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«مقاله پژوهشی»

شناسایی ابعاد، مؤلفه‌ها و شاخص‌های آموزش فراشخصی‌سازی‌شده با بهره‌گیری از هوش مصنوعی

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چکیده

پژوهش حاضر باهدف شناسایی ابعاد، مؤلفه‌ها و شاخص‌های آموزش فراشخصی‌سازی‌شده با بهره‌گیری از هوش مصنوعی صورت گرفت. نوع پژوهش به لحاظ نوع داده کیفی بود که به لحاظ ماهیت شامل مراحل فراترکیب و دلفی بود. جامعه آماری در بخش کیفی و مرحله فراترکیب کلیه مبانی نظری و پیشینه مرتبط پایگاه‌های داده خارجی و در مرحله دلفی ۱۵ مشارکت‌کننده (خبره) با روش نمونه‌گیری غیر تصادفی هدفمند انتخاب شدند. روش گرداوری داده‌ها در مرحله فراترکیب مرور سیستماتیک ادبیات و در مرحله دلفی کاربرگ بود و روایی و پایایی موردبررسی قرار گرفت که نتایج بیانگر روا و پایا بودن ابزارهای پژوهش بود. روش تجزیه‌وتحلیل داده‌ها در مرحله فراترکیب، تحلیل سیستماتیک و در مرحله دلفی ضریب توافق کندال بود با نرم‌افزارهای Maxqda-V2018 و Spss-V23 بود. یافته‌ها نشان داد، آموزش فراشخصی‌سازی‌شده با بهره‌گیری از هوش مصنوعی شامل بعد شناختی با مولفه‌های تحلیل سطح دانش پیشین(۵شاخص)، سبک یادگیری فردی(۶شاخص)، سازگاری شناختی(۶ شاخص)، حافظه و یادسپاری (۶ شاخص) وحل مسئله و تفکر انتقادی(۶ شاخص)؛ بعد عاطفی با مولفه های شناسایی حالات هیجانی (۶ شاخص)، انگیزش درونی (۶ شاخص)، خودکارآمدی یادگیرنده(۶ شاخص)، رضایت یادگیرنده (۶ شاخص) و درگیری هیجانی در یادگیری(۶ شاخص)، بعد رفتاری با مولفه های الگوهای تعامل با سیستم(۶ شاخص)، مشارکت در فعالیت‌های گروهی(۶ شاخص)، نظم و پیگیری یادگیری(۵ شاخص)، رفتارهای جست‌وجوی دانش(۶ شاخص) و تعامل با بازخورد(۶ شاخص) و بعد زمینه‌ای با مولفه‌های شرایط محیطی یادگیری(۶ شاخص)، فناوری و ابزار مورد استفاده(۶ شاخص)، تطبیق فرهنگی و زبانی(۶ شاخص)، دسترسی و عدالت آموزشی(۶ شاخص) و تحلیل داده‌های یادگیری(۶ شاخص) بود.

واژه‌های کلیدی

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ORIGINAL ARTICLE

Identifying The Dimensions, Components, and Indicators of Hyper-Personalized Education Using Artificial Intelligence

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ABSTRACT

The present study was conducted with the aim of identifying the dimensions, components, and indicators of hyper-Personalized education using artificial intelligence. The type of research was qualitative in terms of data type, which included meta synthesis and Delphi stages in terms of nature. The statistical population in the qualitative section and meta synthesis stage included all theoretical foundations and relevant background from external databases, and in the Delphi stage, 15 participants (experts) were selected using purposive non-random sampling. The data collection method in the meta synthesis stage was a systematic literature review, and in the Delphi stage, a worksheet, and validity and reliability were examined, and the results indicated that the research tools were valid and reliable. The data analysis method in the meta synthesis stage was systematic analysis, and in the Delphi stage, the Kendall agreement coefficient was used with Maxqda-V2018 and Spss-V23 software. The findings showed that hyper-Personalized education using artificial intelligence included a cognitive dimension with the components of prior knowledge level analysis (5 indicators), individual learning style (6 indicators), cognitive adaptation (6 indicators), memory and memorization (6 indicators), and problem solving and critical thinking (6 indicators); an affective dimension with the components of identifying emotional states (6 indicators), intrinsic motivation (6 indicators), learner self-efficacy (6 indicators), learner satisfaction (6 indicators), and emotional involvement in learning (6 indicators); a behavioral dimension with the components of interaction patterns with the system (6 indicators), participation in group activities (6 indicators), learning discipline and pursuit (5 indicators), knowledge seeking behaviors (6 indicators), and interaction with feedback (6 indicators); and a contextual dimension with the components of learning environmental conditions (6 indicators), technology and tools used (6 indicators), cultural and linguistic adaptation (6 indicators), educational access and justice (6 indicators), and learning data analysis (6 indicators).

KEYWORDS

Hyper-Personalized Education, Use of Artificial Intelligence, Individual Learning.

Introduction

Hyper-personalization in education is an emerging pedagogical approach that, through the integration of artificial intelligence (AI) technologies and big data analytics, enables the design of unique and individualized learning pathways for each learner. Unlike traditional personalization—which typically relies on general categorizations such as age groups or educational levels-hyper-personalization possesses the capability to analyze diverse and real-time data, including prior knowledge, learning styles, interactive behaviors, interests, as well as emotional and motivational characteristics of each individual (Saurav & Kumari, 2025; Desai, 2022). This approach allows educators and learning systems to tailor content, activities, exercises, and feedback precisely to the specific needs of each learner.

Artificial intelligence, particularly machine learning and deep learning algorithms, plays a pivotal role in this domain. By analyzing behavioral patterns, convolutional and recurrent neural networks can identify learners' levels of attention, motivation, and emotional engagement throughout the learning process. The collected information is then used to adjust learning pathways, provide targeted exercises, and suggest personalized content (Desai et al., 2022; Micu et al., 2022). Moreover, analyzing environmental and contextual data—such as study time, type of device used, and surrounding conditions—enables the delivery of adaptive and flexible learning experiences tailored to individual circumstances.

Hyper-personalization also offers predictive capabilities. Using predictive learner behavior models and advanced data analytics, systems can determine optimal learning pathways, forecast potential weaknesses and content retention lapses, and schedule effective review sessions for each learner (Tiwari, 2024; Desai et al., 2022). These features enhance motivation, improve learning performance, and reduce dropout rates in online educational environments.

From an organizational and managerial perspective, the implementation of hyper-personalized learning requires a comprehensive framework that integrates learners' cognitive, emotional, motivational, and environmental dimensions with technical considerations, data privacy, and educational inclusivity in a unified approach (Prem, 2025; Vuyyuru, 2025). Such an integrated model facilitates the development of intelligent educational systems, data-driven decision-making, and the optimization of learning experiences for every learner.

AI-driven hyper-personalization in education, beyond being a mere technological tool, represents a learner-centric and data-driven learning strategy capable of creating tailored, effective, and motivating educational experiences. It holds the transformative potential to enhance learning quality, increase learner engagement and loyalty, and improve the overall effectiveness of educational institutions.

One of the main challenges of traditional education systems lies in the standardization of teaching methods and content for all students, despite individual differences in abilities, learning styles, and learning pace. AI-powered hyper-personalized education enables the customization of learning pathways, course content, and exercises to match each student's specific needs and characteristics. This approach enhances learning effectiveness, reduces academic underperformance, and promotes more meaningful and individualized learning experiences.

Furthermore, the use of AI in education can significantly boost student motivation and engagement. Through instant feedback, targeted exercises, and interactive activities, learners perceive that the educational process is designed specifically for them, which in turn fosters interest and intrinsic motivation. At the same time, the collection and analysis of educational data by intelligent systems enable the prediction of learning challenges, curriculum improvement, and more informed managerial decision-making, thereby enhancing overall educational quality.

AI-based hyper-personalized education also plays a vital role in preparing students for future demands and the knowledge-based economy. In a world where skills and job requirements are rapidly evolving, this approach equips learners with the competencies of tomorrow and facilitates lifelong learning. Moreover, AI has the potential to reduce educational inequalities caused by disparities in school and teacher quality, ensuring more equitable access to high-quality education, even in under-resourced areas.

Ultimately, AI-powered hyper-personalization also transforms the role of teachers. Educators can devote more time to creative, advisory, and supportive activities rather than repetitive teaching and manual grading. Consequently, learning becomes more effective for students while teachers can focus on fostering learners' human, social, and creative skills.

Despite the high potential of AI in educational personalization, several challenges and issues arise in the implementation of this approach. One of the most critical concerns is the protection of students' privacy and data security. Intelligent systems require vast amounts of personal, academic, and behavioral data to provide personalized instruction, which raises serious concerns about data protection and potential misuse.

Another major challenge involves unequal access to technology and digital infrastructure. Many schools and students lack stable internet connections, proper hardware, or high-quality digital resources, which can exacerbate educational disparities and limit equal opportunities for benefiting from AI-driven learning.

Additionally, the lack of technical and pedagogical skills among teachers and instructors poses a significant barrier. Successful implementation of AI systems requires teachers who are competent in data analysis, technology utilization, and personalized content design. However, many educators are not yet familiar with these tools and methodologies.

Another concern relates to the quality of algorithms and the risk of bias in AI decision-making. Machine learning algorithms may be trained on incomplete or biased datasets, leading to unfair recommendations or learning pathways. Such bias can undermine educational equity and reduce trust in intelligent systems.

The high costs associated with developing and maintaining AI-based educational systems also represent a major limitation. The design, implementation, and continuous updating of these systems demand significant investment, which may not be feasible for many schools and educational institutions.

Each of these challenges plays a crucial role in determining the success of AI-based hyper-personalized education. Data privacy and security are of utmost importance, as the trust of students, parents, and teachers in AI-based systems directly depends on how well personal information is protected. Ignoring these concerns could lead to user resistance and decreased system effectiveness.

The issue of unequal access to technology and digital infrastructure is also fundamental since without equitable access to hardware, the internet, and digital resources, not all students can benefit from personalized learning. This could exacerbate existing educational gaps and threaten fairness in education.

The shortage of teachers' technical and pedagogical competencies is equally critical. Even the most advanced AI algorithms cannot achieve personalized learning goals without proper teacher training and support. Empowering teachers through professional development is therefore key to successful implementation.

Algorithmic quality and the risk of AI bias are also of paramount importance, as biased algorithms can generate inequitable learning pathways and reduce users' trust in intelligent educational systems. Ensuring algorithmic transparency and accuracy is essential for achieving educational equity in AI environments.

Finally, the high costs of developing and maintaining AI systems present practical and economic challenges. Financial constraints may delay large-scale implementation and limit the full realization of personalized learning benefits. Effective resource management and strategic financial planning are thus vital for the long-term success of this approach.

Research indicates that several key factors influence the success of AI-based hyper-personalized education. One of the most critical factors is the quality of student data and information. AI systems rely on accurate and comprehensive data about academic performance, learning styles, and student behavior to deliver personalized instruction. Studies show that incomplete or inaccurate data can lead to inappropriate learning pathways and reduced educational effectiveness.

The design of intelligent algorithms and machine learning models is another crucial determinant of success. Accurate and flexible algorithms can identify individual learning patterns and offer adaptive learning pathways suited to each student's needs. Research emphasizes that transparent and interpretable algorithms increase user trust and lead to broader acceptance of personalized learning systems.

A third factor is teachers' skills and preparedness to work with AI technologies. Studies suggest that even the most sophisticated systems cannot achieve educational goals without teacher support and empowerment. Training teachers to use data, analyze outcomes, and design personalized content is therefore of particular importance.

Technological infrastructure sustainability and access to digital resources also play a decisive role. Research demonstrates that access to stable internet connections, appropriate hardware, and high-quality educational software significantly determines the success of hyper-personalized learning systems. A lack of such infrastructure can severely undermine personalized learning effectiveness.

Finally, students' motivational and personal characteristics are also influential. Studies indicate that motivation, self-confidence, engagement, and self-regulation shape the intensity and quality of learners' responses to personalized education. Successful intelligent systems enhance these human factors through engaging activities and instant feedback mechanisms.

Over the past two decades, the topic of AI-driven hyper-personalized education has garnered increasing attention from researchers. Early studies focused on the application of intelligent tutoring systems that analyzed student performance, provided individualized feedback, and adapted learning pathways according to each learner's abilities and needs (Anderson et al., 1995). In recent years, advances in machine learning algorithms and access to big data have enabled the development of AI-based personalized learning systems capable of predicting learning needs and delivering customized content (Chen et al., 2020).

Figure 1 illustrates the evolutionary trajectory of hyper-personalized education from 2012 to 2025 as a chronological pathway. The primary goal is to transform the learning process into a unique and dynamic experience for each learner—an experience grounded in artificial intelligence, data mining, and a deep understanding of learners' cognitive, emotional, and behavioral characteristics. In essence, educational personalization along this pathway evolves from a simple model of online learning into a holistic and intelligent system that encompasses all dimensions of human learning.

The inception of this transformation began in 2012 with the emergence of Massive Open Online Courses (MOOCs). These platforms provided open and global access to education and represented the first step toward adaptive and flexible learning. In 2015, the first applications of artificial intelligence in education were introduced with the goal of personalizing educational content. This stage, often referred to as the era of "early tutors," focused on aligning learning pathways with the individual abilities and needs of students.

Subsequently, in 2017, the rise of learning analytics marked a major breakthrough in the analysis of educational data. Analytical algorithms examined learners' performance, identified learning patterns, and offered personalized recommendations. This progression led, in 2019, to the development of adaptive content, where educational systems became capable of dynamically adjusting instructional materials according to each student's strengths and weaknesses. In 2020, the expansion of distance learning during the COVID-19 pandemic created an unprecedented opportunity for the use of digital tools, making the role of personalization in online education more prominent than ever.

From 2021 onward, artificial intelligence began to move toward more human-like and intelligent interactions. Educational chatbots were introduced, capable of conversing with learners, answering their questions, and providing continuous personalized experiences. By 2022, technology had reached the stage of emotion recognition, enabling systems to analyze learners' emotional states through their voices, facial expressions, and behaviors, and to respond appropriately to their psychological conditions. This advancement paved the way for multimodal personalization in 2023, during which textual, auditory, visual, and behavioral data were analyzed simultaneously—transforming education from a one-dimensional process into a multisensory and immersive learning experience.

In 2024, the concept of predictive learning pathways emerged. AI systems, through the analysis of students' past performance data, became capable of predicting their future learning trajectories and outcomes while offering optimized recommendations. This approach elevated education from a reactive model to a proactive and strategic one. Finally, by 2025, personalized education reached the stage of holistic meta-learning, wherein AI systems, by integrating cognitive, emotional, and social dimensions, create a fully unified and human-centered learning experience aimed at the learner's comprehensive development rather than merely knowledge transmission.

Overall, this evolutionary trajectory demonstrates that personalized education has advanced from the simple delivery of uniform content to a sophisticated stage capable of understanding and predicting learners' emotions, behaviors, needs, and goals. This transformation signifies the shift of educational systems from generic instruction toward intelligent, humanized, and holistic education—one in which learning becomes a uniquely individualized experience and the boundary between technology and humanity in the learning process gradually dissolves.

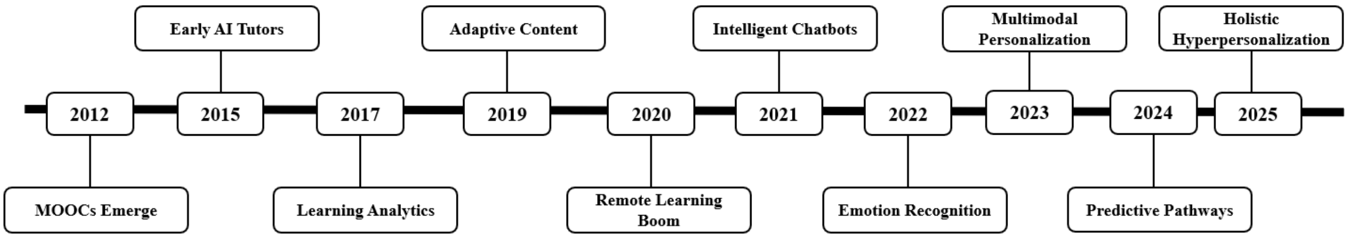

Figure 1. The Evolutionary Trajectory of Hyper-Personalized Education through Artificial Intelligence

Recent studies indicate that the use of artificial intelligence (AI) in personalized education increases students' motivation, engagement, and academic performance. For instance, research conducted in the fields of online and electronic learning has demonstrated that adaptive learning systems can accelerate learning and reduce educational gaps (Kulik & Fletcher, 2016; Baker & Inventado, 2014). Moreover, applied studies in schools and universities show that AI-based personalized learning platforms provide immediate feedback, individualized learning paths, and activities tailored to each student's learning style.

From a theoretical perspective, several foundational frameworks and theories underpin hyper-personalized learning:

1. Cognitive Learning Theory: This theory emphasizes information processing and the way individuals learn. Hyper-personalized learning systems apply its principles in practice by identifying each student's knowledge level, processing speed, and learning style to provide customized learning pathways (Sweller, 1988).
2. Constructivist Learning Theory: This theory highlights learner activation and the construction of knowledge through experience and interaction. AI systems can facilitate active learning activities, immediate feedback, and interactive content that place learners at the center of the learning process (Piaget, 1972; Vygotsky, 1978).
3. Adaptive Learning Theory: This theory directly relates to personalized education, asserting that instructional systems should adjust content and learning trajectories according to individual behavior, progress, and needs. AI algorithms can perform such adaptive processes automatically and intelligently (Brusilovsky, 2001).
4. Self-Regulated Learning Theory: This theory emphasizes the learner's ability to plan, monitor, and evaluate their own learning. Personalized systems strengthen students' self-regulatory skills by providing feedback, suggesting appropriate activities, and offering tailored learning paths (Zimmerman, 2002).

Empirical evidence demonstrates that applying AI in personalized education yields significant positive outcomes both theoretically and practically. Cognitive, constructivist, adaptive, and self-regulated learning theories collectively form the scientific foundation for designing hyper-personalized learning systems and reveal that intelligent education can enhance individual learning, motivation, and academic performance.

Based on the foregoing, the lack of AI-enabled hyper-personalized education leads to undesirable conditions and significant limitations within educational systems. One of the most critical problems is the standardization of teaching methods and content for all students, which fails to address individual differences in abilities, learning pace, and interests. This results in decreased motivation, diminished academic performance, and a higher likelihood of educational underachievement among certain students.

Another challenge concerns the lack of immediate feedback and interactive instruction suited to each learner. In traditional systems, teachers are often unable to provide personalized feedback and timely performance analysis for each student, which slows down the learning process and deprives learners of opportunities to correct mistakes and strengthen weaknesses.

The absence of personalization also contributes to educational inequality and gaps among students with varying abilities. Learners with special needs or distinct learning styles may achieve lower success and experience inferior learning outcomes, whereas others may benefit sufficiently from standardized instruction.

Furthermore, the failure to utilize learning analytics and AI-driven decision-making deprives schools and educators of valuable insights that could improve curricula, anticipate learning challenges, and optimize instructional trajectories. Consequently, educational efficiency declines, and resources are wasted.

Ultimately, the absence of hyper-personalization restricts the teacher's role and impedes the development of students' self-regulatory abilities. Learners have fewer opportunities for active learning, personalized interaction, and self-directed study management, while teachers spend most of their time on traditional lecturing and grading rather than fostering creative and social skills.

It is noteworthy that unresolved challenges associated with AI-based hyper-personalized learning have wide-ranging negative consequences across cultural, social, economic, psychological, technological, and educational dimensions. Culturally, the absence of personalized education can exacerbate inequality and educational discrimination, limiting equal opportunities for access to quality learning. This may lead to increased social dissatisfaction and a diminished sense of educational justice in various communities.

Socially, the lack of personalized learning reduces students' participation and engagement in the educational process. Learners whose needs are not met may disengage from classes and school activities, which, in the long run, weakens social capital and collective cohesion.

Economically, the failure to employ AI in personalized education reduces the efficiency of educational systems and wastes financial resources. Moreover, students who lack the necessary personal and professional skills for future demands are less likely to succeed in the labor market, negatively impacting economic growth and workforce competitiveness.

Psychologically, uniform and non-personalized education can lower students' motivation, confidence, and self-efficacy. Learners whose styles and needs are not adequately addressed may experience anxiety, mental fatigue, and a lack of motivation toward learning.

From a technological standpoint, neglecting AI and learning analytics hinders the development and application of modern educational technologies. This contributes to the educational system's lag behind global transformations and weakens its ability to adapt to digital learning and lifelong education environments.

From educational and professional perspectives, failing to resolve these issues leads to decreased instructional quality, increased academic inequality, and limited opportunities for active and creative learning. Students may not sufficiently develop self-regulation, critical thinking, and problem-solving skills, while teachers cannot optimally allocate their time and resources toward student growth.

Accordingly, addressing the identification of dimensions, components, and indicators of AI-based hyper-personalized education has numerous theoretical and practical implications. Theoretically, this research can provide a comprehensive, evidence-based framework for understanding personalized learning processes and integrate existing theories of cognitive, constructivist, adaptive, and self-regulated learning with AI applications. Such a framework enables researchers and developers of intelligent educational systems to identify and measure key components and indicators of personalized learning.

Practically, identifying these dimensions and indicators can lead to the design of more effective intelligent educational systems that offer learning pathways aligned with each learner's abilities, styles, and needs. This enhances learning efficiency, increases motivation and engagement, and reduces academic disparities.

From a socio-cultural standpoint, this research can contribute to educational equity and equal learning opportunities, as AI-based personalized systems founded on scientific evidence can adapt to the needs of students from diverse social and cultural backgrounds.

From a technological and managerial perspective, such research can guide the optimization of algorithms, learning data analytics, and the intelligent utilization of educational infrastructure. This improves decision-making quality in schools and educational institutions, enabling teachers to focus more on learner support and creative instructional activities.

Overall, this line of research—by defining dimensions, components, and indicators—can improve educational systems, foster educational justice, enhance learning quality, and strengthen the interaction between humans and technology in learning environments, thereby clarifying AI's role in achieving scientifically and practically grounded personalized learning.

Conducting a study on "Identifying the Dimensions, Components, and Indicators of AI-Based Hyper-Personalized Education" can directly address existing scientific and research challenges in the domains of education and technology. By identifying the key dimensions and components of personalized learning, such research can propose a precise conceptual and operational framework that elucidates the development path of AI-driven educational systems. This enables scholars and practitioners to better understand individual learning phenomena and student–technology interactions, integrating existing theories of cognitive, constructivist, adaptive, and self-regulated learning with empirical evidence.

Scientifically, this study can bridge existing knowledge gaps and form a foundation for future research on personalized education and AI applications. Identifying accurate indicators and components allows for the measurement of personalized learning effectiveness, and the results can serve as standardized criteria for developing intelligent educational systems in schools and universities.

Practically and educationally, this research can support the design and implementation of intelligent, adaptive systems that tailor learning trajectories to each student's abilities, interests, and needs. This promotes learning effectiveness, motivation, engagement, and reduces educational gaps. Furthermore, teachers can utilize the identified indicators and components to improve their instructional processes, shifting their roles from traditional teaching toward guidance and learner support.

Socially and culturally, research in this field can strengthen educational justice and equality of opportunity, as scientifically grounded personalized systems can adjust to the diverse needs of learners from various social and cultural contexts. Ultimately, conducting such research will foster positive transformations in the educational system by enhancing learning quality, developing self-regulation skills, strengthening critical thinking, and promoting human–technology interaction in educational contexts.

In conclusion, the present research not only expands the scientific body of knowledge in the field of AI-based personalized learning but also provides a practical framework for improving educational systems, paving the way for positive and sustainable transformation in education.

Considering the points mentioned, this research yields both immediate and long-term benefits. In the short term, it enables the design of intelligent and adaptive educational systems that adjust learning paths based on each learner's abilities, interests, and needs, thereby enhancing learning efficiency, motivation, and engagement. Teachers can also make data-driven pedagogical decisions and devote more time to creative and advisory activities. In the long term, the findings will contribute to developing theoretical and operational frameworks for AI-based personalized education, forming a foundation for future research. These outcomes can help reduce educational disparities, strengthen self-regulation, critical thinking, and lifelong learning skills, and improve students' readiness for future needs and the labor market. Furthermore, the research fosters innovation and technology integration in education, maximizes learners' human and technological capacities, and ultimately contributes to sustainable and positive transformation in educational systems.

Methodology

Type of Research

In this study, the research is applied in terms of purpose, qualitative in terms of data type, and inductive in terms of reasoning approach.

The statistical population of the first phase (meta-synthesis) includes all relevant scientific articles and documents available in domestic and international databases, as well as existing laws and policies in this domain. In this phase, 16 articles were selected using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol through purposeful non-random sampling. The inclusion criteria for selecting articles in the meta-synthesis method consisted of:

- Recency And Direct Relevance to the Research Topic,
- High Scientific Quality and Credibility,
- Publication In Reputable Domestic or International Databases,
- Appropriate Methodological Design, And
- Diversity of perspectives.

In the second phase (Delphi technique), the statistical population consisted of academic faculty members in educational technology, designers of e-learning systems, researchers in adaptive learning, data science specialists in education, designers of educational recommender systems or learning chatbots, and experts in learner behavior analysis. According to Linstone and Turoff (2011), the minimum number of experts for a Delphi panel is typically between 10 and 18; therefore, in this study, 15 experts who were directly or indirectly involved in AI-based personalized education were selected through purposeful non-random sampling.

The criteria for selecting experts included:

- Holding at least a Ph.D. degree and having teaching experience in fields related to the research topic,

- Having expertise and participation in practical projects or relevant research experience,
- Knowledge of artificial intelligence, data science, and educational constraints,
- Ability to provide analytical insights,
- Diversity of perspectives, commitment to participation,
- Professional experience or decision-making responsibility in the field of study.

Data Collection Tools

In the first phase (meta-synthesis), data collection was conducted through a systematic review of relevant literature and authoritative scientific sources. This process involved a targeted search across academic databases, journals, books, and dissertations related to the research subject.

To ensure content validity in the meta-synthesis phase, it was verified that the selected studies comprehensively covered the conceptual dimensions of the topic. Articles were meticulously screened, and the flow diagram (illustrating the search and selection process) was used to identify the most suitable studies. Temporal, spatial, methodological (synthesis, review, qualitative), and thematic (keyword-based) limitations were defined to refine the search scope.

The screening process was conducted in both coarse and fine stages, followed by the application of the 27-item PRISMA checklist, independent analysis by the researcher and a statistical expert, Cohen's Kappa coefficient to measure inter-rater agreement, adherence to standardized criteria, replicability (transparency in execution), and the use of MAXQDA software for precise tracking and coding of data. Finally, all codes were reviewed and refined based on expert feedback to identify and resolve inconsistencies.

For ensuring reliability in the meta-synthesis process, audit trail documentation, intra-researcher consistency, and inter-researcher consistency methods were applied. The findings confirmed that the data from the meta-synthesis phase were both valid and reliable.

In the second phase (Delphi technique), a Delphi worksheet was used as the data collection tool. Experts were asked not only to rate each indicator but also to provide comments, suggestions, or propose new indicators they deemed relevant.

To ensure validity, the Delphi questions were designed to be clear, simple, and directly related to the study's objectives, using accessible language and well-defined conceptual statements for the closed-ended questionnaire items. Prior to implementation, content validity was assessed using the Content Validity Ratio (CVR) formula, and the results confirmed that the worksheet adequately and comprehensively covered the intended concepts.

For assessing reliability of the Delphi worksheet, both internal consistency and test–retest reliability methods were applied. The findings from the Delphi phase demonstrated that the worksheet was both valid and reliable, ensuring robustness and accuracy in expert evaluations.

Table 1. Distribution of the Researcher-Developed Questionnaire Indicators and Its Validity and Reliability

Dimension	α	CR	ω	AVE	MSV	ASV	1	2	3	4
1. Cognitive	0.73	0.80	0.83	0.54	0.40	0.21	0.73			
2. Affective	0.81	0.82	0.85	0.57	0.43	0.25	0.69	0.75		
3. Behavioral	0.75	0.84	0.88	0.59	0.47	0.27	0.58	0.66	0.79	
4. Contextual	0.77	0.81	0.86	0.62	0.49	0.29	0.52	0.51	0.49	0.73

Based on the results presented in Table 1, the reliability of the dimensions is confirmed, as both Cronbach's alpha and the composite reliability (CR) coefficients are greater than 0.7. Moreover, the average variance extracted (AVE) values are above 0.5, indicating acceptable convergent validity, since the conditions CR > 0.7, CR > AVE, and AVE > 0.5 are met. Additionally, discriminant validity is also confirmed because the criteria MSV < AVE and ASV < AVE are satisfied.

Data Analysis Method

To identify the dimensions, components, and indicators of hyper-personalized learning through artificial intelligence, the thematic analysis method was employed using MAXQDA Analytics Pro 2018 software. In this process, common themes and patterns were extracted and analyzed from the texts of the selected articles as well as the open-ended questions from the Delphi worksheets. Subsequently, in the Delphi stage, the closed-ended questions were analyzed using mean and standard deviation to assess the results and determine the level of agreement among experts. In addition, Kendall's coefficient of concordance (W) was applied to evaluate the degree of consensus among the experts regarding the prioritization of the closed-ended questionnaire items, utilizing IBM SPSS Statistics version 27.

Findings

Phase One: Meta-Synthesis

In the first phase of the qualitative study, based on findings from the meta-synthesis method, the dimensions, components, and indicators of hyper-personalized education leveraging artificial intelligence were identified. This phase employed a systematic review approach following the PRISMA model combined with the meta-synthesis technique to identify the relevant dimensions. The following steps were undertaken:

Steps in the Research Synthesis to Identify Components of Hyper-Personalized AI-Based Education:

Phase 1: Defining the research scope and selecting relevant studies

- a) Establishing search parameters, including publication date and type of research.
- b) Defining criteria for selecting documents collected in the previous stage.
- c) Determining search strategies and databases.

Phase 2: Systematic evaluation of selected documents

- a) Coarse screening
- b) Fine screening
- c) In-depth analysis

Phase 3: Synthesis – creating new knowledge from separate elements Two types of synthesis were conducted in this stage:

1. Aggregative synthesis: Comparable to a physical combination, where findings from selected studies are combined, similar to what is typically observed in quantitative meta-analyses.
2. Transformative synthesis: Comparable to a chemical reaction, where the findings from other studies are transformed into new data, combined with other data, and reinterpreted to produce a new conceptual identity.

Flowchart of Article Selection Process: In this step, restrictions were applied regarding temporal and spatial scope (external databases), research type (synthesis, review, and qualitative), and thematic focus (keywords). Subsequently, coarse and fine screening were conducted. Based on the PRISMA flow model, 16 articles were ultimately selected, and their quality was examined and analyzed in depth.

27-Item Checklist for Assessing Article Quality:

Given the novel and interdisciplinary nature of the present study titled *"Identifying*

Dimensions, Components, and Indicators of Hyper-Personalized Education Using Artificial Intelligence," access to Persian-language research sources in this area was very limited or nearly impossible. The concept of "hyper-personalized education" is also emerging in the global academic literature and has gained attention in recent years due to advances in AI, machine learning, and cognitive sciences. Therefore, expecting an extensive body of Persian-language literature is not reasonable.

Initial searches in domestic scientific databases (e.g., NoorMags, ISC, IranDoc) revealed studies on "personalized learning" and "AI in education," but none addressed the concept of hyper-personalization or its specific dimensions and indicators. Conversely, international sources, particularly from 2018 to 2025, contain numerous studies on adaptive learning, learner analytics, educational data mining, and intelligent educational systems, directly contributing to theoretical frameworks and models relevant to hyper-personalization.

Since the aim of the present research was to identify conceptual and empirical dimensions and components of hyper-personalized AI-based education, consulting the most recent and reputable international sources was indispensable. The meta-synthesis approach with PRISMA necessitated access to a broad spectrum of qualitative studies, theoretical models, and analytical frameworks globally to integrate valid findings and produce a comprehensive and contextualized representation of the concept.

The selection of English-language sources was therefore not only due to the lack of relevant Persian sources but also due to scientific necessity to utilize up-to-date international knowledge in educational technologies and AI. This approach also aimed to enhance the scientific rigor, citation reliability, and alignment with current global research trends. Ultimately, the findings from international sources were translated, reinterpreted, and analyzed within the Iranian educational and cultural context to allow the localization of identified concepts and indicators.

Quality Assessment Results: The 27-item checklist results indicated that all selected articles had either acceptable or high quality, as the quality score for each item was either above 75% or between 50%–75%. Any item below 50% would be considered of low quality.

Inter-Rater Reliability (Cohen's Kappa): Cohen's Kappa measures agreement between two raters, each categorizing N items into C mutually exclusive categories. The formula is:

$$K=\frac{pr(a)-pr(e)}{1-pr(e)}=\frac{(0.56-0.332)}{1-0.6}=0.59$$

Given the Kappa value of 0.59, it can be concluded that the agreement between the two raters was adequate.

Analysis and Synthesis (Aggregative and Transformative):
Finally, synthesis was conducted to identify the dimensions of hyper-personalized AI-based education. Based on the review, indicators were extracted, and a conceptual word cloud was generated to visualize the identified concepts.

Phase Two: Delphi Technique

In the second phase, to screen and survey experts, the indicators identified in the meta-synthesis phase were presented in a Delphi worksheet. Experts were asked to rate each indicator on a scale from 1 to 5. Indicators with a mean score below 4 were removed from the Delphi process.

- Round 1: 5 indicators scored below 4 and were eliminated.
- Round 2: Continuing without the 4 eliminated indicators, 6 indicators were revised based on expert feedback; no indicators were removed, and experts confirmed the combination of components and dimensions.

- Round 3: To finalize the model, the Delphi process continued. All indicators scored above 4, confirming consensus.

Kendall's W:

To ensure response reliability, Kendall's coefficient of concordance was used to indicate the level of agreement among Delphi panel members. Findings indicated strong expert consensus in rounds 2 and 3, leading to the conclusion of the Delphi process after round 3.

The results of round 3 of the Delphi technique are presented in the following table.

Table 2. Dimensions, Components, and Indicators of Hyper-Personalized AI-Based Education

Construct	Dimension	Component	Indicators
Hyper-Personalized Learning Using Artificial Intelligence	Cognitive	Prior Knowledge Analysis	Use of adaptive testing; Automatic pre-knowledge assessment; Adjustment of learning paths based on prior knowledge; Conceptual error analysis; Determination of individual learning goals
		Individual Learning Style	Identification of visual, auditory, or kinesthetic preferences; Adjustment of content according to cognitive style; Recommendation of resources matching learning style; Analysis of content interaction behavior; Providing feedback in appropriate formats; Tracking learning style changes over time
		Cognitive Adaptivity	Matching content difficulty level to mental capacity; Prediction of learner's cognitive load; Suggestion of targeted exercises; Controlling information quantity; Adjusting learning speed; Real-time measurement of cognitive progress
		Memory and Retention	Use of intelligent spaced repetition; Reinforcement of recall through short quizzes; Scheduling reviews based on probable forgetting curves; Analysis of individual retention patterns; Providing intelligent reminders; Identifying weaknesses in knowledge retrieval
		Problem-Solving and Critical Thinking	Designing problem-based scenarios; Identifying problem-solving approaches; Providing analytical feedback; Assessing logical decision-making; Strengthening critical reasoning; Analyzing behavioral data during problem-solving processes
	Affective	Emotional State Recognition	Emotion analysis via facial or vocal expressions; Tracking emotions through user interaction; Detecting anxiety, boredom, or interest; Adjusting content based on emotional state; Delivering motivational messages; Predicting emotional changes throughout learning
		Intrinsic Motivation	Analyzing learner's interests; Recommending content aligned with interests; Designing engaging challenges; Using intrinsic rewards (positive feedback); Enhancing sense of ownership in learning; Maintaining motivation through diverse learning paths
		Learner Self-Efficacy	Providing reinforcing feedback; Measuring educational self-confidence; Designing tasks aligned with ability levels; Suggesting gradual small achievements; Tracking personal growth over time; Reducing performance anxiety
		Learner Satisfaction	Evaluating satisfaction with content; Analyzing positive system interactions; Collecting continuous feedback; Adapting content to user preferences; Providing personalized improvement suggestions; Predicting dissatisfaction risks

		Emotional Engagement in Learning	Measuring emotional engagement levels; Detecting moments of high focus; Applying gamification elements; Enhancing positive emotions in activities; Reducing mental fatigue; Maintaining long-term learning enthusiasm
	Behavioral	Interaction Patterns with System	Recording clicks and learning paths; Analyzing time spent on activities; Identifying repetitive behavior patterns; Assessing active engagement in learning sessions; Detecting passive behaviors; Adjusting recommendations based on observed behavior
		Participation in Group Activities	Analyzing collaboration with peers; Measuring individual roles in discussions; Evaluating quality of group interactions; Identifying social communication patterns; Recommending appropriate learning groups; Encouraging greater collaborative engagement
		Learning Discipline and Follow-Up	Monitoring attendance in online sessions; Recording task completion delays; Analyzing adherence to learning schedules; Sending intelligent reminders; Providing feedback on temporal progress
		Knowledge-Seeking Behavior	Analyzing utilized resources; Detecting diversity in searches; Evaluating quality of selected materials; Suggesting more relevant resources; Monitoring research habits; Strengthening analytical thinking in search behavior
		Interaction with Feedback	Examining responses to system feedback; Assessing feedback use for performance improvement; Analyzing reaction speed to feedback; Detecting indifference to feedback; Providing more personalized feedback; Measuring feedback effectiveness on performance improvement
	Contextual	Learning Environment Conditions	Identifying physical learning environment; Analyzing light, sound, and study time; Adjusting content based on environmental conditions; Detecting distractions; Recommending optimal concentration settings; Analyzing effective temporal learning patterns
		Technology and Tools Used	Identifying device type (mobile, laptop, etc.); Analyzing user interface compatibility; Assessing internet stability; Adjusting multimedia content; Suggesting technical optimizations; Monitoring technical issues affecting learning
		Cultural and Linguistic Adaptation	Adapting content language to learner; Considering cultural differences; Localizing examples and scenarios; Detecting potential cultural mismatches; Recommending culturally relevant resources; Enhancing cultural belonging in learning environments
		Accessibility and Educational Equity	Identifying physical or technical limitations; Providing accessible versions; Adjusting content level for all users; Tracking inequality in access; Suggesting compensatory solutions; Promoting inclusivity in education
		Learning Data Analytics	Collecting multi-source data; Cleaning and processing data; Analyzing personal learning patterns; Predicting future performance; Providing personal dashboards for users; Using data to enhance hyper-personalization systems

Discussion and Conclusion

In this study, based on the meta-synthesis approach, expert interviews, and the Delphi technique, the dimensions, components, and indicators of hyper-personalized education leveraging artificial intelligence (AI) were identified and presented. The framework includes cognitive, affective, behavioral, and contextual dimensions, each of which is detailed below.

1. Cognitive Dimension

The cognitive dimension pertains to the learner's mental and intellectual processes, which play a critical role in understanding, processing, and applying knowledge. In hyper-personalized education, AI utilizes cognitive data to analyze learning styles, mental abilities, and individual cognitive needs in order to deliver appropriately tailored instructional content.

- Prior Knowledge Analysis: Machine learning algorithms analyze past performance and initial assessments to identify the learner's current knowledge level. Based on this analysis, AI recommends educational content aligned with the learner's mastery level. This process establishes the foundation for determining the starting point of personalized learning.
- Individual Learning Style: Hyper-personalization identifies the learner's preferred learning pattern (visual, auditory, reading–writing, or kinesthetic) and adjusts content delivery to match the individual's cognitive style. This adaptation is performed dynamically using behavioral and cognitive data.
- Cognitive Adaptation: This refers to the system's ability to adjust content difficulty and complexity based on the learner's cognitive capacity and engagement level. AI analyzes feedback and response times to align the learning pathway with the learner's mental capabilities.
- Memory and Retention: AI can design personalized review schedules using spaced repetition and memory-enhancing algorithms to improve long-term retention of information.
- Problem-Solving and Critical Thinking: At more advanced levels, intelligent educational systems provide challenging scenarios, simulated environments, and multi-option analyses to cultivate learners' problem-solving abilities and critical thinking skills.

2. Affective Dimension

The affective dimension addresses the learner's emotions, motivation, and attitudes during the learning process. In hyper-personalized education, AI can analyze facial expressions, voice tone, or interaction patterns to detect the learner's emotional state in real time and optimize the learning experience from an emotional perspective.

- Emotion Recognition: Emotion-detection systems can identify states such as fatigue, stress, or enthusiasm and provide appropriate instructional responses—for instance, adjusting the type of content or learning schedule.
- Intrinsic Motivation: Personalization algorithms maintain the learner's intrinsic motivation by designing progressive success pathways, providing positive feedback, and setting achievable goals.
- Learner Self-Efficacy: This refers to the individual's belief in their ability to succeed in learning tasks. Intelligent systems enhance self-efficacy by offering reinforcing feedback and designing tasks that match the learner's ability level.
- Learner Satisfaction: In hyper-personalized education, the alignment between the learner's expectations and their actual learning experience directly influences satisfaction. AI increases satisfaction by adjusting content and learning pace according to individual preferences.
- Emotional Engagement in Learning: Positive emotional interaction with educational content promotes greater focus and deeper learning. Intelligent systems enhance emotional engagement through interactive environments and gamification techniques.

3. Behavioral Dimension

The behavioral dimension examines observable learner actions and conduct within the learning environment. At this level, behavioral data serve as the primary basis for analyzing performance and personalizing system settings.

- Interaction Patterns with the System: Metrics such as clicks, session duration, and navigation paths are used as indicators to assess engagement and learning efficiency.
- Participation in Group Activities: Intelligent systems monitor and analyze the learner's interactions with others in collaborative online activities (e.g., discussion forums or group projects) to provide strategies for enhancing cooperation.
- Learning Discipline and Follow-up: Hyper-personalization identifies patterns of organization, scheduling, and consistent follow-up in learning. By sending reminders or implementing adaptive planning, it facilitates sustained educational activity.
- Knowledge-Seeking Behaviors: Analyzing how learners search for resources, their choice of keywords, and study pathways helps the system suggest new content aligned with individual curiosity and informational needs.
- Response to Feedback: How learners react to feedback (e.g., correcting mistakes or ignoring suggestions) serves as a measure of their cognitive readiness and motivation, assisting the system in adjusting the level of educational support.

4. Contextual/Environmental Dimension

The contextual or environmental dimension refers to external factors—environmental, cultural, technological, and social—that influence the learning experience. In hyper-personalized learning, artificial intelligence takes the learner's context and conditions into account to provide a more realistic, equitable, and effective educational experience.

- Learning Environment Conditions: Factors such as time, location, and the learner's level of focus (e.g., ambient noise or room lighting) can be dynamically considered in adjusting instructional content.
- Technology and Tools Used: The choice of device (mobile, tablet, or laptop) and the level of internet access can affect how content is delivered. AI optimizes content format based on the user's device.
- Cultural and Linguistic Adaptation: Hyper-personalization must align with the learner's cultural, linguistic, and normative characteristics. Algorithms leverage linguistic and cultural data to localize content appropriately.
- Access and Educational Equity: This component aims to ensure equal learning opportunities for all learners. AI can identify gaps in access and suggest alternative resources or low-cost learning pathways.
- Learning Data Analysis: Data generated from learner-system interactions serve as the foundation for continuous improvement of hyper-personalized learning. Through learning analytics, successful patterns are identified, and new recommendations are generated.

The findings of this study, which identify the four dimensions—cognitive, emotional, behavioral, and contextual—as the core components of AI-based hyper-personalized learning, are strongly aligned with multiple international studies in the field of digital and intelligent hyper-personalization.

In the first instance, the results of this study show the greatest congruence with Tiwari (2024). Tiwari emphasizes that AI-based hyper-personalization is effective only when data analysis extends across four layers: cognitive, emotional, behavioral, and contextual. He highlights the critical role of "prior knowledge analysis," "learning style identification," and "predicting educational needs" in designing hyper-personalized learning experiences—elements that correspond directly with the cognitive dimension components in the present study, such as prior knowledge analysis, memory, and critical thinking.

Similarly, the findings align with Desai et al. (2022), who demonstrated that AI can predict learning patterns and adapt educational pathways according to individual needs through cognitive and behavioral analysis. Their observation that "hyper-personalization models enhance learner self-efficacy and motivation" directly corresponds to the emotional dimension in this study, which encompasses intrinsic motivation, satisfaction, and self-efficacy.

Additionally, this study's results show strong correspondence with Micu et al. (2022), who presented deep learning-based systems for detecting user behavior and emotions, illustrating that the integration of cognitive, emotional, and environmental data enables real-time adaptation of learning experiences. This aligns closely with the present model's cognitive adaptation and emotional state recognition components.

From a contextual perspective, the results are consistent with Prem (2025) and Bozkurt et al. (2025), emphasizing the importance of environmental, cultural, and technological factors in tailoring hyper-personalized learning pathways.

Finally, regarding the behavioral dimension, the findings correspond with Davenport (2023) and Vuyyuru (2025). This study demonstrates that AI-based hyper-personalization must utilize behavioral data to analyze participation, interaction patterns, and feedback responses, guiding learning dynamically and continuously. Vuyyuru (2025) similarly underscores that continuous behavioral analysis is key to designing unique learning pathways, which aligns with the behavioral components identified in this research, such as group participation, learning regularity, and feedback engagement.

In summary, the study confirms that AI-driven hyper-personalized learning functions most effectively when it integrates these four dimensions, reflecting and reinforcing trends observed in international literature across cognitive, emotional, behavioral, and contextual domains.

Therefore, it can be stated that the findings of this study show the highest degree of alignment with the research of Tiwari (2024), Desai et al. (2022), Micu et al. (2022), Prem (2025), and Bozkurt et al. (2025). These studies collectively emphasize the necessity of multidimensional data analysis, integration of cognitive and emotional components, and the adaptation of learning to cultural and environmental contexts. Consequently, the model proposed in this research is consistent with contemporary global approaches in the field of AI-based hyper-personalized learning and can provide a theoretical and practical foundation for the development of intelligent educational systems within the Iranian context.

Research Limitations

The present study, entitled *"Identifying the Dimensions, Components, and Indicators of Hyper-Personalized Learning Using Artificial Intelligence,"* despite employing rigorous and recognized scientific methods such as meta-synthesis with the PRISMA model and the Delphi technique, is influenced by several internal and external limitations. Among these limitations are social, cultural, political, psychological, technological, and economic factors, which have directly or indirectly affected the process of data collection, analysis, and interpretation.

Rapid social and technological transformations in the field of digital education have caused a considerable portion of the sources used in the meta-synthesis phase to be influenced by the specific temporal context in which they were produced, leading to partial misalignment of some findings with the current realities of Iran's educational system. Additionally, individual differences among experts participating in the Delphi phase, in terms of experience, attitude toward technology, and familiarity with AI concepts, could have introduced variability in the evaluation of the research dimensions and components.

Moreover, political constraints and the lack of clear policy frameworks for AI in education in the country have limited the full localization of findings, making the exclusive use of international sources unavoidable. Cultural and social differences in attitudes toward new educational technologies and acceptance of AI in learning environments may also influence the interpretation and prioritization of the identified components. Furthermore, technological limitations within Iran's educational infrastructure and restricted access to standardized educational data have resulted in some findings derived from international sources being not fully implementable under current local conditions. Economic factors also pose significant barriers to the practical implementation of the identified dimensions and indicators, as AI-based education requires substantial investment in infrastructure and capacity-building for human resources.

Despite these limitations, the researcher has sought to enhance the validity of the findings by applying rigorous criteria in source selection, employing a coherent methodology, and integrating insights from multidisciplinary experts. Therefore, the results of this study can serve as a foundational step for theoretical development, capacity identification, and paving the way for future research within the cultural and educational context of Iran.

Research Recommendations

Considering the limitations identified in the present study, future researchers are advised to adopt multi-stage and mixed-method approaches to enhance the accuracy, validity, and generalizability of findings. Specifically, combining contemporary field studies with integrative research methods can help capture social changes and the dynamic nature of educational technologies, while longitudinal studies allow for the examination of time-dependent effects of these changes. To minimize the impact of individual and psychological differences among experts, it is recommended to use multi-round Delphi techniques alongside quantitative analysis of consensus, while ensuring diversity in panel members' expertise and practical experience to enrich perspectives.

Moreover, collaboration with educational policy-making institutions and leveraging policy analysis and international comparisons can facilitate the localization of findings within national policy frameworks. Examining cultural and social factors through in-depth interviews, educational ethnography, and large-scale survey research can clarify the acceptance of emerging technologies and societal attitudes toward AI in education.

Regarding technological and economic constraints, future researchers are encouraged to conduct experimental and pilot studies in real educational settings to evaluate the feasibility and effectiveness of hyper-personalized learning models. Partnerships with universities and educational technology companies, the use of open-source tools, and the design of lightweight AI systems are practical strategies to mitigate technical and financial limitations. Additionally, cost–benefit analyses and collaboration between academia and industry can support the large-scale and practical implementation of research findings.

Implementing these strategies will enable future researchers to overcome existing limitations, generate findings with higher reliability, validity, and generalizability, and pave the way for the theoretical and practical development of AI-based hyper-personalized learning within Iran's cultural and educational context.

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