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AI-Powered Virtual Assistants in Education: A Systematic Review of Applications and Implications (2014–2025)

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Abstract. The integration of Artificial Intelligence (AI) in education has revolutionized both learning and teaching processes, with Virtual Assistants (VAs) emerging as one of its most impactful applications. This systematic review synthesizes empirical studies published between 2014 and 2025 that examine the role of AI-powered VAs in primary, secondary, and tertiary education. Four research questions are addressed: (1) the educational uses and implications of VAs, (2) the most frequently applied models and algorithms, (3) their contribution to learner motivation and self-determination, and (4) the benefits and challenges of instructional design supported by VAs. A total of sixty-two studies were analyzed following PRISMA guidelines. The findings indicate that VAs are most often implemented in activity-based, emotion-aware, and classroom management contexts, primarily through algorithms such as natural language processing models, convolutional neural networks, and decision trees. While VAs enhance personalization, interaction, and inclusiveness, persistent concerns remain regarding cultural diversity in emotion recognition, data privacy, and pedagogical alignment. One major conclusion of this study is that a persistent gap remains between technological innovation and educational theory, highlighting the need for Virtual Assistants to be pedagogically embedded within authentic classroom environments.

Keywords: Artificial Intelligence in Education, Virtual Assistants, Intelligent Tutoring Systems, Systematic Literature Review, Personalized Learning.

1. Introduction

Interest in Artificial Intelligence (AI)–enhanced Virtual Assistants (VAs) has grown steadily in recent years, particularly in education [1], where they aim to improve both teaching effectiveness and administrative efficiency through innovative, pedagogically sound practices [2–4]. The integration of AI into VAs has the potential to transform the educational experience, significantly contributing to improved learning performance, supporting self-regulated learning, and enhancing interaction between teachers and students [5]. These intelligent systems serve as supportive tools in the educational process, facilitating repetitive daily tasks such as classroom management, planning, and coordination, particularly in technology-enriched classrooms such as STEM (Science, Technology, Engineering and Mathematics)-focused virtual classrooms [6–8]. VAs promote a student-centered learning approach by providing individualized learning experiences and encouraging student motivation, creativity, and active engagement [9, 10].

When incorporated into conventional teaching, they can enhance classroom organization and contribute to the more efficient delivery of educational goals [11–13]. Technologically, VAs rely on advanced systems such as AI, Machine Learning (ML), and Deep Learning (DL) [14, 15]. Many applications utilize Natural Language Processing (NLP), ML algorithms, and DL techniques to enable natural communication with users, personalize content, and offer predictive capabilities [6, 16]. Others operate through predefined rule-based logic, responding to specific commands without adaptive behavior.

The use of neural networks has further expanded the capabilities of VAs. Convolutional Neural Networks (CNNs) are used for visual input analysis (e.g., emotion recognition), while Recurrent Neural Networks (RNNs) are effective for sequential data and natural language processing [17]. These technologies are already being applied across all educational levels-primary, secondary, and tertiary-particularly in subjects that involve experimentation, require safety protocols, or benefit from simulation-based instruction [13, 18–20]. Contemporary research indicates that VA integration in classrooms can lead to better study organization, increased motivation and participation, and accessible personalized learning experiences for all learners [21].

This systematic review provides an overview of empirical research on the use and importance of virtual assistants in education over the past decade. In particular, it examines:

1. **RQ1:** What are the functions, results, and implications of integrating artificial intelligence and intelligent techniques into virtual assistant applications in education?
2. **RQ2:** Which models and algorithms are most commonly used?
3. **RQ3:** What is the role of virtual assistants in student motivation and autonomy?
4. **RQ4:** What are the benefits and challenges of using VAs in classroom-supported instructional design?

One contribution of the present review is its particular targeting of Virtual Assistants as a particular subtype of AI-based education technologies, whereas most existing systematic reviews cover larger categories such as Intelligent Tutoring Systems, generic chatbots, or education-at-large with respect to AI. By specializing the focus on VAs, the current work offers an enriched mapping of the pedagogic roles, algorithmic basis, and implication for student motivation and self-regulation. In addition, the present review synthesizes not only the technology features but also the education implications, including the compatibility of VA functionality with established learning theories such as ICAP, the Constructivism, and the Zone of Proximal Development. This dual focus—technological as well as pedagogical—distinguishes the current work from previous surveys. Finally, by including literature between 2014 and 2025, the current review includes the most contemporary development covering the most recent trends such as the development for emotion-aware systems and metaverse-inspired learning environments, thereby providing an updated and comprehensive repository for researchers as well as practicing educators.

The systematic review analyzes 62 selected studies from an initial pool of 316 academic records retrieved across databases before duplicate removal, covering publications between 2014 and 2025. It evaluates the key functions, outcomes, and challenges of AI-based VAs, identifies widely used algorithms, and assesses their role in motivation and autonomy. It also discusses the critical success factors influencing their adoption in educational settings.

Findings show that core functions include performance prediction, learning monitoring, automated assessment, and adaptive support. Traditional AI techniques like NLP, decision trees, and CNNs are prevalent, while more advanced methods such as deep reinforcement learning are less common. VAs deliver high-quality, personalized recommendations that enhance academic outcomes and accommodate individual learner needs.

The review proposes the following implications:

1. Deeper integration of educational theories (e.g., Bruner, Gagné, Vygotsky) into VA design.
2. Adoption of advanced AI to enrich human–AI interaction.
3. Increased empirical studies in real-world classrooms to assess pedagogical efficacy.

2. Methodology

This methodology section outlines the systematic process followed to identify, select, and analyse academic studies related to the use of Virtual Assistants (VAs) in primary, secondary, and higher education. The goal is to understand their role in enhancing school organization, promoting student autonomy, and improving learning outcomes.

2.1. Research methods

This literature review follows the systematic protocol proposed by Kitchenham et al. (2007), one of the most widely used standards for conducting systematic reviews in software and educational research. A SoTA (State-of-the-Art) review tool was employed for data extraction and management. The initial search was conducted in peer-reviewed journals, primarily through the Scopus database and supplemented by Web of Science, to ensure comprehensive coverage and minimize publication bias.

The review process began with the identification of 62 relevant papers. The studies were first characterized according to their frameworks and definitions of virtual assistants in education, followed by classification based on country of origin, research focus and applied technologies. The final dataset includes studies from 34 different countries, with China contributing the highest number (12), followed by the USA (10) and India (9). Pakistan, UK, and the UAE contributed three studies each, while other countries contributed one or two (see Fig. 1).

This global distribution reflects the international interest in the educational role of virtual assistants and provides a diverse basis for the analysis.

The search strategy used Boolean operators (e.g., OR, AND) to combine key terms related to education and intelligent technologies, targeting titles, abstracts, and keywords. Only peer-reviewed journal articles written in English and published between 2014 and 2025 were considered.

The selected time frame of 2014–2025 was chosen to capture the decade in which Artificial Intelligence–powered Virtual Assistants (VAs) evolved from conceptual prototypes into mature educational technologies. The year 2014 marks the appearance of the first AI-driven tutoring systems and conversational learning agents, while extending the review to 2025 ensures the inclusion of the most recent studies reflecting generative AI developments and the integration of large language models in education.

The search terms used are shown in Table 1.

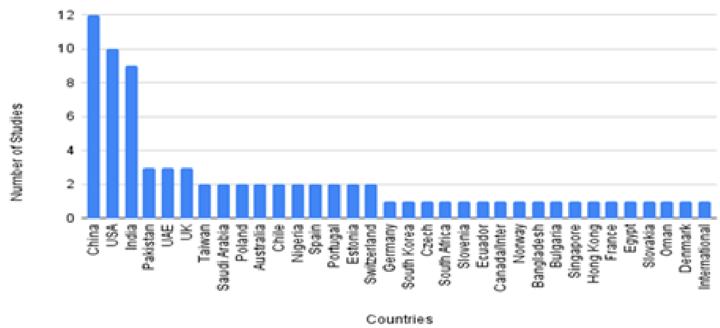

Fig. 1. Numbers of papers per country

Table 1. Key search terms used in the systematic review

Search terms
(Virtual Assistant * OR Chatbot * OR Teaching Assistants* OR Computer Simulation* OR Simulation Training * OR Deep Learning * OR Artificial Intelligence* OR Learning Experiences)
AND (Primary education* OR Secondary education* OR Higher education*)

Although some of the keywords in Table 1 (e.g., "Computer Simulation" and "Simulation Training") are broader than the term Virtual Assistant, their inclusion was intentional. The aim was to capture studies describing intelligent or interactive learning environments that integrate AI-driven agents, conversational interfaces, or simulation-based assistants often referred to under different terminologies. This broader scope minimized the risk of omitting relevant works where Virtual Assistants were embedded within simulation or training contexts but not explicitly labeled as such. All retrieved records were subsequently filtered during the screening phase to ensure that only studies meeting the Virtual-Assistant-related inclusion criteria were retained.

2.2. Inclusion and exclusion criteria

Based on the four core research questions of this systematic review, the inclusion and exclusion criteria were organized into three levels: general criteria, specific inclusion criteria, and exclusion conditions (see Fig. 2).

The inclusion and exclusion criteria were designed to ensure both relevance and methodological quality. Studies were included if they presented empirical results, conceptual models, or system implementations directly involving AI-powered Virtual Assistants for educational purposes. Excluded were non–peer-reviewed materials, opinion papers, and studies focusing solely on non-AI virtual environments or traditional chatbots without educational intent. This process ensured a coherent and high-quality dataset aligned with the objectives of the systematic review.

At the general level, studies were evaluated according to their relevance to the topic, methodological quality, completeness, independence, transparency, and reproducibility.

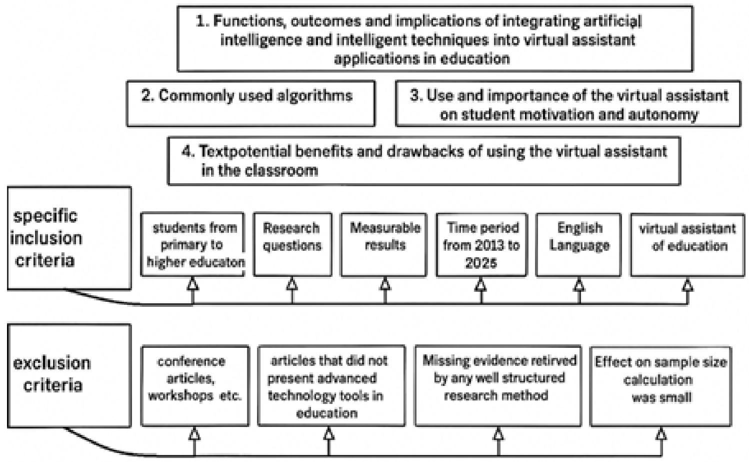

Fig. 2. Framework of Inclusion and Exclusion Criteria

Only those that demonstrated academic validity and alignment with the objectives of the review were retained.

The specific inclusion criteria required that studies:

- Focused on students in primary, secondary, or higher education
- Formulated clear research questions
- Reported measurable results
- Were published between 2014 and 2025
- Were written in English
- Focused on the use of virtual assistants in educational settings.

Examined the functions, outcomes, and implications of integrating AI into virtual assistant applications, commonly used algorithms, the role of virtual assistants in supporting student motivation and autonomy, and pedagogical benefits and drawbacks of using virtual assistants in the classroom.

The exclusion criteria included:

- Conference papers, workshop summaries, or non-peer-reviewed material,
- Studies that did not present technological tools or advanced technology applications in education,
- Articles lacking clear methodological documentation or reliable research evidence,
- Studies with minimal or negligible impact due to insufficient sample size justification.

2.3. The screening process

This screening process was designed to ensure methodological transparency and rigor in accordance with the PRISMA guidelines [22] and the systematic review framework by Kitchenham et al. (2007). The process involved three main phases: Planning, Conducting,

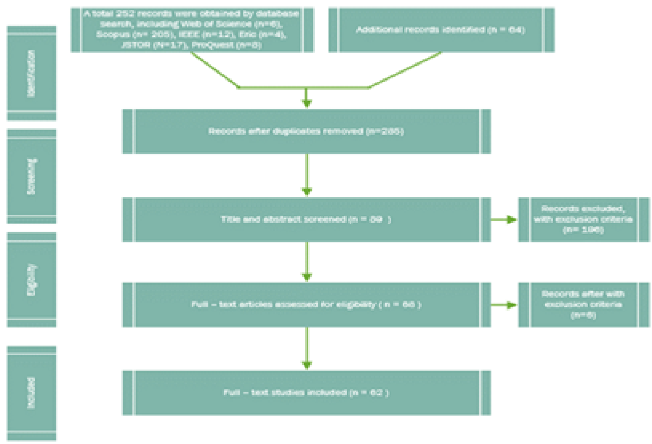

Fig. 3. PRISMA Flowchart: Study Identification and Selection Process

and Assessing. A total of 316 records were retrieved using predefined search terms across multiple databases. After removing 31 duplicates, 285 records remained. Titles and abstracts were screened, narrowing the pool to 89 articles. A full-text review was conducted on 68 articles, resulting in a final selection of 62 eligible studies. The process followed five structured steps: (1) removing duplicates, (2) screening titles and abstracts, (3) full-text eligibility review, (4) snowball sampling via Google Scholar, and (5) data extraction from selected articles (see Fig. 3).

2.4. Analysis

A series of steps were followed to achieve an unbiased search strategy [23]. The search started from the most popular databases by collecting information that was mainly related to the way people interact with computers and computer systems, and specifically to HCI issues, such as computer science/engineering and educational technology. The articles that met the inclusion criteria were analyzed using the bibliometric analysis approach [24]. The qualitative content analysis method was carried out to categorize the articles [25]. Classified information was collected from the articles and that was relevant to the research questions.

The systematic review of AIVA (Artificial Intelligence Virtual Assistant), based on a collection of 62 articles published between 2014 and 2025, provides important insights into the role played by the virtual assistant in the field of education. The early years (2014–2015) laid the foundations with studies on basic models of intelligent tutoring and the emergence of the first chatbot systems. During the period 2016–2023, research gradually intensified, with particular emphasis on affective computing and the development of learning environments incorporating emotion recognition.

The COVID-19 pandemic appears to have acted as a catalyst, as the years 2020–2022 saw a significant increase in publications. Research during this period mainly focused on adaptive learning, self-regulated support, and the integration of AI/VA into online and hybrid education. In 2023 and 2024, research interests became even more diversified, with

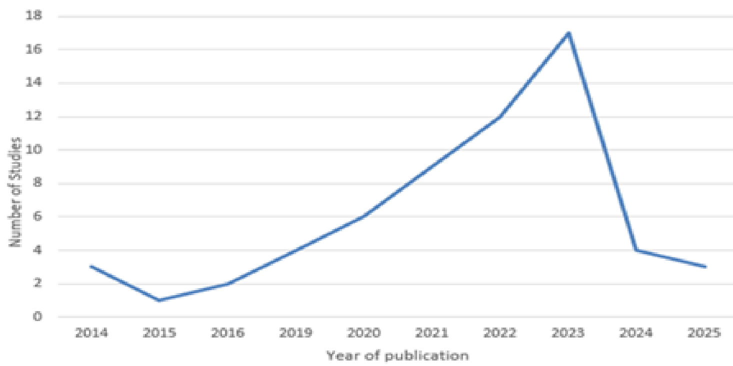

Fig. 4. Existing papers on AI/VA research over time

the introduction of virtual and augmented reality, metaverse-inspired learning environments, and the application of advanced deep learning models. Finally, the studies published in 2025 reveal a clear shift towards ethical, emotional, and inclusive applications. (see Fig. 4).

3. Research results

3.1. RQ1. What are the functions, results, and implications of integrating artificial intelligence and intelligent techniques into virtual assistant applications in education?

Recent studies examining the integration of artificial intelligence (AI) and intelligent techniques in educational virtual assistants (VAs) highlight a wide range of functions and pedagogical implications. These functions include instructional personalization, emotion-sensitive support, classroom space management, and assistance for students with special needs.

A considerable portion of the literature (n = 24) focuses on activity-based educational support, where VAs contribute to simulations, practice exercises, real-time guidance, and the enhancement of student engagement through gamified or interactive learning experiences [17, 26].

Another important group of studies (n = 19) concerns classroom space management, where VAs help improve classroom organization, scheduling, and coordination, aiming to facilitate more effective teaching and learning processes [7].

A further significant cluster of studies (n = 16) centers on emotion-based applications, in which VAs are designed to recognize and respond to students' affective states by leveraging advanced AI models (e.g., CNNs, facial recognition). These systems foster adaptive learning environments by integrating affective feedback mechanisms based on learners' emotional states [16, 27].

In parallel, a smaller set of studies (n = 3) addresses support for students with special needs, emphasizing adaptive functionalities that respond to individual learning difficulties [28–30].

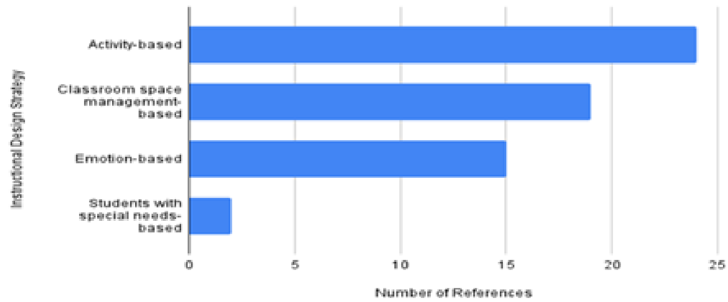

Fig. 5. Intelligent Systems design strategies in education

Overall, the selected studies were analyzed and classified into four main categories: educational subjects, emotion recognition, special needs, and classroom space management. These documents were analyzed and grouped into four main categories: educational subject, emotion recognition, special needs, and classroom space management (see Fig. 5).

The Intelligent Systems used are shown in Table 2.

Table 2. Intelligent Systems design strategies in education

Instructional design strategies	**Primary Studies**
Activity-based	Mathew et al. (2021), Pande et al. (2021), Malik et al. (2022), Halvoník & Psenak (2021), Chi & Wylie (2014), Sabharwal et al. (2023), Neuendorf & Kumar (2016), Adhikari et al. (2023), Zapata et al. (2024), Ng et al. (2024), Sunday et al. (2023), Moral-Sánchez et al. (2022), Memik & Nikolic (2021), Prinsloo et al. (2024), Ogbonnaya (2020), Hobert (2023), Cobos-Guzman et al. (2021), Alawadhi & Thabet (2023), Tarng et al. (2023), Zupic & Čater (2015), Gutierrez, Villegas-Ch & Govea (2025), Sajja et al. (2023), Senapati, S. (2022), Ng et al. (2024)
Emotion-based	Zhang et al. (2021), El-metwally et al. (2023), Zhai & Wibowo (2023), Wang et al. (2020), Li et al. (2020), Wang et al. (2014), Owusu et al. (2014), Biswas & Sil (2020), Hegde et al. (2016), Prasad & Chandana (2023), Shahzad et al. (2023), Khattak et al. (2022), Fakhar et al. (2022), Liu et al. (2019), Fang et al. (2022), Niu et al. (2021), Sehar (2021)
Classroom space management-based	Martin et al. (2024), Gonzalez (2021), Chandel et al. (2019), Farah et al. (2022), Ribeiro et al. (2019), González et al. (2022), Kuppusamy & Joseph (2021), Hu (2023), David et al. (2023), Audras et al. (2022), Stoyanov et al. (2022), Bahaddad (2025), Van Busum & Fang (2025), Lee & Kim (2023), Kadepurkar et al. (2020), Pereira et al. (2022), Premalatha et al. (2020), Quan et al. (2022), Alcala, D'Achille & Bruckman (2023)
Students with special needs-based	Balsam et al. (2019), Ricci et al. (2023), Islam et al. (2023)

The integration of Artificial Intelligence (AI) into educational Virtual Assistant (VA) applications has brought significant pedagogical and organizational changes. VAs support the personalization of learning by adapting to students' learning styles, pace, and cognitive preferences, leading to improved and learner engagement [31]. They automate assessment, track learner progress, and offer personalized feedback, thereby reducing the burden on teachers and enhancing instructional efficiency [32].

Digital tutors, such as chatbot-based assistants, have been widely adopted in programming education and STEM-related fields. These systems help students overcome conceptual difficulties, offering real-time feedback and customized explanations through natural language interaction [28]. Research shows that learners report high levels of satisfaction with chatbot tutors, particularly due to their ability to provide immediate, contextualized support during complex tasks [33].

Additionally, emotion-aware VAs can recognize learners' affective states and adjust feedback accordingly, thereby creating a psychologically supportive and inclusive learning environment. This is particularly important for students with special educational needs, where VAs can offer consistent adaptive support and help bridge instructional gaps [32].

The theoretical foundation of many successful implementations is rooted in the ICAP framework, which categorizes cognitive engagement into four levels: Interactive, Constructive, Active, and Passive. VAs that foster interactive and constructive learning (e.g., through dialogue and reflection) tend to enhance cognitive outcomes more effectively than passive content delivery [34].

Rather than replacing educators, virtual assistants are intended to complement their instructional role by automating repetitive tasks and allowing teachers to focus on mentorship, creativity, and emotional support [35]. However, successful integration depends not only on their technical capabilities but also on considerations such as user trust, data privacy, and ethical transparency.

3.2. RQ2. Which models and algorithms are most commonly used?

In recent years, Virtual Assistants (VAs) have rapidly evolved within educational contexts, with the integration of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Augmented Reality (AR), and Virtual Reality (VR) technologies. These technologies have been embedded into intelligent educational systems such as chatbot tutors, intelligent tutoring systems, and recommendation engines chatbot tutors, intelligent tutoring systems, and recommendation engines to personalize instruction, assess student performance, and offer real-time feedback.

The COVID-19 pandemic further intensified the adoption of such technologies due to the increased demand for remote learning. During this period, the rise of metaverse-inspired platforms, blending VR, AR, and AI, provided more immersive and realistic educational experiences, making these tools indispensable in modern educational environments [36–38].

Virtual Teaching Assistants (VTAs) are increasingly used to reduce teacher workload while enhancing student outcomes. VTAs play a critical role in areas like exam preparation, after-school tutoring, automated grading, and performance analytics. Their impact depends on thoughtful integration that balances academic outcomes with student well-being [32].

Fig. 6. Online Platforms used in the field of Education

A variety of educational platforms now incorporate AI, VR, and AR to enhance engagement and interaction in learning environments. These platforms – such as Labster, Nearpod, ENGAGE, Oculus Education, AltspaceVR, Google Expeditions, Unimersiv, UroVers, and PedUroVerse – demonstrate how AI-driven analytics and immersive simulations are being embedded into teaching practice. They collectively illustrate the convergence of adaptive learning, experiential instruction, and data-supported feedback in modern education [33] (see Fig. 6).

Labster offers interactive virtual science laboratories for biology, chemistry, and physics, while Nearpod enhances lesson interactivity and supports real-time student assessment. ENGAGE and Oculus Education focus on the use of VR/AR for immersive instruction, and Unimersiv provides experiences in history, art, and science. Platforms like AltspaceVR and Google Expeditions emphasize social and exploratory dimensions of learning, while UroVers and PedUroVerse provide high-fidelity surgical simulations [33, 37–43].

In parallel, various development tools facilitate deep learning and ML implementation in educational contexts. Libraries like TensorFlow, Keras, scikit-learn, OpenCV, Pandas, and Numpy support the construction of scalable systems capable of personalizing instruction.

The following Table 3 gives the educational VR/AR Platforms.

Studies Emphasize the integration of STEM centers into virtual education. Platforms like ViToS enable game-based learning supported by VAs and educational robots. These environments enhance access to STEM content, encourage collaboration, and deliver real-time, personalized feedback [31, 37, 39–41]. These platforms improve the attractiveness and accessibility of educational content, particularly in STEM fields, and support collaborative resource sharing between universities and secondary schools. Embedded virtual assistants facilitate real-time feedback and enable a degree of personalization that supports differentiated instruction and student autonomy [13, 31–33, 39].

A core area of research focuses on emotion recognition using automatic facial expression recognition systems. Convolutional Neural Networks (CNNs) and variants such as

Table 3. Educational VR/AR Platforms

Platform	**Description**
Labster	Offers virtual labs in physical and scientific sciences, including biology, chemistry, and physics.
Nearpod	Enhances interactive teaching and helps teachers monitor and evaluate students (ICT-focused).
Unimersiv	Uses VR and AR to provide educational experiences in geometry, history, art, and science.
ENGAGE	Allows participation in multi-use virtual environments using VR and AR technology.
Oculus Education	Provides pre-designed or user-created VR learning environments and supports remote educational activities.
AltspaceVR	Facilitates communication and collaboration in virtual social environments using VR.
Google Expeditions	Offers VR-based educational experiences such as exploring landscapes, monuments, and ecosystems.
UroVers	Provides virtual surgical simulations to train doctors in various scenarios.
PedUroVerse	Provides virtual surgical simulations to train doctors in various scenarios.

DenseNet are commonly employed in this domain. These models process visual input to detect learners' affective states in real time, enabling emotionally responsive systems [36, 44–54].

Table 4 presents the Integrated Technologies for Machine Learning and Educational Simulations commonly used in modern research. This ecosystem includes core deep learning frameworks such as TensorFlow and Keras, alongside machine learning libraries like scikit-learn. These are integrated with the Unity game engine to create immersive virtual learning environments. To support these systems, specialized Python libraries – including Pandas for data manipulation, NumPy for numerical computation, and OpenCV for computer vision – are utilized. Together, these technologies enable seamless data processing, real-time simulation, and intelligent content personalization in educational contexts.

The growing use of virtual assistants and intelligent systems in education is reflected in four main categories of instructional design strategies (see Table 5.

These systems collectively aim to deliver personalized, adaptive, and emotionally intelligent learning support. They also relieve teachers from repetitive tasks, enhance student autonomy, and promote more inclusive, engaging, and effective learning environments [5, 13, 55, 32, 35].

The deep learning techniques used in the last decade to build automatic facial expression recognition systems with the convolutional neural network (CNN) be one of the most effective and widely used models for developing an automatic emotion recognition system [36, 44, 45, 47, 51, 54]. Also, the Dense Net (Densely Connected Convolutional Network) technique is widely used in image recognition applications and has demonstrated excel-

Table 4. Integrated Technologies for Machine Learning and Educational Simulations

Name	**Description**
Keras	Open source library developed by François Chollet. It is used for building and training neural network models both by beginners because of its ease of use and by advanced users because it is a powerful and versatile tool.
Unity	A game engine widely used to create educational and interactive applications. Unity supports integration with AI frameworks and APIs for immersive learning and simulation environments.
matplotlib	Open source library used to create charts, graphs and data visualizations in the Python programming language.
numpy	High performance arrays and functions library in Python. It also provides the ability to perform fast calculations on large data sets.
opencv-python	Open source library used in Python programming languages to process, analyze, recognize and manipulate images and videos.
Pillow	The Pillow library (known as PIL - Python Imaging Library) is easy to use and provides many features for creating and manipulating images in Python applications. Its functions are: opening images from various file formats, editing features (size, color, text, rotation, filters, etc.) and saving the processed image in various file formats, such as JPEG, PNG, GIF, BMP and more.
tensorflow	TensorFlow is an open source library widely used in artificial intelligence, machine learning and image processing developed by Google. It has become one of the main tools for implementing machine learning algorithms.
imutils	imutils is a utility library used by developers using Python and OpenCV. It provides utility functions to simplify and speed up image processing, performing various tasks and especially in applications such as computer vision and object recognition.
imageio	imageio is a Python library used for managing and editing images. It is used to load, save, edit images from various file formats. One of its most basic functions is managing image metadata, such as tags, user information, and more.
scikit-learn	scikit-learn (also known as sklearn) is an open source library in Python, widely used in the field of data science and machine learning for developing models, analyzing data, and solving prediction and classification problems.
Pandas	pandas is a flexible and extensible Python programming library used for data analysis and manipulation. It provides functions for data processing (remove, add, rename columns, replace, etc.), analyze graphical representations and time data. Pandas also supports importing data from various sources, such as CSV files, Excel, SQL databases, and data environments in interaction with other libraries. Finally, it allows the merging and joining of data from various sources based on common characteristics.
joblib	joblib is a Python library used to easily store and load Python objects.
datetime	datetime is a programming library used to manage dates and times.
pickle	pickle is a Python library used to store and load Python objects.
Time APIs	Time APIs (Application Programming Interfaces) are programming interfaces that provide access to time-related data and services. These interfaces are typically used to retrieve information such as the current time, dates, times, time zones, and other related information.

Table 5. Virtual Assistants and Intelligent Systems

System Category	Description
Activity-based systems	Enhance student engagement through simulations, gamification, and interactive environments (e.g., Labster, Nearpod).
Emotion-based systems	Use AI to detect and respond to student emotions, fostering supportive and emotionally responsive learning environments.
Classroom space management systems	Improve logistical organization, scheduling, and coordination within the classroom setting.
Special needs-focused systems	Provide adaptive and individualized support for learners with disabilities or learning difficulties.

lent performance in face analysis. When performing the analysis, it uses synchronized face images from a database that includes face images of different rotations, illuminations, and expressions [36, 40, 50, 54].

Table 6 presents an overview of Facial Expression Recognition (FER) techniques used in educational contexts.

Table 6. FER Techniques

Author	Technique	Dataset
El-metwally et al. [14]	DNN, MFCC, STFT	DCASE2016, CHiME-home
Zhai & Wibowo [24]	WGAN, NLP, CNN	generators/critics
Fakhar et al. [38]	CNN, HOG	FER-2013, JAFFE, CK+
Quan et al. [39]	Cross-modal attention, BERT, Bi-GRU	CMU-MOSI, CMU-MOSEI
Wang et al. [41]	CNN	JAFFE, CK+
Wang et al. [42]	SVM	JAFFE
Owusu et al. [43]	GF, MFFNN	JAFFE, Yale
Li et al. [44]	CNN	JAFFE, CK+
Biswas et al. [45]	DCT, SVM	JAFFE, CK+
Hegde et al. [46]	KLSWFDA, Gabor, SVM	JAFFE, YALE, FD
Prasad & Chandana [47]	DoG +, Median filter, EfficientNet+, YOLOv4+, DenseNet	RGB-D-T
Liu et al. [48]	CNN, Image Preprocessing	JAFFE, CK+, FER2013
Niu et al. [49]	LBP and ORB Features	CK+, JAFFE, MMI
Shahzad et al. [50]	CNN, AlexNet, VGG-16	MLF-W-FER
Fang et al. [51]	Ghost-CNN	RAF-DB, FER2013, FERPlus
Khattak et al. [52]	CNN	JAFFE, CK+, UTKFace

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3.3. RQ3. What is the role of virtual assistants in student motivation and autonomy?

Recent research consistently shows that Virtual Assistants (VAs) significantly enhance learner motivation, autonomy, and personalized engagement in virtual learning environments. These systems tailor educational content to student interests, offer emotionally intelligent feedback, and support self-regulated learning [18, 32, 35].

VAs foster autonomy by allowing students to control the pace and direction of their learning. For instance, they can independently navigate digital content, access on-demand assistance, and engage in exploratory problem-solving activities. This independence promotes deeper understanding and confidence [32].

Furthermore, VAs provide real-time feedback and constructive guidance that reinforces positive learning behaviors. Studies indicate that such interactions encourage students to persist in challenging tasks, improve their self-efficacy, and take ownership of their learning outcomes [5, 11, 30].

Beyond the immediate feedback provided by virtual assistants, the effectiveness of AI-generated feedback depends greatly on its design. Generic feedback is often perceived as limited and impersonal, whereas context-specific feedback is regarded as targeted, useful, and supportive. In some cases, students even view it as a “partner” in the learning process. The most significant benefits emerge when AI- and human-generated feedback are combined, as each complements the other [56].

Recent empirical evidence further supports these observations. A ChatGPT-enhanced virtual assistant (SRLbot) significantly improved students’ self-regulated learning strategies, motivation, and science knowledge compared to a rule-based chatbot. Students valued the personalized recommendations and flexibility of the system, which reduced anxiety, strengthened their autonomy, and fostered more sustainable learning habits [57].

According to the ICAP framework [32], VAs support higher-order cognitive engagement (Interactive and Constructive levels), as they facilitate active dialogue, collaboration, and reflective thinking. This form of engagement correlates with stronger motivation and better academic performance.

Research in STEM and programming education environments [11, 28, 31, 40] highlights the VA’s role in gamified, scenario-based, and emotionally adaptive learning activities. For example, a usability evaluation of the Imikode Virtual Reality Game showed that students reported higher engagement, improved understanding of object-oriented programming, and overall positive experiences when interacting with a VR-supported learning environment [58].

Additionally, studies show how VAs contribute to student persistence by offering consistent support even in complex learning tasks or VR-based simulations, fostering both affective and cognitive engagement [11, 26].

In summary, Virtual Assistants contribute significantly to student development by enhancing motivation through personalized and gamified learning experiences, fostering learner autonomy through self-paced and independent exploration, and increasing emotional engagement via responsive, adaptive feedback. Additionally, they support cognitive growth by aligning with ICAP-based learning behaviors and promote greater inclusion and participation, particularly among underrepresented or disengaged learners . The Fig. 7 illustrated, which maps the learning outcomes enabled by intelligent virtual assistants.

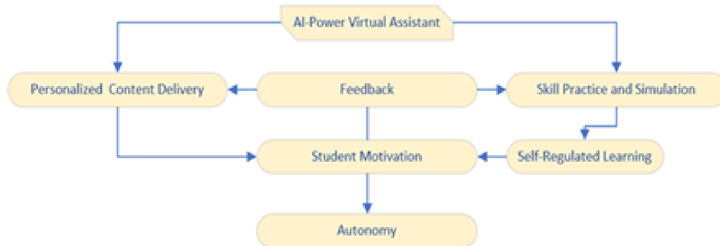

Fig. 7. Learning Outcomes Enabled by Intelligent Virtual Assistants

3.4. RQ4. What are the benefits and challenges of using VAs in classroom-supported instructional design?

In recent years, the integration of Virtual Assistants (VAs) powered by Artificial Intelligence (AI) into educational environments has brought significant shifts in instructional design and classroom dynamics. These tools aim to personalize the learning experience and adapt to students' emotional and cognitive needs [21, 35].

In particular, platforms informed by EduTech and Metaverse technologies-such as VR, AR, AI, and big data-create more engaging, immersive, and flexible learning spaces. These systems accommodate learners' individual needs, adjust content pacing, and promote inclusive participation by offering multimodal instructional formats [38]. Additionally, smart classrooms, often integrated with VAs, assist in classroom organization, energy efficiency, and attendance monitoring, alleviating teachers' operational workload [17, 21, 59].

Emotion-aware Vas, especially those that incorporate facial expression recognition (FER) and real-time sentiment analysis, enhance the learning experience by adapting their responses based on students' affective states. These systems recognize emotions such as joy, fear, sadness, or confusion, contributing to tailored feedback and improved emotional engagement [27, 44, 60]. Despite their promise, challenges remain regarding accuracy, ethical concerns, and cultural variation in emotional expression [61].

Moreover, the incorporation of dialog systems enriched with empathy, humor, and cultural sensitivity enhances student-system interaction. Such features help reduce anxiety and increase satisfaction, particularly during difficult learning tasks [62]. At the same time, the reliance on technology in education introduces valid concerns. These include digital inequity, data privacy, potential overdependence on automated systems, and the risk of dehumanizing the learning experience [31, 35].

Beyond pedagogical considerations, recent studies emphasize that user acceptance of chatbots in education depends on factors such as trust, usability, and emotional intelligence. A recent study found that integrating machine learning and semantic web technologies into chatbot design enhanced their reliability and responsiveness in educational technical support systems. Students and instructors particularly valued fast responses, emotional sensitivity, and seamless integration with widely used platforms such as WhatsApp, which collectively increased satisfaction and adoption rates [63].

While these findings highlight the conditions under which chatbots can be positively received, other research warns that the increasing reliance on AI in education also carries risks for students' well-being.

Recent research highlights that AI-powered educational decision support systems (AI-EDSS) have a profound impact on students' digital well-being. For vulnerable learners in particular, these systems may amplify existing inequalities or create new forms of disadvantage, thereby raising pressing concerns about fairness, equity, trust, and ethical responsibility in higher education [64].

In addition to these considerations, ensuring fairness in AI systems is increasingly viewed as a prerequisite for their sustainable use in education. An interactive human-in-the-loop approach has been introduced to mitigate algorithmic bias in machine learning models for undergraduate admissions. The findings show that carefully designed bias adjustment processes can reduce inequities for sensitive groups (e.g., gender, race, first-generation students) while also strengthening trust in AI-supported decision-making. This perspective underscores that fairness and user trust are interdependent, and that technical solutions must be complemented by human oversight to achieve ethical and equitable integration of AI in education [65].

The following Table 7 provides an overview of the key benefits and limitations associated with the classroom use of VAs.

Table 7. Benefits and Limitations of Virtual Assistants in Classroom-Based Instruction

Aspect	**Benefits**	**Limitations**
Personalized Learning	Adapts content to student needs and pace	
Real-Time Feedback	Encourages persistence and improves outcomes	
Emotion Recognition and Support	Supports emotional engagement and well-being	Cultural and contextual variability in emotion interpretation
Gamified and Scenario-Based Learning	Enhances motivation and immersion	Requires advanced user control skills, possible frustration
Smart Classroom Integration	Automates classroom management and saves energy	Technical complexity and infrastructure needs
Digital Equity		Limited access for underserved students
Data Privacy and Ethics		Concerns over surveillance, bias, loss of teacher role
Emotional Misinterpretation Risk		Challenges in accurately reading and reacting to emotions

Even though the investigated studies aggregate the virtual assistant contribution to personalization, motivation, and classroom management positively, critical consideration of the consistency and robustness across findings is required. One crucial observation is the rate at which most empirical evidence has been drawn on the basis of small scales or short-term investigations conducted in controlled conditions, which limits the generalizability across conditions. For instance, although emotion-aware systems using CNNs and FER approaches report promising findings for the promotion of engagement, most studies indicate that cultural diversity in the expression of emotional states undermines accuracy and inclusivity. In a similar context, activity-based VAs achieve motivation increase, but the most part of these interventions rely on the use of gamification, which possesses high concern for the long-term maintenance motivation post the novelty effect has diminished. Another major issue is the lack of comparative research. Few studies contrast the operational performance of AI-powered assistants with established teaching strategies or with other computer- or online-based tools, making it difficult to identify the unique contribution of VAs. Furthermore, where performance on the technical level is appropriately documented (e.g., recognition models efficacy, swiftness of response), fewer still examine the pedagogical richness of these interventions, for instance, the degree to which they abide by common theories of learning or have long-term impact on self-regulation abilities. This skewness suggests a disconnection between technological innovation and learning theory, and highlights the future need for VAs to be evaluated not only methodologically but also as pedagogical tools that occur organically in natural classroom ecologies.

4. Discussion

Technological advancements over the past decade have brought significant changes to the way we approach the educational process, as highlighted in this review. The findings confirm the development of modern digital assistants that support educators and provide students with access to digital learning and simulation environments, offering an interactive educational experience [14]. Realistic simulations, using intelligent learning environments supported by Virtual Assistants (VAs), enhance deeper understanding and promote interactive student engagement, having a positive impact on academic performance [13, 26, 31, 37]. This review identified recurring patterns and emerging trends in the areas of instructional practice, student motivation, affective learning, and classroom management [55]. It also recognizes challenges and limitations, and proposes directions for future development and research.

Beyond a descriptive synthesis of the results, the reviewed studies reveal notable differences in how AI-powered Virtual Assistants (VAs) are conceptualized, implemented, and evaluated. These variations often stem from divergent theoretical orientations and instructional goals. For instance, systems emphasizing adaptive feedback and personalized scaffolding reflect principles consistent with Vygotsky's Zone of Proximal Development and Gagné's Conditions of Learning, whereas game-based or exploratory assistants align with Bruner's constructivist approaches. Conversely, some studies emphasize automation or administrative efficiency at the expense of pedagogical grounding, revealing a gap between technological advancement and instructional design.

Furthermore, contradictions across studies – particularly regarding learner engagement and performance outcomes – can be explained by contextual differences such as subject area, target population, or level of human–AI interaction. Some studies report improved motivation when VAs provide socio-emotional support, while others observe diminishing returns when excessive automation reduces learner agency. This contrast underscores the importance of balancing intelligent automation with human-centered design.

Taken together, these findings advance the state of the art by revealing that the pedagogical value of AI-powered VAs depends not only on their algorithmic sophistication but also on their theoretical integration into learning processes. Bridging technical and educational perspectives thus represents the next critical step for research in this field.

The literature highlights VAs as promising tools for personalized learning and improved educational outcomes. According to theoretical frameworks such as ICAP, they support collaborative learning processes and interactive activities [34]. Beyond providing high-quality resources, virtual assistants also emotionally engage learners. The ability to interact with a learning environment that dynamically responds to students' needs enhances their interest and engagement, fostering active participation [5, 35, 58, 55].

Moreover, current applications are found to handle time-consuming and repetitive tasks, allowing educators to focus more on their pedagogically valuable work. Simultaneously, studies emphasize the support VAs offer for differentiated and personalized learning [10, 17]. Recent systems can adapt learning content to each student by providing real-time personalized feedback, thereby enhancing learning progress based on individual needs [3, 5, 11]. Additionally, research shows that when VAs offer immediate feedback, emotionally sensitive communication, and guidance at a learner-defined pace, they promote autonomy and learning interest [5, 26].

Equally notable, emotion recognition systems based on Convolutional Neural Networks (CNNs) and Facial Expression Recognition (FER) algorithms [54] extend this socio-emotional dimension by detecting learners' affective states and adjusting responses to sustain engagement [27, 36, 51]. Furthermore, game-based learning activities and the integration of augmented and virtual reality environments (VR/AR) enhance interest and active participation, particularly in STEM subjects [40, 43].

From a pedagogical perspective, studies present VAs not only as teaching aids but also as emotionally supportive tools. By taking over repetitive administrative or instructional tasks, they reduce teacher workload and increase time for student interaction, facilitating individualized support, guidance, and the cultivation of critical thinking skills [10, 11, 55].

At the same time, the adaptability of VAs paves new paths for inclusive education by supporting students with special educational needs and promoting equity and accessibility [26, 29].

Despite their many benefits, several challenges have been identified. One of the main issues is the inaccuracy in emotion recognition due to cultural differences and diversity in facial expressions [45, 36]. Additionally, there is a risk of diminished human empathy and reduced educational interaction between teacher and student [13, 35].

It is also worth noting that adopting an environment with advanced learning systems requires a high level of user control skills. This level affects students' ability to effectively engage with the educational content [18, 26]. Consequently, there is a risk of inequality in access due to a lack of technological literacy [35]. Inadequate digital skills may lead to student frustration, as they may be unable to fully benefit from the learning environment. The integration of technology in education requires not only technical competence but also a deeper understanding of issues such as personal data protection and how such systems influence learning relationships within the classroom [25, 60].

From a pedagogical perspective, these insights bridge the gap between technology and learning theory. The most favorable results found in this synthesis come from interventions offering constructive or interactive learning activities, as framed by the ICAP model, while the principles of Vygotsky, Gagné, and Bruner remain central for adaptive feedback, sequencing, and discovery learning.

From a cognitive perspective, principles from Gagné's Conditions of Learning continue to inform feedback sequencing and instructional design in VA-supported environments. Furthermore, the inclusion of the ICAP framework illustrates how VAs can move learners away from passive reception towards constructive, active, and interactive engagement.

Very little theoretical basis in most studies, however, is an intimidating gap. Lacking an explicit pedagogical basis, VAs risk being built largely on grounds of technical feasibility rather than pedagogical imperative. Future research should strengthen this alignment between technical innovation and pedagogical theory to ensure that AI-powered Virtual Assistants enhance, rather than replace, human-centered teaching.

5. Conclusions

The findings of this review enhance our understanding of the use of advanced, modern systems that integrate technologies such as VR, AR, AI, and other related innovations. These systems simulate realistic and interactive learning experiences, which were strengthened during the pandemic and have continued to attract increasing interest and application in recent years.

This review is valuable both for developers aiming to design or implement educational virtual assistants (VAs), and for educators seeking to enhance their teaching practices through digital systems supported by VAs. Emphasis is placed on student motivation, engagement, and academic performance.

Moreover, the findings include evidence from previous experimental studies, empirical data, and valuable insights into how the integration of advanced technologies with virtual assistants can enhance learning processes. Collectively, the reviewed evidence demonstrates that when designed with pedagogical intent, AI-powered Virtual Assistants substantially enrich learning environments and foster deeper understanding, while providing educators with effective support for instruction and assessment.

This study highlights the importance of advanced technologies in education and offers clear directions for the future development of educational environments. Finally, it emphasizes the necessity of aligning technological innovation with pedagogical design and ethical responsibility to maximize educational impact. Overall, this review underscores the transformative potential of AI-powered Virtual Assistants in education while emphasizing that their sustainable integration requires ongoing collaboration among educators, psychologists, and developers to balance innovation with ethical and pedagogical integrity.

Even though the present review offers an overarching description of AI-driven Virtual Assistants for education, there are certain limitations that need to be addressed. To begin with, the analysis was limited to English articles indexed primarily in Scopus and Web of Science. In doing so, potentially relevant studies written in other languages or indexed in smaller databases might have gone unnoticed, possibly limiting the cultural and regional scope of the findings. Second, the overwhelming majority of the studies included used small sample sizes, pilot studies, or short-term interventions, which impairs the generalizability of the observed outcomes. This is especially true for studies on the recognition of affect or gamified settings, where the novelty effect tends to transiently exaggerate motivation and engagement. Third, there was an overrepresentation in the methodology used by the reviewed studies, with many placing strong emphasis on technical performance indicators (e.g., the accuracy or the swiftness of the model) over long-term pedagogical effects. Lastly, the heterogeneity of the studies included – covering different schooling levels, settings, and disciplines – impeded the possibility of conducting direct comparisons or meta-analytic synthesis.

These limitations also open meaningful directions for future research. Future studies should prioritize longitudinal and comparative designs to evaluate the long-term pedagogical impact of AI-powered Virtual Assistants across diverse educational levels and contexts. Researchers are encouraged to enhance cross-cultural validation, particularly for emotion-aware systems, ensuring inclusivity and fairness. In practice, stronger collaboration among educators, developers, and policymakers will be essential to integrate Virtual Assistants into curricula, teacher training, and assessment frameworks while maintaining pedagogical coherence and ethical integrity.

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