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Artificial Intelligence and Response to Intervention (RTI) Frameworks in Inclusive Education: An Analytical Review

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Abstract: This study aims to analyze research trends concerning the integration of Artificial Intelligence (AI) and the Response to Intervention (RTI) framework within inclusive education contexts through a systematic analytical review of thirty-three (33) peer-reviewed empirical studies. The study sought to construct an analytical map of the thematic, methodological, and geographical dimensions of scholarly production at this interdisciplinary intersection and to examine the degree of maturity in the integration between the two domains. The study also aimed to provide an interpretive analytical reading of the conceptual and procedural patterns underlying the integration of artificial intelligence applications and Response to Intervention (RTI) systems within inclusive education contexts.

These findings suggest that the field is still transitioning, with only partial functional integration with predictive analytics and decision-support at the forefront, rather than truly integrated models embedded in MTSS. It also suggests a lack of longitudinal experimental studies, with a predominance of conceptual articles and a strong focus on the U.S.

Based on these findings, the levels of partial, procedural, and structural integration were proposed as a metaphor for the growth of this field. Development of experimental models of integration of AI-based tools into the full structure of the RTI system is encouraged to move from an instrumental use of AI tools toward a sustainable structural integration of AI in inclusive education.

Keywords: Artificial Intelligence; Response to Intervention (RTI); Inclusive Education; Multi-Tiered Systems of Support (MTSS); Structural Integration; Predictive Analytics.

1. Introduction

Digital innovation is transforming education systems worldwide at an unprecedented pace, including the rapidly expanding use of Artificial Intelligence (AI) for classroom assistance, educational data analytics, and personalized instruction. Existing literature suggests that such technologies can enhance accessibility, customization, and analytical support for instruction, including in inclusive settings [1]. Policy briefs from international organizations stress the importance of deploying AI fair and inclusive manner, advocating for the safeguarding of learners with disabilities and special needs [2].

Inclusive education within this arena focuses on entering all students into the mainstream educational environment, with support as needed [3]. Although inclusive education is gaining support, early identification, selection of appropriate interventions, and individualized decision-making are barriers to the process. Response to Intervention (RTI) was designed to address those barriers with a tiered support system based on continual progress monitoring and data-driven decisions [4].

As AI continues to advance, there has been a growing interest in the capabilities of AI to predict learning risk and instructional practices in ways that might streamline MTSS processes such as RTI [5]. But these two areas are still largely parallel in the literature, and an explicit framework to unite them is not clear in the context of inclusive education. Accordingly, the present study adopts an analytical review approach that not only aims to identify existing research trends, but also seeks to interpret the conceptual and procedural patterns underlying the integration of artificial intelligence applications and Response to Intervention (RTI) systems within inclusive education environments.

In the context of the present study, the term “integration” does not merely refer to the coexistence of artificial intelligence technologies and Response to Intervention (RTI) practices within inclusive education environments. Rather, it refers to

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the extent to which artificial intelligence applications are functionally, procedurally, and structurally embedded within the processes of early identification, progress monitoring, intervention planning, educational decision-making, and the implementation of multi-tiered support systems within the RTI/MTSS framework.

There are also ethical concerns related to bias, privacy, and educator training for AI [2].

1.1 Research Problem

Inclusive education for students with disabilities and special educational needs is a significant part of the current educational reform for equity and equal opportunity. Response to Intervention (RTI) is a tiered model of instruction and data-driven decision-making using continuous performance monitoring [4]. Artificial Intelligence (AI) has been increasingly applied for data analysis, risk prediction, and intervention personalization in education [1].

Although these functions overlap, the literatures on AI and RTI indicate that research on AI and research on RTI have followed parallel paths, without a systematically organized body of work that explicates their relationship within inclusive education. More specifically, the scientific literature lacks a clear conceptualization of how artificial intelligence can be integrated into Response to Intervention (RTI) systems across operational and decision-making levels within inclusive educational environments.

Therefore, an analytical review of this emerging area that organizes the intersection of these two domains and identifies patterns and gaps is needed. This type of analysis is essential not only for identifying research trends, but also for interpreting the nature and depth of integration between artificial intelligence and Response to Intervention (RTI) frameworks across diverse inclusive education contexts.

Accordingly, the present study aims to answer the following primary research question: How has the literature conceptualized and studied the role of AI and the RTI framework in inclusive education settings?

1.2 Objectives of the Study

The main purpose of this study is to analytically examine, through an analytical review of recent scientific literature, how the integration of Artificial Intelligence (AI) applications and the Response to Intervention (RTI) framework within inclusive education contexts has been discussed in the academic literature, to map the thematic, methodological, and geographic tendencies of the research and to identify the gaps that prevent the development of a coherent and systematically organized integrative framework. The study also seeks to develop an interpretive understanding of the levels and patterns of integration between artificial intelligence and Response to Intervention (RTI) systems within inclusive education contexts.

The study also aims to clarify the forms and levels of integration between artificial intelligence applications and Response to Intervention (RTI) systems, as reflected in the scientific literature analyzed and reviewed in this study.

1.3 Significance of the Study

This study is significant because it addressed an emerging interdisciplinary area of research regarding Artificial Intelligence, Multi-Tiered Systems of Support (MTSS), and inclusive education that has largely developed independently from one another. This study provides theoretical organization and a conceptual synthesis of this emerging area; it also contributes to providing an interpretive analytical framework for understanding the evolving levels of integration between artificial intelligence applications and Response to Intervention (RTI) systems within inclusive education. A methodological overview of the current research trends; and practical support for a more coordinated and systematic application of artificial intelligence in multi-tiered systems of support in inclusive education.

1.4 Delimitations of the Study

This review is limited by several methodological constraints related to the nature of the analytical approach employed in the study. The review was confined to the analysis of thirty-three (33) peer-reviewed studies selected according to the adopted inclusion criteria, while gray literature was excluded in order to maintain the academic quality of the sources used.

Although the final sample of the study was limited to 33 studies, this number reflects the emerging and relatively fragmented nature of research addressing the integration of artificial intelligence and the Response to Intervention (RTI) framework within inclusive education contexts. The study selection process was also guided by strict inclusion and exclusion criteria to ensure methodological relevance, conceptual consistency, and academic quality among the studies included in the review.

Beginning with the date range of the publication of this article, the time frame for inclusion into the analysis of the literature has been set at 2003 through 2026; This is due to the emergence of the RTI model and AI application in education as emerging areas of research.

Furthermore, all literature reviewed was limited to publications written in either English or Arabic; All literature reviewed were academic journals from online databases.

Lastly, all literature reviewed had to be related to inclusive education settings and how they use Artificial Intelligence and RTI.

1.5 Limitations of the Study

The results of this review depend on the strength and design of the research that has been studied. Because all of the research reviewed in this study was based on published work and did not include a re-examination of the original data, these results are influenced by both the depth and breadth of the research that is available for examination in the literature.

Additionally, because there were relatively few studies used in this review and a considerable amount of variability in their methodology, the findings may have limited generalizability across educational environments and context. Furthermore, this field is also considered to be in an early and highly evolving state of development; therefore, it is rare to find experimental or longitudinal studies evaluating the integration of artificial intelligence into RTI/MTSS models within inclusive education. As such, the findings of this review should be viewed as preliminary and evaluative (rather than broadly generalizable).

Finally, while a conceptual model has been suggested that describes different levels of integration, this needs to be empirically validated in order to demonstrate validity and utility across various educational contexts. Likewise, the proposed classification system was constructed via the interpretive analysis of studies examined in this review, rather than being tested directly via empirical methods. Therefore, the construct validity of this classification system is currently in a very early developmental phase and will require additional evaluation to establish its reliability and usability across diverse educational and technology-based contexts.

As well, because artificial intelligence technology is changing so rapidly, the current results provide a "snapshot" in time that could change as the field develops over time.

1.6 Key Terms of the Study

Artificial Intelligence in Education: Artificial Intelligence in education is defined as the application of algorithms and computational models capable of simulating certain human cognitive processes, such as analysis, prediction, and decision-making, with the aim of supporting learning and improving educational processes [6]. In the present study, Artificial Intelligence refers to the set of analytical applications and algorithms, including predictive analytics, adaptive systems, and decision-support systems, that were employed within the included studies to support early identification processes, personalize interventions, or enhance decision-making within the Response to Intervention (RTI) framework in inclusive education contexts.

Response to Intervention (RTI): Response to Intervention is defined as a multi-tiered framework for delivering academic and behavioral support, grounded in continuous progress monitoring, data-based decision-making, and graduated interventions based on students' responsiveness [4]. In this study, RTI refers to the educational multi-tiered system (Tier 1–Tier 3) as described in the included studies, used as an organizational framework to analyze the degree to which AI tools were embedded within processes of monitoring, assessment, decision-making, and intervention adjustment in inclusive educational environments.

Inclusive Education: Inclusive education is defined as an educational approach aimed at ensuring the participation of all students, including those with disabilities and special educational needs, within general education classrooms through the removal of barriers and the provision of appropriate support systems [7]. In this study, inclusive education refers to the educational context in which Multi-Tiered Systems of Support (MTSS/RTI) are implemented to support students with disabilities or learning difficulties within general education classrooms, as reflected in the studies included in the analytical review.

Predictive Analytics: Predictive analytics is defined as the use of data mining techniques and statistical models to forecast future outcomes based on historical data [8]. In this study, predictive analytics refers to the models and algorithms employed in the included studies to predict academic risk or the likelihood of students' responsiveness to interventions within the RTI framework.

Multi-Tiered Systems of Support (MTSS). MTSS is defined as an organizational framework that integrates both academic and behavioral interventions across tiers of increasing levels of intensity based on data-driven instructional decision-making [9]. MTSS in this study refers to the organizational structure that encompasses RTI and is considered in terms of how AI tools were embedded in the planning, delivery, and evaluation of the support.

1.6.1 Integration Between Artificial Intelligence and Response to Intervention

Theoretical Definition

Integration between artificial intelligence and the Response to Intervention (RTI) framework refers to the use of artificial intelligence applications within multi-tiered support systems to support processes of early identification, data analysis, progress monitoring, and data-driven educational decision-making, thereby contributing to the improvement of educational interventions within inclusive environments [6].

Operational Definition

In this study, integration refers to the extent to which artificial intelligence applications are embedded within the operational, educational, and decision-making processes of the Response to Intervention (RTI) framework and Multi-Tiered Systems of Support (MTSS), whether at the functional, procedural, or structural level, as reflected in the studies included in the analytical review.

1.6.2 Functional Integration

Theoretical Definition

Functional integration in this research is defined as applying artificial intelligence technologies or digital systems to provide for certain educational functions like the ability to predict potential problems with students' education; identify potential issues early on; monitor a student's educational performance; etc., that do not require significant changes to the structural organization of an educational support system [17].

Operational Definition

Functional integration was defined in this research as utilizing artificial intelligence-based technologies or digital systems to support specific educational functions within Response to Intervention (RTI), such as early identification of potential educational risks; predicting future educational difficulties; and monitoring a student's academic progress, while no systemic changes were made to the existing organizational structure of the educational support system.

1.6.3 Procedural Integration

Theoretical Definition

Procedural integration refers to the incorporation of technological tools or applications into the educational procedures and practices used in teaching, assessment, and decision-making, in ways that support the implementation of educational processes more efficiently and in a data-driven manner [5].

Operational Definition

In this study, procedural integration refers to the incorporation of artificial intelligence tools into the educational and intervention procedures used within Response to Intervention (RTI) systems, with the aim of supporting data-driven educational decision-making and improving the effectiveness of educational interventions.

Structural Integration. Structural integration of technology within a system refers to the integration of a technology within the structures and decision-making processes of an organization, rather than treating it as something outside of the core of an organization’s work [10]. In the context of the current study, structural integration refers to the extent that the AI tools are integrated into the entire operational structure of the RTI system, including planning, determining tiers, designing interventions, and evaluation.

Research Trends. Within the scholarly literature, a pattern of research topics, designs, and temporal and geographical settings have previously been identified as research trends according to a similar examination of the scholarly literature in a field [5]. In this study, research trends refer to the patterns of themes, methods, and temporal and geographical settings found through analyzing the characteristics of the included studies (n = 33) as represented in the analytical mappings.

2. literature review

2.1 Digital Transformation in Education and the Logic of Inclusive Justice

Educational systems have shifted from a knowledge transmission to a data-driven model based on performance metrics. Kitchin [11] suggests that digitalization has transformed the knowledge structure and the structure of education, and Williamson [12] argues that the ‘datafication of education’ has transformed the nature of decision-making in education with data now playing a central role in processes of evaluation, planning, and intervention. Siemens [13] associates this with the emergence of learning analytics as a discipline devoted to understanding patterns in learning and predicting future trends.

In this regard, Siemens and Long [14] define learning analytics as the measurement, collection, analysis, and reporting of data about learners for purposes of understanding and optimizing learning and the environments in which it occurs. Papamitsiou and Economides [15] describe an increasing use of big data analytics techniques in predicting academic performance, while Ferguson and Clow [16] argue that the challenge is not so much in gathering data, but in interpreting it pedagogically in a responsible and sound way.

AI applications have moved beyond limited intelligent tutoring systems to predictive models for institutional decision-making. While Holmes et al. [17] describe the potential for personalization and early risk detection, Zawacki-Richter et al. [5] show that the dominant applications include prediction, automated assessment, and recommender systems. Transparency and explainability remain concerns [6].

In efforts towards digital transformation in mainstream educational settings, the concept of digital justice becomes prominent, referring to not just access to digital technology, but equitable and meaningful use of digital technology. Digital divides are multidimensional [12] and to meet learner needs, digital learning environments must be designed with learner variability in mind [18]. Digital transformation without inclusive design guided by Universal Design for Learning (UDL) principles could increase inequities. It is crucial to remove barriers in the design stages and not retrofit barriers later [19]. In a review of research on the use of technology by students with disabilities, Al-Azawei, Serenelli and Lundqvist [20] conclude that technology effectiveness and use depend on how the technology is used within and as part of the inclusive design of pedagogical activities. Without deliberate effort to create equity and accessibility, digital technologies have the potential to reproduce systems of exclusion [2].

In order to ensure ethical implementation, UNESCO's Recommendation on the Ethics of Artificial Intelligence emphasizes fairness, non-discrimination, and privacy protection, as well as adherence to the Sustainable Development Goals, including ensuring that learners with disabilities are included [2].

2.2 Inclusive Education as an Organizational Model Supporting Diversity

Contemporary inclusive education has emerged from a rights-based approach that recognises the fundamental and indivisible right to education, as ratified in the Convention on the Rights of Persons with Disabilities [7]. The transition from the medical to the social model of disability represented a transformative moment as the focus shifted away from deficit within the individual towards barriers in the environment [21]. In education, Ainscow [3] conceptualizes inclusion as a continuous process of changing the school to eliminate barriers to learning and participation and Florian [19] argue that the central principle of inclusive practice is to develop classroom activities based on the premise that it is normal for learners to be diverse and rather than that some learners are exceptions to the norm. Inclusion has been more than an absorptive policy; it has been viewed as an ethical and organizational commitment embodying educational justice.

Increasingly, the field has embraced models emphasizing addressing of learners' needs rather than grouping them by their disabilities. In this respect, Slee [22] warns that categorical approaches can lead to segregation, not support, while Florian & Black-Hawkins [23] advocate for graduated and flexible responses. Collins et al. [24] argue that inclusion is only as effective as the evidence-based interventions in place, not simply effective through placing students with disabilities in general education classrooms.

In addition, inclusion has come to be regarded not merely as presence in the classroom, but as participation and attainment. Slee [22] exhorts against 'formal inclusion' that maintains the status quo of school culture, and Ainscow [3] argues that authentic inclusion necessitates changes in policies, practices, and culture within the school to help true access and participation.

Inclusive settings, confront several challenges. One is early identification of student learning needs, as traditional definitions based on discrepancies between intelligence and achievement rates can delay instruction [4]. Another is the intensity of student needs and the complexity of addressing a range of needs via differentiated instruction in busy classrooms [23]. A third is the reliance on professional judgment, in the absence of standardized procedures, that can lead to variability in services [25]. A fourth is the capacity of data collection and analysis systems; where data use is dependent on institutional culture and on teachers' ability to interpret educational data [26].

These issues highlight the need for a structured framework, such as Response to Intervention (RTI), which can organize support in a stepped and data-driven approach based on student progress monitoring. They also indicate a need for analytical and AI tools that can serve this process of identification and decision-making within inclusive classrooms.

2.3 Response to Intervention (RTI) in Inclusive Education: Structural Foundations and Implementation Constraints

Response to Intervention (RTI) was developed as an organizational model based on tiered support in academics and behavior as indicated by data on student performance. It is associated with Multi-Tiered Systems of Support (MTSS) that incorporates academics and behavior within a unified system of interventions based on data-driven decision-making [9]. According to McIntosh and Goodman [27], this movement signified a shift from the reactive logic of diagnostic referral to a more proactive and preventative logic of systematic monitoring.

Fuchs and Fuchs (2006) state that RTI is not designed for disability identification but as a means to enhance the instruction of all students. RTI moves away from the "wait-to-fail" model, which is recognized as detrimental to adequate instruction because it waits for failure to intervene and thereby compounds the problem [28], through periodic performance indicators to recognize students in need of early intervention.

An important component of RTI is formative progress monitoring, using tools like Curriculum-Based Measurement (CBM) that provide a sensitive indicator of change in performance [29]. There is evidence that using data to make instructional changes lead to increased student achievement [30].

The RTI model consists of three graduated tiers. Tier 1 represents high-quality general education instruction provided to all students, with the expectation that most learners will respond adequately when instruction is implemented effectively [4,9]. Tier 2 provides targeted, evidence-based interventions delivered in small groups [31]. Tier 3 involves intensive, individualized interventions that rely heavily on precise data to determine and adjust the intensity of support [9].

Despite its structural robustness, RTI implementation faces practical challenges. The first concerns delay in data analysis due to reliance on manual processes, which may slow decision-making [26]. The second involves the burden of frequent data collection, particularly in overcrowded classrooms [32]. The third relates to variability in predictive accuracy depending on selected cut scores and measurement tool. Additionally, traditional implementation may limit personalization due to human and technical constraints [27].

Accordingly, while RTI’s strength lies in its organizational structure based on early intervention and systematic monitoring, limitations in supporting analytical tools may constrain the speed and precision of responsiveness. The gap, therefore, does not reside in the logic of RTI itself, but in the efficiency of data analysis and intervention personalization. This provides opportunities for implementation of advanced analytic technologies, such as Artificial Intelligence, to maximize the potential dynamism of RTI as an approach to inclusive education.

2.4 Artificial Intelligence in Education (Functional and Analytical Dimensions)

In recent years, due to growing capacities for collection and analysis of real-time data, Artificial Intelligence in Education has expanded qualitatively across educational systems. AI is no longer an auxiliary tool for instruction, but an analytical framework for prediction, personalization, and data-based decision-making [13,5]. Holmes et al. [17] contend that technologies have moved from being supportive tools for instruction to analytical systems that are capable of detecting hidden patterns in learner data and acting on them.

These AI applications include predictive models to identify students at risk of failure and dropout, recommender systems to support personalized learning pathways, adaptive assessment systems that tailor the test-taker experience to student responses, and big data analytics to help decision-making in schools and universities [8,13] Predictive models allow early intervention to prevent poor learning outcomes. Recommender systems and adaptive learning systems can improve student engagement and provides personalized learning experiences when coupled with robust instructional design [17, 6, 5].

Perhaps the greatest promised benefit of AI is personalization of education, allowing for the creation of dynamic learning experiences based on data about performance and learning patterns, rather than solely on professional judgment. Technical problems of integrating AI represent an equally important challenge when it comes to incorporating AI in education. In fact, there are also several other types of challenges associated with incorporating AI in education. Ethical and organizational challenges present barriers to successfully adopting AI systems in classrooms and educational settings. When AI transforms raw data into decisions made through algorithms, it raises questions about fairness, privacy and accountability [2, 5]. One of the primary concerns related to bias in AI is that the model could be reflecting some type of bias within the training data itself, or the way in which the AI was designed, and potentially continue to create or maintain inequalities among groups [33]. Protecting student data from being accessed without permission will require both a combination of technological and regulatory strategies (i.e., differential privacy, etc.) along with creating clear data governance policies [34, 2]. Trust in AI is also built upon transparency and explainability, so that educators have the ability to develop and utilize the output produced by AI systems as well as hold developers accountable [6]; therefore, developing this capability for educators is essential if they are going to accept AI systems in their own classrooms [17]. The Response to Intervention (RTI) framework is a system that can use such a capacity of AI if the association between algorithmic tools and tiered intervention logic is re-evaluated.

2.5 The Intersection of Artificial Intelligence and Response to Intervention (RTI) in Inclusive Education

The incorporation of Artificial Intelligence within the framework of Response to Intervention (RTI) practices represents a new field of study where tiered intervention methodologies meet advanced data analytics. RTI is a process that emphasizes regular progress monitoring in its decision-making framework [4]. Artificial Intelligence (AI) introduces predictive and adaptive capabilities that can process data in real-time, surpassing traditional manual data interpretations [13,5]. The integration of these two systems can significantly improve the logic underlying intervention strategies implemented within inclusive educational environments.

RTI relies upon periodic data collection and manual analysis in its traditional implementation. AI, can detect early performance patterns that might not be obvious, even to experienced teachers and assist in flagging students at academic risk, increasing the preventive aspects of the system and further addressing the "wait-to-fail" problem [17,5]. Multivariate models can assist decision making when moving students between tiers by identifying growth and engagement patterns to reduce misclassification that might happen when only relying on static cut- scores on quantitative measures [17]. With data collection and analysis automated, monitoring can become a continuous analysis rather than the periodic process it is now, reducing the amount of measurement required and improving immediacy [29].

But, beyond these instrumental uses, integration can also serve different functions that reallocate the Response to Intervention (RTI) roles of identifying, diagnosing, personalizing, and evaluating. The predictive role is establishing models that predict early risk indicators [8], recognizing that these predictions do not necessarily lead to improved results without embedding them within the appropriate context [36]. The diagnostic role is breaking down patterns of performance to more qualitatively understand learning difficulties [13,5]. The adaptive role is further developing the system's ability to adjust the learner's pathway on the fly, and personalizing learning [19,35]. The evaluative role is continuous accountability and cumulative analytics and evaluation of these interventions over time [30].

The ethical facet is crucial in such integration. Employing algorithmic systems in determinations that impact students' promotion and retention mandates comprehensive measures to guarantee equity, transparency, and avoidance of societal biases [2,33,18,34] Achieving algorithmic fairness, privacy, and explainability must be intrinsic to the design and not relied upon as retrospective regulatory interventions [35].

This intersection, then, indicates the possibility for a significant change in education practice, intervention via RTI: from a model analyzed at times and dependent upon humans, RTI could become an intelligent support system able to predict, explain, adapt, and evaluate itself, so long as these changes occur under the auspices of a conceptual and moral vision.

2.6 Structural Gaps in the Literature and Positioning of the Present Study

Despite the apparent compatibility between AI and RTI methodologies, this paper's literature review indicates that the intersection of AI and RTI has not yet integrated into a mature, integrative framework. AI is viewed as a set of analytical techniques and RTI as a framework for intervention, without a clear understanding of how the processes of identification, diagnosis, adaptation, and evaluation might be distributed across tiers of support [4,5]. The result is a technically applied, but organizationally disjointed use of AI within the context of educational decision-making.

The second gap is a paucity of long-term applied studies that measure the effects of AI adoption in a tiered system of interventions within a real-world school setting. Most studies are limited as short-term or simulated studies, or conducted in higher education settings, rather than school-based Multi-Tiered Systems of Support [5,19] Recent reviews indicated that there remains a gap between technological models developed and those that evaluate long-term impact on student achievement, or in narrowing the achievement gap.

A third gap is the contextual bias in research production, which tends to concentrate in digitally advanced countries, with limited representation from developing contexts. Policy reports identify digital infrastructure as a crucial factor for AI applicability, making the transfer of models across different contexts uncertain [18,2].

The fourth gap pertains to the lack of consideration of ethical matters in the model design. Algorithmic fairness and privacy are topics that are considered within policy debates separately from the technical development [33,2]. Recent research shows that the lack of bias auditing and explainability at the design stage may lead to the perpetuation of inequalities, especially when classifying students and predicting their placement in tiers [33].

Rather than being an absence of studies on these topics, however, we identify an absence of synthesis at their intersections (i.e., RTI as an organizational system, AI's technical capacity for analysis, and ethical/contextual aspects of implementation) and therefore provide the purpose of our current study as a systematic review of these areas with respect to identifying historical/chronological, geographical and methodological trends; and mapping out the structure where future research will need to focus.

3. Methodology

The research used a systematic review that utilized thematic analysis to assess how Artificial Intelligence (AI) has been integrated into the Response to Intervention (RTI) model in an inclusive education environment.

The purpose of the review was to gather and integrate disparate areas of scholarly work, determine predominant themes found in the body of literature, analyze intersections between AI, RTI, and Inclusive Education, and highlight structural gaps in this developing area of scholarship.

Unlike many other reviews which utilize some form of statistical aggregation (i.e., meta-analyses), this study was conducted using a Comparative Synthesized Analysis of all included studies along structured thematic dimensions. To increase both methodological integrity and analytic credibility for the review, each included study was evaluated through a systematic quality assessment using CASP adapted criteria.

3.1 Search Strategy

We searched the peer reviewed databases ERIC, Scopus, Web of Science and IEEE Xplore for relevant information as part of our systematic search. The results were checked against each other with a "citation tracker" via Google Scholar. Our search was limited to articles published from January 1st 2000 to December 31st, 2023.

A composite search string using Boolean operators AND/OR as follows:

("Artificial Intelligence" OR "Artificial Intelligence in Education")

AND
("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS")

AND
("Inclusive Education" OR "Special Education")

This was intended to capture the ways AI has been researched as part of tiered support systems in inclusive settings. Table (1) describes the databases searched along with the targeted publication outlets.

Table 1: Details of Databases and Adopted Search Strings

Database	Targeted Publication Outlets	Adopted Search String
ERIC	Peer-reviewed journal articles in education and teaching	("Artificial Intelligence" OR "Artificial Intelligence in Education") AND ("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS") AND ("Inclusive Education" OR "Special Education")
Scopus	Peer-reviewed articles, experimental and analytical studies	("Artificial Intelligence" OR "Artificial Intelligence in Education") AND ("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS") AND ("Inclusive Education" OR "Special Education")
Web of Science	Indexed journals and peer-reviewed conference proceedings	("Artificial Intelligence" OR "Artificial Intelligence in Education") AND ("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS") AND ("Inclusive Education" OR "Special Education")
IEEE Xplore	Technical and applied studies in educational Artificial Intelligence	("Artificial Intelligence" OR "Artificial Intelligence in Education") AND ("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS") AND ("Inclusive Education" OR "Special Education")
Google Scholar	Supplementary source for comprehensiveness verification and citation tracking	("Artificial Intelligence" OR "Artificial Intelligence in Education") AND ("Response to Intervention" OR "RTI" OR "Multi-Tiered Systems of Support" OR "MTSS") AND ("Inclusive Education" OR "Special Education")

The initial search process yielded a corpus of studies that underwent duplicate removal, followed by title and abstract screening. Following this, full text articles were assessed against the inclusion and exclusion criteria, thirty-three (33) studies were the final selection selected for analysis.

3.2 Eligibility Criteria

To help this alignment, the following criteria were applied to include studies in the review: Studies published between 2000 and 2025 in either Arabic or English that directly or indirectly addressed one or more of the following topics: Artificial Intelligence in learning/ education; Response to Intervention (RTI) or Multi-Tiered Systems of Support (MTSS);

and inclusive education. Preference was for empirical, analytical, or systematic reviews and conceptual studies directly related to data-based decision-making.

Papers were excluded if they were purely theoretical (i.e., non-empirical), not related to education, or purely technical applications without an educational aspect. Duplicate entries and non-peer-reviewed conference proceedings or non-academic publications were also excluded.

3.3 Study Selection Process

A total of 1,406 studies were identified through the initial search and non-duplicate records (n=943) and those that were not deemed irrelevant on thematic grounds, non-English, and/or grey literature (n=159) were retained for preliminary screening (n=304). A total of 170 studies were excluded during the title and abstract screening, leaving 137 studies to be reviewed in full-text. Of these, 104 studies were excluded because they did not meet the criteria for mixed methods and/or integrated design and/or their reported findings were not sufficiently relevant to the integration domains, leaving a final sample of 33 studies. Although the final sample of the study was limited to thirty-three (33) studies, this number reflects the emerging and relatively fragmented nature of research addressing the integration of artificial intelligence and RTI/MTSS frameworks within inclusive education contexts. The selection process was guided by strict inclusion and exclusion criteria that considered methodological relevance, conceptual consistency, and direct alignment with the objectives of the study. Accordingly, the final sample was considered sufficient to conduct an in-depth analytical review aimed at identifying conceptual patterns, methodological trends, and levels of integration within this emerging interdisciplinary field.

This process was guided by the PRISMA framework (Moher et al., 2009). A PRISMA 2020 flow diagram of the study selection process is presented in Figure (1).

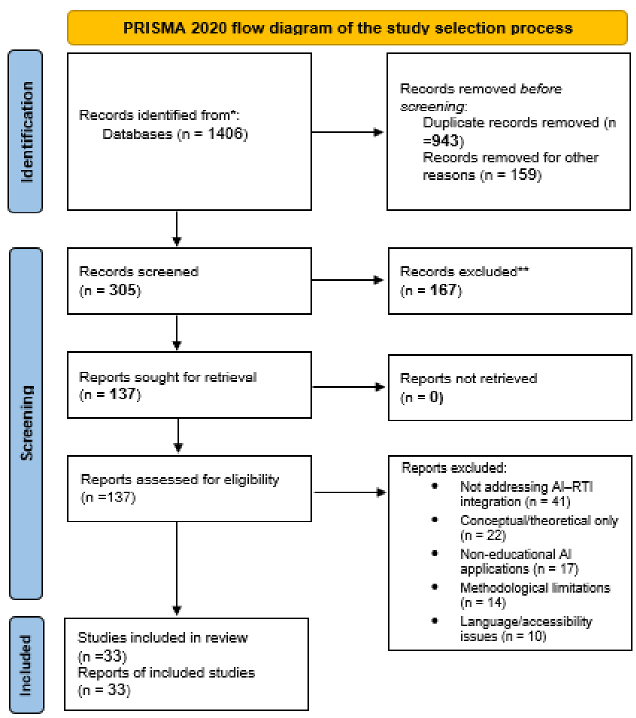

Fig. 1: PRISMA 2020 Flow Diagram of the Study Selection Process

3.4 Coding Reliability

The study used an initial 33 research papers as the basis for creating 5 categories of coding indicators, namely; Temporal, Geographical, Methodology, Theme, and Ethics. In order to determine if there is consistency in how different people will apply these coding indicators, one of the researchers applied the coding instrument to 20 percent of the data set (n=7). The researcher's application of the coding tool was done independently. An assessment of the degree of agreement between the two researchers was made via use of Cohen's Kappa coefficient. The value obtained from this analysis was .84, therefore indicating that there was a very strong level of agreement. A review of where the researchers disagreed on the coding took place after both had completed their independent assessments. Upon completion of the review process, each researcher agreed upon the application of the coding instrument to all remaining studies (see Table [2]).

Table 2: Inter-Rater Coding Reliability Indicators

Coding Dimension	Number of Studies	Cohen's Kappa (κ)	Reliability Level
Research Design Type	7	0.86	Very High
Thematic Domain	7	0.81	High
Type of AI Application	7	0.84	Very High
RTI Tier Level	7	0.89	Excellent
Ethical Dimension	7	0.78	High
Overall Average	—	0.84	Very High

3.5 Study Quality Assessment Procedures

To increase the methodological quality of this literature review, the included studies were examined for quality using a modified version of CASP's Descriptive Criteria for assessing qualitative studies. The evaluation assessed the studies based on five primary characteristics or indicators: the purpose/objectives of the study; the methodology used in the study; the clarity, and consistency of results/findings; how well the study established an association between Artificial Intelligence (AI), and the Response to Intervention (RTI) model; and finally, the rigor of the science applied. These assessments were completed separately by two independent reviewers with expertise in educational research and inclusion education. After completing each reviewer's individual assessment of each study, their ratings were compared and discussed as necessary to resolve any inconsistencies and achieve agreement on final ratings.

The high-quality studies clearly identified their research goals, appropriately used methodology, had consistent findings, were highly relevant to the artificial intelligence and Response to Intervention (AI–RTI) framework, and provided a sufficient degree of scientific rigor. Studies that at least partially satisfied one or two aspects of these requirements or did not contain sufficient detail about the methodologies employed, were considered to have acceptable quality. Conversely, studies that presented significant methodological limitations or lacked clarity in analytical details regarding the methods used were determined to be of limited quality.

Studies were evaluated by examining the overall consistency in relation to their stated objectives, their methodology, the clarity of their findings, and their relevance to the analytical purpose of the current literature review. Therefore, studies were generally categorized into three different levels of descriptive quality; high-quality, acceptable-quality, and limited-quality. The quality assessment process for studies was systemically implemented across all studies that were included in this review to enhance the reliability, consistency of analysis, and robustness of the conclusions derived from this literature review.

The outcomes of the quality assessment show that all but a few of the studies included in the analysis showed good levels of methodological quality. Most of the studies presented had well defined goals, appropriate methodologies, consistent and relevant findings and are directly related to how artificial intelligence is being used with RTI systems in inclusive educational settings. This increases the overall reliability and analytic ability of the conclusion drawn from this review; at the same time, it points out there continues to be a need for future longitudinal and experimental studies supported by empirical research.

The detailed quality assessment results for the included studies are presented in Table 3.

Table 3: Quality Assessment of the Included Studies Based on Modified Descriptive Criteria Derived from the Critical Appraisal Skills Programme (CASP)

No.	**Author / Year**	**Clarity of Objectives**	**Methodological Appropriateness**	**Clarity of Findings**	**Relevance to the AI–RTI Framework**	**Scientific Rigor**	**Overall Quality**
1	Deno, S. L. [29]	Strong	Strong	Strong	Acceptable	Strong	Strong
2	Fuchs & Fuchs [4]	Strong	Strong	Strong	Strong	Strong	Strong
3	Sugai & Horner [48]	Strong	Strong	Strong	Acceptable	Strong	Strong
4	Shinn, M. R. [53]	Strong	Strong	Strong	Acceptable	Strong	Strong
5	Vaughn & Fuchs [41]	Strong	Strong	Strong	Strong	Strong	Strong

6	Burns & Gibbons [8]	Strong	Strong	Strong	Strong	Strong	Strong
7	Torgesen [28]	Strong	Strong	Strong	Acceptable	Strong	Strong
8	Stecker, Fuchs, & Fuchs [30]	Strong	Strong	Strong	Acceptable	Strong	Strong
9	Siemens & Long [14]	Strong	Strong	Strong	Strong	Strong	Strong
10	Bienkowski et al. [47]	Strong	Strong	Strong	Strong	Strong	Strong
11	Siemens, G. [13]	Strong	Acceptable	Strong	Strong	Acceptable	Acceptable
12	Baker & Inventado [8]	Strong	Strong	Strong	Strong	Strong	Strong
13	Fuchs et al. [4]	Strong	Strong	Strong	Strong	Strong	Strong
14	Collins et al. [24]	Strong	Strong	Strong	Strong	Strong	Strong
15	Burns et al. [49]	Strong	Strong	Strong	Acceptable	Strong	Strong
16	Luckin, R., et al. [6]	Strong	Acceptable	Strong	Strong	Acceptable	Acceptable
17	Ferguson & Clow [16]	Strong	Strong	Strong	Strong	Strong	Strong
18	Chen, L., et al. [39]	Strong	Strong	Strong	Strong	Strong	Strong
19	Floridi et al. [10]	Strong	Acceptable	Strong	Strong	Acceptable	Acceptable
20	Zawacki-Richter et al. [5]	Strong	Strong	Strong	Strong	Strong	Strong
21	Romero & Ventura [40]	Strong	Strong	Strong	Strong	Strong	Strong
22	OECD [18]	Strong	Acceptable	Acceptable	Strong	Acceptable	Acceptable
23	Holmes & Tuomi [36]	Strong	Acceptable	Strong	Strong	Acceptable	Acceptable
24	Beirat et al. [42]	Strong	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable
25	Alkazalah [43]	Strong	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable
26	Al Saleh & Al Sror [44]	Strong	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable
27	Qusef et al. [46]	Strong	Strong	Strong	Strong	Strong	Strong
28	Li, Yan, & Zeng [1]	Strong	Strong	Strong	Strong	Strong	Strong
29	Melo López et al. [38]	Strong	Strong	Strong	Strong	Strong	Strong
30	Julien [51]	Strong	Acceptable	Acceptable	Strong	Acceptable	Acceptable
31	Alatawi [52]	Strong	Strong	Strong	Strong	Strong	Strong
32	Pagliara et al. [37]	Strong	Acceptable	Strong	Strong	Acceptable	Acceptable
33	Altakhaineh et al. [45]	Strong	Strong	Strong	Strong	Strong	Strong

4. Results

General Characteristics of the Studies Included in the Analytical Review

Based on the eligibility criteria, thirty-three peer-reviewed scientific articles were included in this final analysis (see Table 4). Data from these studies were organized into a cohesive analytical framework that allowed for systematic review of their temporal, geographical, and methodological aspects as well as the thematic patterns of AI and RTI within inclusive education.

The distribution of countries and regions of the 33 included studies shows differences in research production within and between countries and regions (Figure 2). The United States contributed the highest proportion of studies with 14 (42%), followed by international or multi-country studies with 7 (21%), Jordan with 4 (12%), Germany and Switzerland each with 2 (6%) separately, and Canada, the United Kingdom, and Saudi Arabia each with 1 study (3%) individually.

Table 4: Descriptive Summary of the Studies Included in the Analysis (n = 33)

No.	Author / Year	Country	Methodology	Study Objective	Key Findings
1	Deno, S. L. [29]	United States	Theoretical Analysis	To clarify the role of Curriculum-Based Measurement (CBM) in supporting decision-making within RTI.	CBM provides accurate and sensitive data for detecting performance changes, supporting intervention decisions.
2	Fuchs & Fuchs [4]	United States	Theoretical Analysis	To present an integrated conceptual framework for RTI, outlining its theoretical foundations, implementation mechanisms, and preventive role in reducing inappropriate special education referrals.	RTI is an effective preventive framework based on early and tiered intervention, reducing misidentification when implemented systematically using data.
3	Sugai & Horner [48]	United States	Conceptual Analysis Supported by Case Studies	To expand the RTI model to include behavioral interventions alongside academic support.	Integrating behavioral interventions within RTI reduces classroom problems and improves academic engagement.
4	Shinn, M. R. [53]	United States	Descriptive-Analytical	To examine the effectiveness of RTI in early identification of students at academic risk.	RTI demonstrates greater diagnostic accuracy compared to traditional discrepancy models.
5	Vaughn & Fuchs [41]	United States	Applied Analysis	To analyze RTI effectiveness in supporting students with learning difficulties within general education settings.	RTI success depends on high-quality Tier 1 instruction and accurate Tier 2 identification; early intervention reduces academic difficulties.
6	Burns & Gibbons [8]	United States	Applied Study	To clarify the role of data-based decision-making within RTI.	Continuous data use improves educational decision accuracy and intervention effectiveness.
7	Torgesen [28]	United States	Analytical	To examine the impact of early RTI-based reading intervention.	Early and intensive reading interventions significantly improve academic performance and reduce the need for

					later remediation.
8	Stecker, Fuchs, & Fuchs [30]	United States	Theoretical	To clarify the role of Progress Monitoring within RTI.	Continuous performance monitoring is foundational to RTI success and enables immediate intervention adjustment.
9	Siemens & Long [14]	United States	Analytical	To analyze the role of big data and learning analytics in educational decision-making.	Learning analytics reduces ambiguity in educational decision-making and supports early data-based intervention.
10	Bienkowski et al. [47]	United States	Analytical Review	To analyze educational data mining and learning analytics in improving teaching and learning.	Data mining and learning analytics enhance progress tracking and early intervention effectiveness.
11	Siemens, G. [13]	Canada	Conceptual	To define Learning Analytics and its role in digital education environments.	Learning analytics is a strategic tool for understanding learning patterns and predicting academic risk.
12	Baker & Inventado [8]	United States	Systematic Review	To review educational data mining techniques for predicting academic difficulties.	Predictive models accurately identify students at risk, supporting preventive intervention.
13	Fuchs et al. [4]	United States	Field Study	To measure the impact of RTI implementation across tiers.	Significant improvements were observed in Tier 1 and Tier 2 performance when RTI was implemented scientifically.
14	Collins et al. [24]	United States	Systematic Review	To identify evidence-based practices within MTSS.	RTI is among the most empirically supported intervention frameworks.
15	Burns et al. [49]	United States	Applied Study	To examine teacher training effects on RTI implementation.	Teacher training is essential; inconsistent implementation reduces RTI effectiveness.
16	Luckin, R., et al. [6]	United Kingdom	Analytical Report	To analyze the transformative potential of AI in education.	AI enhances personalization and instructional quality but requires infrastructure, teacher training, and data-driven school culture.
17	Ferguson & Clow [16]	Germany	Quantitative Study	To test predictive analytics effectiveness in anticipating intervention response.	Predictive analytics enabled early intervention adjustments and improved academic outcomes.

18	Chen, L., et al. [39]	Germany	Quantitative Study	To evaluate AI-based predictive models in forecasting intervention response.	AI predictive analytics improved prediction of responsiveness to interventions.
19	Floridi et al. [10]	International	Regulatory Analysis	To examine governance and ethical issues in AI adoption in education.	Lack of regulatory frameworks hinders AI deployment; strong privacy and data policies are critical.
20	Zawacki-Richter et al. [5]	International	Systematic Review	To analyze AI applications in higher education.	AI enhances teaching quality and data-based decision-making in higher education contexts.
21	Romero & Ventura [40]	Switzerland	Analytical Review	To map AI research in inclusive education.	Weak shared explanatory models between AI, RTI, and inclusive education; need for integrative practice models.
22	OECD [18]	International	Policy Analysis	To provide global guidance on AI use in education.	AI must support learners with special needs and align with intervention support systems.
23	Holmes & Tuomi [36]	International	Critical Analysis	To examine teacher preparation for AI integration.	Comprehensive teacher training is essential for effective AI-supported interventions.
24	Beirat et al. [42]	Jordan	Descriptive Field Study	To examine challenges faced by special education teachers in AI use.	Special education teachers face significant challenges in AI implementation in inclusive schools.
25	Alkazalah [43]	Jordan	Descriptive-Analytical	To measure AI application in inclusive education management.	Uneven AI adoption; training and resource gaps persist.
26	Al Saleh & Al Sror [44]	Jordan	Quantitative Descriptive	To explore geography teachers' attitudes toward AI integration.	Positive attitudes with variation in practical implementation levels.
27	Qusef et al. [46]	Jordan	Experimental Quantitative	To test AI-based predictive analytics for identifying learning difficulties.	AI improves early identification and support personalization for students with learning difficulties.
28	Li, Yan, & Zeng [1]	International / MDPI	Comprehensive Systematic Review	To examine AI's role in improving access and personalization in inclusive education.	Adaptive AI platforms enhance personalization and reduce educational barriers.
29	Melo López et al. [38]	International / MDPI	Systematic Review	To analyze AI-supported inclusion research and identify barriers.	AI reduces teacher workload and enhances personalization but faces infrastructure and training challenges.
30	Julien [51]	International	Literature Review	To provide an overview of AI in inclusive learning opportunities.	AI enhances engagement but requires strong governance and privacy policies.

31	Alatawi [52]	Saudi Arabia	Mixed Experimental	To examine AI effects on students with intellectual disabilities and learning difficulties.	Adaptive AI supports personalization and engagement for students with intellectual disabilities in inclusive settings.
32	Pagliara et al. [37]	Switzerland / MDPI	Scoping Review	To review AI applications in inclusive education.	AI supports collaborative learning but faces cost and cultural constraints.
33	Altakhaineh et al. [45]	Jordan & UAE	Mixed Methods	To analyze AI integration across multicultural contexts.	AI integration requires contextual adaptation to cultural and institutional differences.

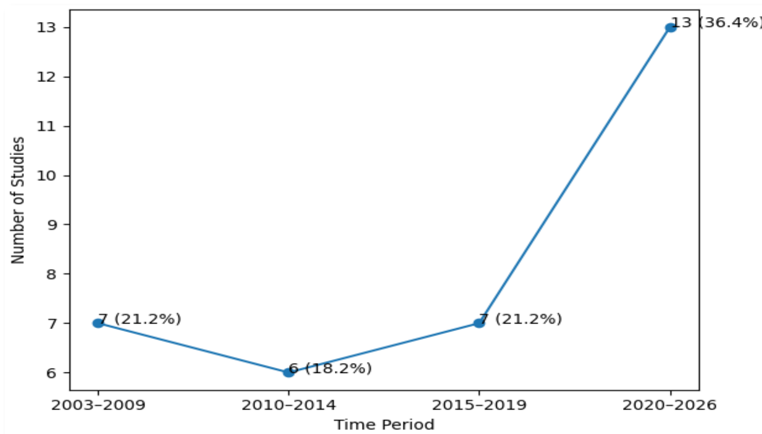

Fig. 2: Temporal Distribution of the Studies Included in the Review (n = 33)

The geographical analysis of the included studies (n = 33) reveals a clear concentration of research production in the United States, which accounted for 42% of the total studies (n = 14), as illustrated in Figure (3). This was followed by internationally scoped studies (21%, n = 7), and Jordan (12%, n = 4). The remaining proportion was distributed across Germany and Switzerland (6% each), and Canada, the United Kingdom, and Saudi Arabia (3% per country).

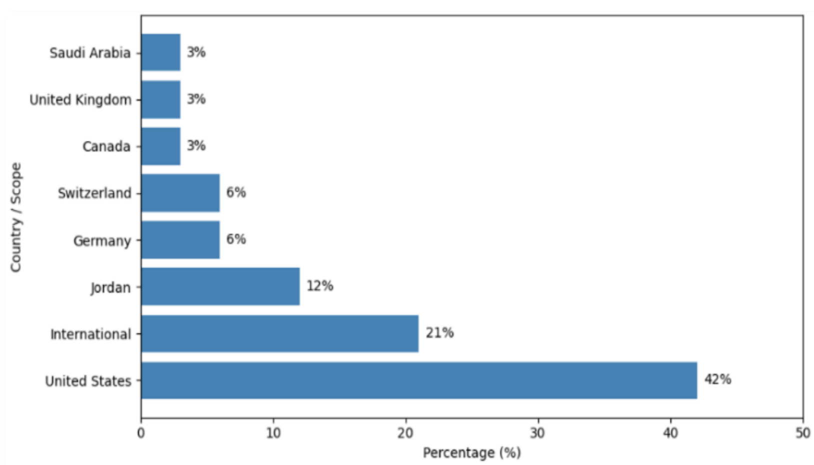

Fig. 3: Distribution of Studies by Country of Publication (n = 33)

With respect to the methodological distribution of the included studies (n = 33), the analysis reveals notable diversity in the research designs employed, as illustrated in Figure (4). Systematic and analytical reviews accounted for 6 studies (18%), representing the same proportion as applied and field-based studies (6 studies, 18%). Theoretical and conceptual analyses comprised 5 studies (15%). Descriptive studies accounted for 4 studies (12%), a proportion equivalent to that of quantitative experimental studies (4 studies, 12%) and non-experimental analytical studies (4 studies, 12%). Mixed-methods studies were represented by 2 studies (6%), as were analytical or regulatory reports (2 studies, 6%). This distribution reflects methodological pluralism with a relatively balanced presence of both analytical and implementation-oriented research perspectives.

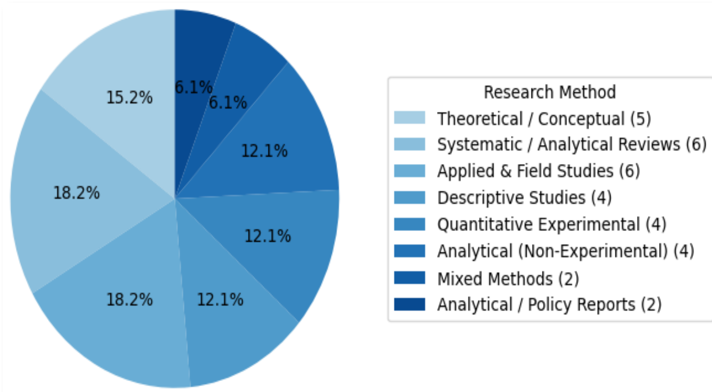

Fig 4: Distribution of Studies by Research Methodology (n = 33)

Figure (5) shows the number of studies that fit each theme. Overall, there has been a abundance of research on RTI without AI and various discussions and descriptions of AI applied to RTI. But the number of studies that examined how AI could be incorporated into RTI and applied to influence one and more of the levels, and tiers, of the RTI process was relatively limited. Studies on RTI without AI applications accounted for 24.2%.

In comparison, research on either Artificial Intelligence or learning analytics separately made up the majority of the sample (16 studies, 48.5%), including studies on Artificial Intelligence and learning analytics in a broader context (10 studies) and studies on regulation and ethics surrounding the use of Artificial Intelligence in education (4 studies).

Studies that examined a direct or quasi-direct connection between AI and inclusive education within a Multi-Tiered System of Support included 9 studies (27.3%).

These findings suggest that most of the existing research continues to focus on either AI or RTI alone, with comparatively few studies that conduct empirical investigations of structural integration across the two.

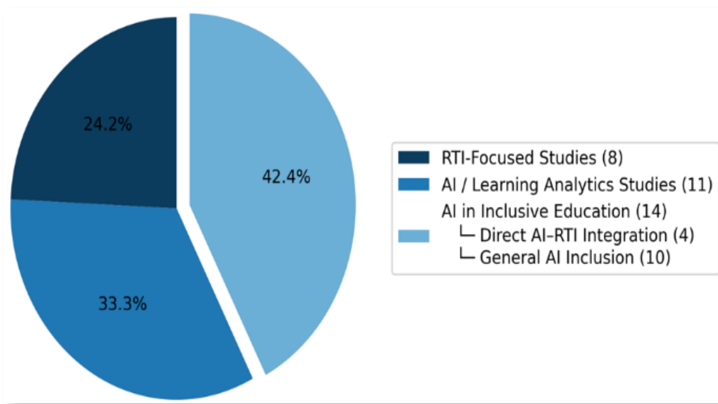

Fig. 5: Thematic Distribution of Research Pathways at the Intersection of AI and RTI (n = 33)

Types of AI used in the studies (n = 33). Predictive Analytics was the most common type of AI technology used in the the studies, including 6 studies (18.2%) followed by Adaptive Systems including 5 studies (15.2%) (Figure 6).

Learning analytics and educational data mining, decision-support systems, and technologies in digital governance and policy each had 4 studies (12.1% in each category). Applications of Generative AI had fewer studies (3 of them, 9.1%).

This pattern indicates that AI applications focused on prediction and analysis, especially those supporting evaluation and decision-making using data within a multi-tiered system of support, have been of greater research interest. In contrast, generative AI applications are new and less tested in research and have, so far, remained more in the realm of discussion related to ideas and permissible uses as opposed to widespread experimentation.

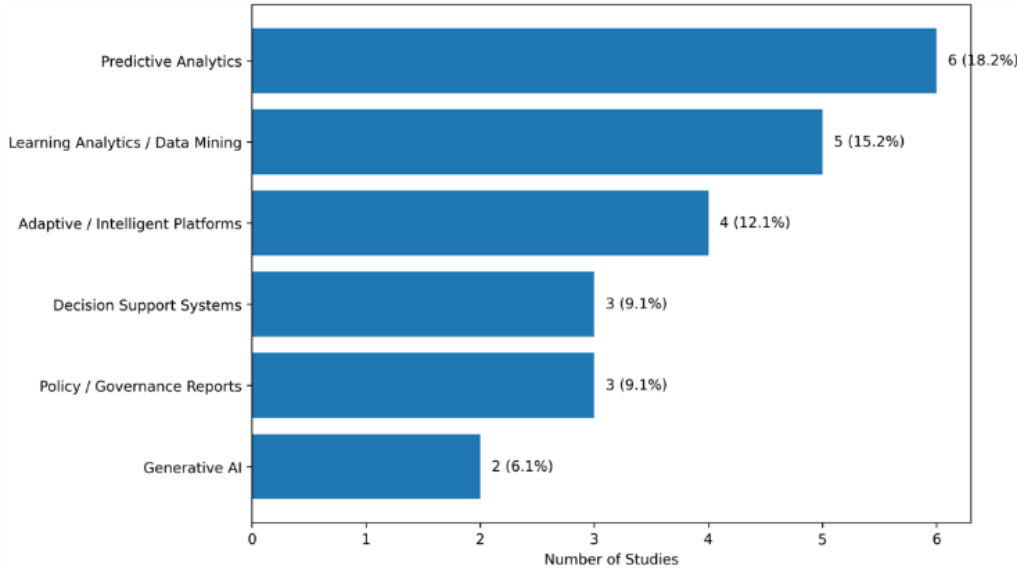

Fig. 6: Distribution of Artificial Intelligence Technologies Used in the Included Studies (n = 33)

With respect to the nature of the target populations addressed in the included studies (n = 33), the analysis presented in Figure (7) indicates that the research landscape is characterized by a predominantly general rather than category-specific focus. Studies concentrating on broad classroom support within inclusive settings and on enhancing data-based educational decision-making constituted the largest proportion (18 studies, 54.5%).

This was followed by research on learning disabilities and early detection of academic risk (6 studies, 18.2%). Research on specific disabilities, for example, intellectual disabilities or specialized uses in special education consisted of 3 studies (9.1%). Policy, regulatory, or ethical studies accounted for 6 studies (18.2%).

These findings indicate that over half of the current literature addresses AI and MTSS from a general systems perspective, with a notably low representation of the most vulnerable learners among researchers in the field.

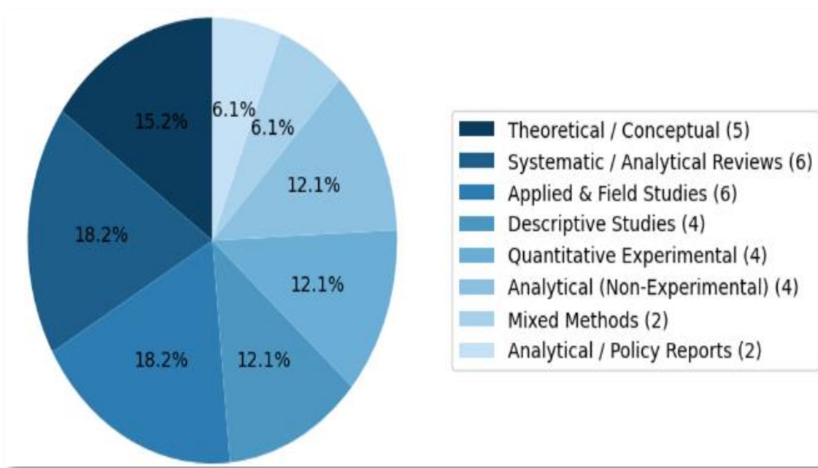

Fig. 7: Distribution of Included Studies by Target Population Characteristics (n = 33)

By reviewing the findings reported in the studies included (n = 33) as shown in Figure 8, recurring patterns could be classified into four main trends: data centrality, predictive analytics and decision support, personalization within inclusive education, and organizational and ethical challenges.

Continuous progress monitoring, Curriculum-Based Measurement (CBM), and data-based decision-making featured in 12 studies (36.4%), reflecting the structural persistence of the Response to Intervention (RTI) literature. Predictive analytics was the leading trend, with 14 studies (42.4%) noting how AI tools helped improve the accuracy of academic risk prediction and support faster educational decision-making.

Additionally, 10 studies (30.3%) investigated adaptive systems for improving personalization and removing obstacles in inclusive education settings, while 8 studies (24.2%) concentrated on governance, data privacy, technical readiness, and teacher training.

These results, collectively, reveal a significant alignment between the data-driven framework of RTI and the data-analytics capacity of AI, while highlighting the unmet need of systematically designed and empirically validated integrative models of inclusively serving all students.

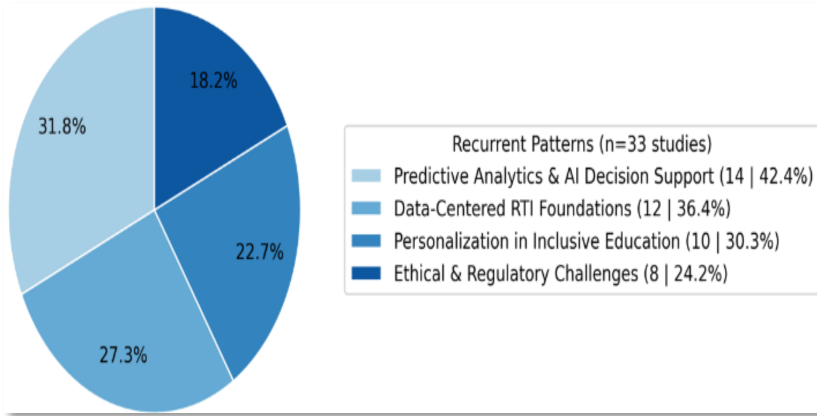

Fig. 8: Distribution of Recurrent Result Patterns in Studies on the Integration of AI and RTI (n = 33)

An analysis of the characteristics of the included studies shown in Figure (9) shows several quantitative indicators of structural gaps in the field.

First, only 9 studies (27.3%) focused on direct integration or quasi-direct integration between Artificial Intelligence and the Response to Intervention (RTI) framework while 24 studies (72.7%) focused on each separately, indicating little integration between the two concepts.

Second, regarding the research design, only 4 quantitative experimental studies (12%) and 2 mixed-methods studies (6%) were conducted in contrast to the numerous systematic reviews, analytical reviews, and theoretical studies.

Third, the United States contributed 14 studies (42%), compared to Jordan and Saudi Arabia with 5 studies (15.2%) jointly and one joint Arab study, showing a clear contextual concentration of research output.

Fourth, this sample did not contain longitudinal studies of the effects of integration over time, nor large-scale quasi-experimental research across a range of inclusive settings.

Fifth, policy-oriented studies and regulations numbered six studies (18.2%), covering digital governance, data protection, technical readiness, and teacher training. There were few studies testing empirically comprehensive and operationalized regulatory frameworks in inclusive school systems.

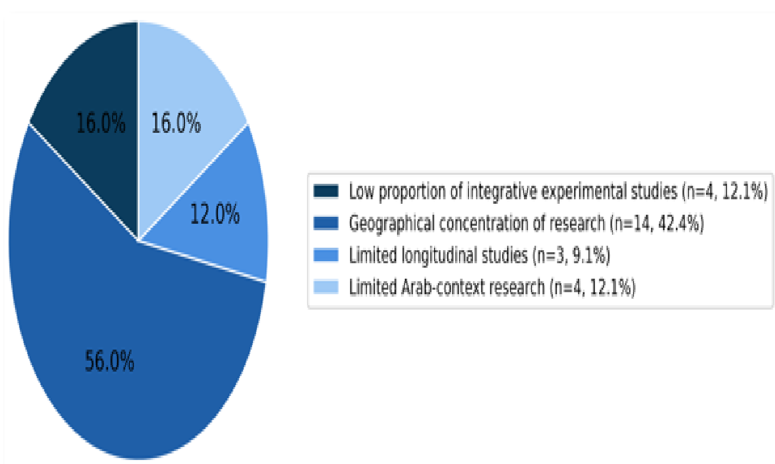

Fig. 9: Patterns of Research Gaps in the Analyzed Literature (n = 33)

5. Discussion

The research question that guided this study was: How has the scholarly research literature addressed the integration of Artificial Intelligence (AI) as well as Response to Intervention (RTI) for inclusive education? With consideration of the results reported in the previous section, it appears that research at the intersection of both domains is still under development. There appears to be a conceptual convergence, but not yet a fully integrated approach in practice. This is evident in that a majority of the research trajectories identified in Figure 5 suggest that studies considering a direct or quasi-direct integration between AI as well as RTI, as opposed to examining only one of these technologies, have not yet exceeded 9 research studies (27.3%) as compared to 24 studies (72.7%) considering one or the other. As seen in Figure 5, 16 studies (48.5%) researched AI applications only as well as 8 studies (24.2%) examined RTI in its traditional form without direct integration of technology.

The distribution supports the characterization of the field being in a ‘phase of structural formation,’ with the two parts being unevenly integrated in depth despite being conceptually overlapping. RTI is rooted in a cycle of progress monitoring and data-based decision making [4,9], and AI brings analytical capacities to enhance this logic [13,8], yet they have yet to be captured in a steadily integrated structure as reflected in the patterns of frequency.

The theme map of research trajectories (Figure 5) shows that many of the studies are still treating one approach or the other as separate and distinct, such as continuing to research the traditional RTI structure without technology [41,24] or looking at AI and learning analytics without MTSS [5,40]. This suggests the two move along separate trajectories rather than together as a system of thinking. This is confirmed with 16 studies (48.5%) still having an AI-focused trajectory and 8 studies (24.2%) remaining in the traditional RTI framework.

In contrast, the outcome patterns previously described (Figure 8) suggest a gradual shift toward predictive analytics and decision-making support [8,16,39]. Fourteen studies (42.4%) described how the AI tools supported the accuracy of predicting academic risk and speeding up instructional decision-making. Predictive models were also an AI technique most frequently occurring among the classified technologies, i.e., 6 studies (18.2%). These suggest a preliminary movement to connect the two frameworks, but this connection is still predominantly functional and piecemeal.

A historical view of the two areas may help explain the landscape. RTI emerged as a reform-based U.S. practice of preventive instruction aimed at reducing inappropriate referrals to special education [4,24], whereas AI in education appears to have taken a more technology-analytic approach to big data, predictive analytics, and rapid digital transformation [13,5]. Despite the different trajectories and epistemological foci, the integration of RTI and AI appears to be a jump to current technological possibility as opposed to a well-integrated theoretical advancement looking to the future. Thus, the results of this study revealed an evident opportunistic converging strength of the data-rich RTI framework and the analytic power of AI, but despite the numerical strength of predictive analytics, there is not yet a well-organized convergent model for how tiered instruction and intelligent data analysis might work together in a seamless and inclusive manner.

The findings of this review should also be interpreted in light of the relative variation in the methodological quality of the included studies, although the majority demonstrated an acceptable to strong level of quality according to the adopted assessment procedures. The findings also suggest that the results of the studies included in this systematic review represent a general research-based foundation for their conclusions. However, the quality of these studies varies based on design, sample size and level of artificial intelligence and Response to Intervention (RTI) integration. Therefore, the findings were analyzed using a cautious analysis approach that was sensitive to both the limitations of generalization of the findings as well as the developing and evolving nature of the research area.

5.1 Temporal Shift in Research Focus: From Structural Foundations to Intelligent Analytics

The dates of the studies (Figure 2) suggest a progression from a structural notion of RTI towards infusing intelligent tools to support RTI. Initial studies focused on conceptual aspects of RTI including intervention in tiers (Tier 1, Tier 2 and Tier 3), progress monitoring, and regulating decisions through data [29,4,41]. Researchers were focused on building a preventive infrastructure that was evidence-based and less on the technological artifacts that might support it [24].

The orientation also appears in the recurrent outcome patterns (Figure 8), where 12 studies (36.4%) focused on data centrality, progress monitoring, and measurement-based decision making, reflecting the persistence of RTI’s foundational logic. It appears that RTI’s conceptual structures have continued to influence the field even after the introduction of technological tools.

Over time, however, the literature began to show a marked shift toward the use of learning analytics and predictive models for early identification and decision-making within MTSS frameworks [13,8,16]. This shift may be seen as a natural response to the increasing availability of digital educational data, expanding computation capacities, and global interest in the application of AI within all spheres of life, including education [5].

This is supported by 14 studies (42.4%) that were included in the predictive analytics and decision support trend with predictive models as the top AI technology used among the categorized AI technologies (6 studies; 18.2%) (Figure 6). AI was no longer an independent technology, but rather, a potential tool to improve accuracy, and effectiveness, of the data-based logic that drives RTI.

Yet, even as the number of tools increased, this represented more of an expansion in their use than a restructuring of the organization of the system. In other words, it appears the field was moving horizontally, expanding the uses and analytics that support it, more than vertically, in terms of its structural integration within the system of tiered interventions. So, the willingness to include AI during this time continued to be limited to decision support rather than changing how the system functioned across the three tiers of support.

More recently, a third stream of research has been introduced, relating to the personalization and adaptability in inclusive educational [1,37,38]. There is an interest in identifying academic risk but also in designing flexible interventions tailored to individual learning profiles and educational barriers.

In numerical terms, personalization within the inclusive educational context was covered in 10 studies (30.3%), and adaptive systems were among the types of AI technologies used in 5 studies (15.2%) (Figure 6). This represents a shift from diagnostic framework to design framework, with a transition from “risk detection” to “system redesign.”

Although important, this stream is still emerging and has not yet developed into an integrative model that could potentially reorganize how analytics and tiers of intervention within RTI are related in inclusive settings.

Such a trajectory could also be positioned within a current global trend of digital transformations experienced over the past decade, accelerated by the ubiquitous adoption of intelligent technologies, improvements in machine learning models, and development of digital infrastructure in schools [36,18].

Rapid expansions of online/remote learning environments have also driven needs for performance monitoring, more accurate personalization of support, and other analytical capabilities in real-time.

Hence, the shift in the literature references a gradual, yet still incomplete change in how tiered educational intervention and intelligent data analysis in support of inclusive education are related to one another, rather than a change in research topics.

5.2 Interpreting the Dominance of Predictive Analytics in the Research Field

The outcome patterns (Figure 8) along with the AI technologies used (Figure 6) suggest that predictive analytics and a risk prediction model were the most popular trajectory within AI in RTI [8,39,16]. Fourteen studies (42.4%) fell into this trajectory and predictive models were the most common AI technology among the categorized techniques.

This dominance suggests that AI entered the field primarily to improve system decision-making, as opposed to helping to redesign the system through decision-making. Such a tendency can be explained through several structural, methodological, and practical considerations.

First, predictive analytics fits quite naturally with the logic of RTI [4]. RTI involves regularly monitoring student performance, early identification of students at risk, and instruction based on data. Thus, tools for predicting academic risk and analyzing performance patterns represent a logical extension rather than a break with this logic. In this sense, predictive analytics had fertile ground within RTI, and so could be adopted more quickly and broadly compared to usages that would require greater restructuring.

Second, predictive analytics is quantitatively measurable and statistically verifiable, which corresponds to the dominant experimental paradigm in intervention-effectiveness research (Chen, et al., 2019). Predictive models use measurable factors (e.g., scores, growth rates, risk indices) that can be field-tested, evaluated for accuracy, and compared with traditional heuristic estimates.

This is particularly notable since there were a few quantitative experimental studies in the sample (4 studies; 12%) as well as two mixed-methods studies (6%) (Figure 4). It appears that models that can be statistically tested and empirically verified hold greater currency in the field than broader integrative models which require more complex designs and longer longitudinal implementation. The prevailing methodological paradigm of the field continues to support models of prediction as the most publishable and verifiable path forward.

Third, predictive analytics are connected to early intervention, which is a key goal of inclusive education and MTSS [4,28]. Early intervention is critical to ensuring that academic problems do not escalate and that students are not inappropriately referred to special education. From this perspective, predictive models have the potential to further bolster the preventive aspect of RTI as part of global movements toward proactive and preventive education, as opposed to reactive remediation. The ethical-preventive interests merge with the analytic possibilities, enhancing the acceptance of this trajectory in inclusive education conversations.

Fourth, an additional explanation for this predominance may be related to funding and technical aspects. Predictive analytics can typically use existing educational datasets, such as student grades, attendance, and test scores, without needing significant changes to the educational setup. Compared to fully adaptive or intelligent learning environments, the implementation of predictive models represents a lower-tier investment with reduced complexity and cost, making them more appealing to decision-makers and funding entities [5]. This pragmatic factor further entrenches the field's focus on easily implementable solutions.

Even though this structure aligns well with the logic of RTI, the preeminence of predictive analytics, it turns out, begs the question of how much further we can go down this path. Focusing on the prediction of risk may lead us to use AI merely in the role of diagnosis, rather than building more comprehensive systems that will change the nature of the interventions themselves, or the educational context generally [40,37].

This concern is even more salient when considering that the number of studies directly or near-directly connecting AI and RTI did not exceed 9 studies (27.3%) of the total sample (Figure 5) out of partial functional uses. It appears, despite the advance in technology, the field is still in the “decision-enhancement” paradigm as opposed to a “system-redesign” paradigm.

Accordingly, the next step of research should not be limited to developing more accurate predictions, but rather designing intelligent intervention systems in which predictions are embedded within the intervention cycle itself, as part of a Multi-Tiered System of Support in inclusive education.

5.3 A Proposed Interpretive Framework for Levels of Integration Between Artificial Intelligence and Response to Intervention (RTI)

Based on the research trajectories, the technologies used, and the common outcome categories within the included studies, it is possible to reorganize the research literature into an interpretive framework of three levels of integration of AI and RTI in inclusive education. This categorization is not intended to create clear distinctions among studies but to provide a lens for interpreting the extent of structural integration of both areas.

The proposed framework also contributes to explaining how different levels of integration are associated with the operational processes of Response to Intervention (RTI) systems and Multi-Tiered Systems of Support (MTSS) within inclusive education contexts. More specifically, the framework links functional integration with processes of early identification, predictive analytics, and continuous progress monitoring. Artificial Intelligence and Response to Intervention (RTI): Procedural Integration and Structural Integration

Procedurally integrated AI-based interventions are customized and adapted for students at all levels of RTI support; structurally integrated AI applications involve the adoption of AI as part of an organization's overall organizational structure.

The thirty-three studies reviewed in this report have been grouped by the degree of integration between artificial intelligence and response to intervention, as described in and figure (10). The rationale for placing each study under its respective level of integration is detailed conceptually and methodologically below.

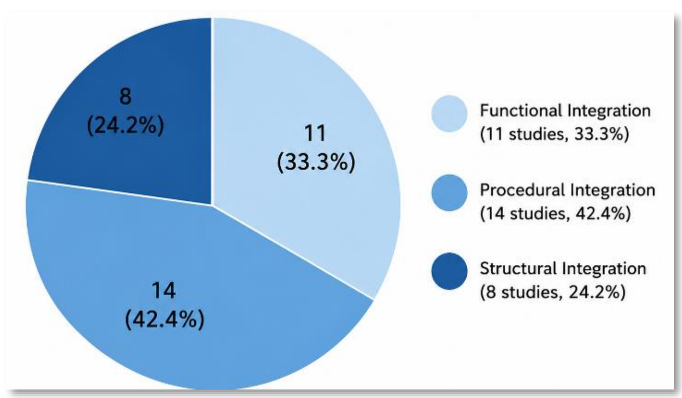

Fig. 10: Distribution of the Included Studies According to the Proposed Levels of Integration Between Artificial Intelligence and the Response to Intervention (RTI) Framework

Procedural Integration was by far the most popular area in terms of the amount of research conducted, with 14 studies (42.4%), indicating that researchers are currently focusing their efforts on using AI to support procedures for implementing RTI, including supporting teachers in developing educational interventions; providing tools for making decisions based upon educational data; and creating a supportive learning environment for students with disabilities. Functional Integration was the next most researched area with 11 studies (33.3%), and utilized AI as an analytical tool to help predict student needs, identify students at risk earlier, monitor student progress, analyze educational data collected via RTI systems, etc. This trend illustrates an increasing interest in utilizing predictive analytics, as well as other forms of data analysis technology to provide educators with timely information to initiate early educational interventions. The lowest number of studies related to Structural Integration with only eight studies (24.2%) categorized under this heading. The focus of the studies was mainly on establishing conceptual/organizational linkages between AI and RTI within MTSS models. Additionally, these studies also addressed issues regarding ethics, and organizationally-related issues of integrating AI into RTI models.

In summary, the above findings clearly demonstrate that much of the existing research continues to view the relationships between AI and RTI solely from either a functional perspective or a procedural one versus more holistically from an integrated model-based perspective. The very few structural studies also illustrate the continued need for additional integrated theoretical and practical models for understanding how AI can be used within a systemic approach to understand its relationship to Multi-Tiered Intervention Systems within Inclusive Education settings.

Level One: Partial Functional Integration

This represents the most common type found in the literature. At this level, AI is being used to support one particular part of the RTI system, such as predicting academic risk or analyzing performance patterns [8,39]. The technology plays an instrumental role in more accurate or quicker decisions for early identification, but it does not challenge the design of the intervention or the tiered structure of the intervention system itself.

This is reflected both quantitatively and visually, where 14 studies (42.4%) aligned with the trajectory of predictive analytics and 12 studies (36.4%) focused on data centrality, progress monitoring, and measurement-based decision making (Figure 8). This represents a clustering of studies around this diagnostic-analytical rung of the system.

AI at this level is seen more as an aid to the system rather than a feature within it. At this level, artificial intelligence primarily functions to support the operational processes of the Response to Intervention (RTI) framework, such as early identification, risk prediction, continuous progress monitoring, and data-driven educational decision-making, without introducing substantial changes to the organizational structure of the intervention system. The prevalence of predictive analytics can be explained by its alignment with the tasks of the RTI system of continuous monitoring of progress and data-driven decision making [4].

Level Two: Procedural Integration

This level advances beyond diagnostic support to include the adaptation of instructional interventions within tiers of support (Tier 1 or Tier 2) using AI. At this level, technology predicts and personalizes content, adapts the intervention's intensity, or suggests differentiated instructional approaches in response to data on student performance [1,38].

Similar tendencies can be found in the investigations of adaptive systems and intelligent tutoring systems in inclusive education environments [37]. Personalized learning pathways in inclusive education occur in 10 studies (30.3%), and adaptive systems occur in 5 studies (15.2%) of the classified AI technologies (Figure 6). These results show that a progression has been taking place in which the diagnostic role starts to have a direct impact on the design of educational interventions.

At this point, the shift is from instrumental use to interactive use, with technology starting to influence classroom practice. Accordingly, procedural integration reflects the incorporation of artificial intelligence into educational and intervention procedures through adaptive learning, differentiated learning pathways, and the planning of individualized interventions across the levels of the Response to Intervention (RTI) framework, though still within the established organizational structure of RTI.

Level Three: Structural Integration

The third level involves embedding AI as a component of the entire MTSS system. At level three, AI is a component of planning, implementing, evaluating, and redesigning the educational environment. Technology is not an external addition but rather an embedded part of the organizational and decision-making structure of the system. At this level, artificial intelligence becomes integrated within the broader operational structure of Multi-Tiered Systems of Support (MTSS) and the Response to Intervention (RTI) framework, contributing to processes of planning, intervention allocation, assessment procedures, institutional decision-making, and system redesign within inclusive education environments.

Such integration requires clearly articulated governance frameworks, stable digital infrastructures, and sustained professional development for teachers [10,36,18] in addition to extended experimental testing across diverse contexts.

Representation of the level appears to be sparse. Studies of direct or quasi-direct integration between AI and RTI (i.e., AI within an RTI framework) comprised no more than 9 studies (27.3%) of the total sample (Figure 5), and there were no longitudinal studies (0%) and only 4 quantitative experimental studies (12%) (Figure 4). This suggests a fully developed and widely applied integrative model is not yet present in the literature, which continues to operate at functional or procedural levels rather than reconfiguring the structural elements of MTSS.

5.4 Geographic Concentration of Research Production at the Intersection of AI and RTI

As shown in Figure 3, the country of the published studies shows a predominance of research produced in the United States and a scarcity of research in other contexts, especially in Arab educational systems. The US had 14 studies (42%), international studies accounted for 7 studies (21%), Jordan had 4 studies (12%), and Saudi Arabia had 1 study (3%).

This focus can be understood in light of the historical and institutional roots of RTI, which emerged and developed within the U.S. educational context as a reform-oriented approach emphasizing data-based accountability, early detection, and minimizing erroneous referrals to special education [4,24]

RTI has its roots in U.S. legislative and institutional history, particularly regarding mandates for educational accountability, layers of standardized testing regimes, and frameworks like MTSS [41,9]. As a result, it developed a strong corpus of research concerning its efficacy, implementation, and measurement [24]. With the rise of AI in education, it seems a natural progression that researchers within the U.S. have begun to explore the ways in which those technologies may support the data-driven logic of RTI [13,8].

With substantial educational data, advanced digital infrastructure, and educational technology innovation funding, US universities and research institutions have the conditions to implement predictive models and intelligent systems for use in school education [5]. Therefore, this geographical concentration represents not only historical dominance but also the capabilities technical and organizational capacity to conduct applied research in this area [36].

In comparison, Arab contexts have attracted a fraction of this global research attention despite growing concerns about inclusive education and digital transformation within Arab schools. Researchers from Jordan and Saudi Arabia contributed 5 studies (15.2%) of the overall sample. This may be due to the novelty of RTI-like implementation across many Arab countries, the variable state of digital infrastructure in some Arab schools, and the pace of experimental research on incorporating intelligent technologies in tiered support systems [42,43]. In fact, some Arab researchers remain focused on attitudinal and descriptive measures of intelligent technology use in schools [44,45].

This geographical perspective invokes a methodological consideration of generalizability. Perhaps models developed in a context rich in technological resources might behave differently in a context with distinct organizational structure, institutional culture, or accountability systems. So, adding more diverse contexts, such as the Arab educational systems, is not simply about adding more data but is a crucial step in validating the contextual generalizability of any putative integrative models [40,37].

This geographical concentration in the literature also indicates the uneven stages of development of this field and a need for comparative and cross-contextual studies to investigate how flexible AI–RTI integration might be across different educational systems.

5.5 Methodological Gaps in the Analyzed Literature

Beyond thematic patterns, it is important to reflect on the methodological features of the studies included in the review. Research design distribution has some implications for the field's maturity as well as generalizability.

Quantitatively, experimental studies accounted for no more than 4 studies (12%), and mixed-methods studies only 2 studies (6%) compared to 6 analytical and review of studies (18%) and 5 conceptual or theoretical studies (15%) (Figure 4). This represents a strong tendency towards analytical studies and reviews rather than systematic field-based experimental testing of the integration of AI–RTI.

First, few experiments directly integrated AI tools within the RTI framework have been conducted. While many individual studies explore the efficacy of RTI and the capabilities of AI, there are few studies that have developed and tested these experiences within real-world classroom settings. This suggests that the current phase of investigation has not moved from conceptual examination to systematic extensive applied research.

Second, there were no longitudinal studies (0%). MTSS models are designed to be addressed and evaluated on an ongoing basis. Understanding how AI–RTI integration performs over time requires longitudinal evaluation to determine the long-term success, continued gains, and ripple effects in inclusive settings.

Third, generalizability was of concern in several of the applied studies because the sample size was relatively small. While small-scale or exploratory studies have great value in the initial phases of developing a field, they do not always provide sufficient statistical basis for making broad inferences. Increasing sample size and diversity would be of great benefit to the strength of the results in informing policy-level decisions.

Fourth, much of the literature has been conceptual or a review rather than empirical. While it is important that a field develop its theoretical work and engage in some degree of futuristic, conceptual scholarship, inordinate attention to this orientation over time may point to the fact that the field is ‘in flux’ and has not yet reached a stage of relative applied stability.

Collectively, these patterns of findings suggest that AI–RTI is still in a formative methodological phase. Although it is analytically and conceptually robust at present, it is not yet sufficiently empirically developed to yield a well-established integrative model with a robust base of extended evidence from multiple contexts.

Accordingly, conducting more large experiments, longitudinal studies, and experiments with more diverse samples are important priorities for maturing the field from a state of theoretical promise to one of reliable practical evidence.

5.6 Future Implications and Research Agenda Development

Based on the structural, methodological, and geographic analyses above, a number of prospective implications emerge that go beyond mere description towards reorienting the field of research toward greater integration and sophistication.

First, these findings point to a need for shifting from partial functional integration toward structural integration that fully integrates and embed AI tools across MTSS operations [40,37]. This is particularly pertinent since only 9 studies (27.3%) reported direct or quasi-direct AI–RTI integration, indicating that most of the research only achieved partial functional integration. The bulk of studies focused on predictive or analytical decision support without creating new intervention models at the three RTI tiers [8,39]. Future studies should focus on experimental designs that embed predictive algorithms and adaptive personalization systems within intervention cycles as opposed to treating them as adjuncts.

Second, longitudinal experimental research measuring long-term effects of integrating AI–RTI over time is warranted. With few quantitative experimental studies (4 studies; 12%) and no longitudinal studies (0%), more robust and longer-term methods are needed to evaluate sustainability, tiered responsiveness, and students with disabilities and special educational needs learning trajectory changes. Multi-site quasi-experimental studies within culturally diverse inclusive settings are much needed to expand the current geographic concentration of research.

Third, what is required is the development of testable governance frameworks for inclusive schools, rather than theoretical scenarios about regulation. This includes operationalizing privacy safeguards, algorithmic bias, transparency in educational decision making and teacher professional development in data literacy and AI-supported decision making [10,36,18]. This will facilitate moving away from pilot projects towards sustainable embedding.

Fourth, there is a need to attend to or focus on specific disability categories within research. While the numbers suggest that the majority of studies appeared to be situated within the context of support for students in inclusive classrooms (18 studies; 54.5%), those that were focused on specific disability categories only accounted for 3 studies (9.1%). This demonstrates a widening gap between the discourse about inclusiveness, and the focused testing of AI tools for learners with complex needs. To advance a just research agenda, we need focused testing within specific disability contexts to support the principles of inclusive education, supported by equity and not equality.

Fifth, considering the increasing rate of global digital transformation, further research should develop multi-layered integrative models combining predictions for early detection, adaptation for individualization, ongoing monitoring of progress, and digital management structures.

Creation of such a model would transition the comparison of AI and RTI from comparison to structural integration, where a system of tiered interventions could be redefined within an inclusive setting.

In sum, this research shows that despite significant progress in analysis and prediction, much remains to be done in the essential area of integration. The low rates of direct integration (27.3%), experimental studies (12%), and lack of longitudinal studies (0%) indicate that the main challenge for the science of the future may not be to create more advanced AI, but to create educational support environments that naturally integrate these AI technologies within their structures and functions.

Taken together, these findings across structural, methodological and geographical aspects of the research imply that the issue within the field is not a lack of technical capacity but rather an inability to stabilize that capacity within the system. The predominance of only partial functional integration, limited experimental and longitudinal evaluation, and concentration within a narrow range of the most developed countries represents a portfolio of approaches that may be a key component of what is resulting in the slow movement towards full structural integration. Rather than a fragmented field, the current state of the field may represent horizontal broadening of applications with limited vertical deepening of the structural reengineering of the MTSS.

Executive Summary

The findings of this review indicate that the consolidation stage of the field of research on AI and RTI in inclusive education has not yet been achieved. Although predictive calculations and AI-supported personalization systems have attracted increasing interest, substantial integration within the RTI framework is still lacking. Articles addressing direct or quasi-direct incorporation only represented 27.3% of the examined studies, articles with quantitative experimental designs were rare (12%) and research has been concentrated in the US (42%), all indicating a technological evolution outpacing structural change.

Collectively, these outcomes indicate that the prevailing approach within the field is to refine the implements within the current system, as opposed to redesigning the MTSS directly. Some degree of functional integration is still common, but full structural integration is rare. And, there continues to be methodological skew, as well as geographic skew, but there is also a lack of longitudinal research across multiple settings.

Thus, the scientific challenge for the next phase will not be to develop more complex algorithms, but to build integrative models that can be tested experimentally over more extended experimental designs, based on explicit governance models, and adaptable across cultures and organizations. A real paradigm shift in the field requires redesigning the support systems so that AI is a component of early detection, personalization, and data-based decision-making and not simply an additional lens.

In this sense, this study offers a view of the research field at a moment of change, and it provides a theoretical and methodological underpinning for carrying out further research in a more unified, fair, and sustainable manner, by moving toward a holistic perspective in considering AI and tiered intervention systems in inclusive education can be jointly considered.

Interpretive Reading of the Proposed Framework

Though not reported in this manner by the original authors, when reorganizing these findings along the lines of the proposed classification, it is clear that most of these studies are found at Level One, as evidenced by a high frequency of predictive analytics (42.4%) and a focus on data centrality and continuous progress monitoring (36.4%), with a moderate frequency Level Two, and a low frequency of Level Three (27.3%) [8,37]. This suggests that the area of research is likely still progressing from a phase of functional use of technology and towards the intelligent reconstruction of the intervention system [40]. This progression also reflects a shift from supporting partial functions of the Response to Intervention (RTI) framework, such as prediction and monitoring, toward integrating artificial intelligence into educational procedures, ultimately culminating in its incorporation into the structural and organizational foundations of inclusive support systems.

Nevertheless, this framework should be viewed as an interpretive and inferential framework derived from the analysis of the studies included in the review, rather than as an empirically validated model with directly established construct validity. Furthermore, the application of the proposed levels of integration may vary according to educational contexts, technological infrastructure, and the degree of institutional readiness within Multi-Tiered Systems of Support (MTSS/RTI). Accordingly, further experimental and longitudinal studies are needed to examine the applicability of this framework across diverse educational settings.

This interpretation provides a synthetic picture beyond enumeration that allows us to deepen our understanding of this stage of maturity of AI–RTI in inclusive education. It can help us begin to shape the future research agenda aimed at moving from partial to structural integration, i.e., better matching what the technology can do to what inclusive education aims to accomplish [36].

The findings of this review echo several international reviews that have noted the predominance of instrumental uses of AI in education, and the relative absence of holistic integrative models. In line with these observations, our quantitative indicators showed that predictive trajectories were the most common pattern (42.4%), whereas studies that examined direct or quasi- direct AI- RTI integration together accounted for only 27.3% of the total sample.

Similarly, Zawacki-Richter et al. [5] noted that most of the research continues to focus on learning analytics and decision support with fewer integrative applications at the institutional level. Romero and Ventura [40] also noted that predictive models and educational data mining continued to dominate our understanding with few frameworks to connect AI to structured support in education. This aligns with Pagliara et al. [37] who noted that the applications within inclusive education tend to address partial personalization or partial task support as opposed to a system redesign.

Furthermore, the present findings support the conclusions of Holmes and Tuomi (2022) and the OECD [18] that many of these are limited to trial stages or are hypothetical recommendations due to regulatory, professional learning and technical readiness issues. Floridi et al. [10] also discuss the lack of robust governance as a barrier to sustainable embedding within institutions.

The present study adds a contrasting analytical perspective to the mostly descriptive reviews of the literature on AI–RTI. It organizes the literature into levels of AI–RTI integration such as partial functional integration, procedural integration, and structural integration.

Scientific Contribution of the Study

The present study contributes the research field of AI–RTI integration within inclusive education settings in several interrelated aspects given the low direct integration (27.3%) and low representation of quantitative experimental research (12%) which indicates a need for deeper analytical framing.

First, the study provides a synthetic reorganization of the body of literature in three domains that have evolved largely in parallel: AI in Education, Multi-Tiered Systems of Support (MTSS/RTI), and inclusive education [5,40]. Instead of a descriptive synthesis of trends, it provides an analytical map of the nature and degree of maturity of integration across these domains.

Second, the study proposes an interpretive framework that identifies three levels of integration (functional, procedural, and structural), thereby providing a tool for future research to interpret and consider where initiatives and applied models fall within the field development. This framework moves the focus away from simply looking at technology use to understanding how integration is organized within the system of tiers of interventions.

Third, this research offers a critical methodological framework of research gaps not only in terms of topics but also research gaps in terms of time, country, and method. This finding contributes to orienting the research agenda toward longitudinal experimental studies, applied models across multiple contexts, and testable theoretical models of governance in inclusive contexts [10,37].

Fourth, at an applied level, this research offers an initial conceptual basis that may aid policymakers in education to advance from basic usage of AI tools towards comprehensive redesign of educational support systems [36,18].

Overall, this review of the literature not only synthesizes the literature but also repositions it within the current state of the field and suggests a direction for progress and integration of AI and tiered intervention systems in inclusive education settings.

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