governance, psychological safety, and transparent policies. Recent studies show that institutional guidelines are becoming a central element of AI governance in higher education. An et al. (2025) analyzed GenAI guidelines issued by the top 50 U.S. universities and showed that institutional responses increasingly address multiple stakeholder groups, including students, faculty, researchers, staff, and administrators. Similarly, Erhardt (2025) examined how Swedish higher education institutions are addressing GenAI through guidelines, policy documents, and public website information, showing that universities are actively trying to convert uncertainty into formal governance structures.

However, the existence of policy does not automatically mean readiness. In higher education, AI adoption often unfolds in loosely coupled organizational settings, where central rules do not immediately translate into consistent local practice. A university may publish GenAI guidelines, but individual faculties, departments, and instructors may interpret them differently. Recent work on global institutional adoption strategies confirms that universities across regions vary considerably in how they frame GenAI adoption, often combining innovation narratives with caution, risk management, and policy experimentation (Jin et al., 2025). Therefore, AI readiness in higher education should be understood as distributed readiness: it must be present not only in strategic documents, but also in departments. Classical adoption models ask whether users intend to use AI technology.

But AI adoption in higher education requires a different question: under what organizational, ethical, and pedagogical conditions can educators consider AI use legitimate? This shifts the analysis from acceptance to readiness. Educators may accept AI as useful but still resist it if they believe it threatens academic judgment, student fairness, professional identity, or the relational nature of teaching.

Recent teacher-training research supports this interpretation. Lademann et al. (2025) found that AI literacy, usage behavior, and attitudes can be influenced through structured teacher training, showing that resistance is not fixed but can be transformed through professional development. This means that universities should not treat resistance as a stable personal trait. Instead, resistance should be seen as a changeable response to the quality of institutional support.

Taken together, recent 2025–2026 studies allow this article to make a stronger theoretical claim: AI resistance in higher education is not a residual category outside adoption models; it is a central mechanism through which universities reveal the incompleteness of their readiness. Resistance shows where AI literacy is insufficient, where policies are unclear, where assessment rules are unstable, where trust is weak, where ethical governance is underdeveloped, and where professional identity feels threatened. This is why resistance should not be suppressed or dismissed as irrational. It should be analyzed as evidence of the organizational work that still needs to be done.

This is particularly important because universities have a dual responsibility: they must prepare students and staff to work with AI, while also preserving norms of critical thinking, academic honesty, intellectual independence, and human-centered education. If AI systems are experienced as black boxes that reshape assessment, personalize learning, or evaluate performance without sufficient transparency, resistance may become ethically grounded rather than merely emotional or instrumental. In such cases, resistance should not be dismissed as irrational. It may express legitimate concern about accountability, fairness, or the displacement of human judgment in educational processes.

5. Conclusion

This study mapped the multidimensional landscape of resistance to AI adoption in educational contexts through a systematic review and bibliometric co-citation analysis of 2,121 peer-reviewed publications. The analysis identified four interconnected research streams: user experience and behavioral intentions, organizational transformation and readiness, ethical and epistemic concerns, and emotional-psychological factors. Together, these clusters demonstrate that resistance to AI adoption in education is not a marginal or purely negative phenomenon. It is a complex response to technological, organizational, professional, ethical, and emotional tensions that accompany the integration of AI into educational practice.

The main conclusion is that AI resistance in higher education should be understood as a diagnostic element of readiness formation. Resistance shows where AI implementation strategies are misaligned with educators' needs, institutional culture, ethical expectations, or professional identities. Poor user experience, lack of pedagogical relevance, insufficient organizational support, unclear governance, algorithmic opacity, and emotional anxiety can all generate resistance. However, these forms of resistance also indicate where universities must intervene if they aim to build sustainable readiness for AI adoption.

This insight also opens a promising direction for further research. Future studies should move from mapping resistance to explaining the mechanisms through which readiness is formed. The present bibliometric analysis identifies the conceptual landscape of resistance, but the next stage should examine how different dimensions of readiness interact. For example, does AI literacy reduce anxiety and algorithm aversion? Does leadership support moderate the relationship between perceived usefulness and behavioral intention? Does ethical governance increase trust in AI? Does psychological safety mediate the effect of organizational culture on experimentation with AI tools? These questions directly connect the present conference paper with a PhD research agenda focused on shaping organizational readiness for AI adoption in higher education.

The study contributes to the literature on AI adoption and organizational change in several ways. First, it systematizes a fragmented research field by identifying four dominant thematic domains of AI resistance. Second, it extends traditional technology acceptance models by showing that AI adoption in education cannot be explained only through perceived usefulness, ease of use, and behavioral intention. These factors remain important, but they must be supplemented with organizational readiness, ethical legitimacy, trust, professional identity, and emotional responses. Third, the study highlights the specific nature of universities as organizations. Unlike ordinary companies, universities are loosely coupled, professionally autonomous, knowledge-producing

institutions. Therefore, AI adoption in higher education requires not only managerial implementation but also collegial negotiation, ethical reflection, pedagogical adaptation, and disciplinary contextualization.

From a practical perspective, the findings suggest that universities should avoid purely instrumental or top-down approaches to AI implementation. Effective AI adoption requires participatory governance, transparent ethical standards, professional development, psychological safety, and clear articulation of how AI supports teaching, research, and administration. Educators should not be treated as passive recipients of technological change. They should be involved as co-designers of AI adoption strategies, because their professional judgment is central to determining where AI can enhance educational quality and where its use may be inappropriate or risky.

The findings also have implications for university leaders and policy makers. Building readiness for AI adoption requires action at multiple levels.

Ethical Declarations

Ethical clearance was not required for the research

AI Declarations

AI (ChatGPT 5.5 Thinking) was used to enhance language quality

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