Trabajo de Fin de Máster
Máster en Sistemas Inteligentes
Julio, 2023

Evaluating the Effectiveness of Human-Centered AI Systems in Education

Nastaran Shoeibi
Tutors: Roberto Therón Sánchez, Francisco José Garcia-Peñalvo

Departamento de Informática y Automática
Universidad de Salamanca

Revisado por:

- Dr. Roberto Therón Sánchez

  Departamento de Informatica y Automatica

  Facultad de Ciencias – Universidad de Salamanca

  Plaza de la Merced S/N – 37008 – Salamanca

  theron@usal.es

- Dr. Francisco José Garcia-Peñalvo

  Departamento de Informatica y Automatica

  Facultad de Ciencias – Universidad de Salamanca

  Plaza de la Merced S/N – 37008 – Salamanca

  fgarcia@usal.es

Autor:

- Nastaran Shoeibi

  Departamento de Informatica y Automatica

  Facultad de Ciencias – Universidad de Salamanca

  Plaza de la Merced S/N – 37008 – Salamanca

  nastaran@usal.es

Acknowledgements

"The beginning and end of any journey can often feel insignificant compared to the people accompanying you. Their support, encouragement, and companionship make the journey worthwhile and memorable."

I would like to express my heartfelt gratitude to my thesis advisors, Roberto Theron Sanchez Francisco and Jose Garcia-Peñalvo, for their invaluable guidance, support, and mentorship throughout the completion of this thesis. their expertise, patience, and encouragement have been instrumental in shaping this work and pushing me to achieve my best. I am truly grateful for his/her unwavering dedication and belief in my abilities.

I am deeply grateful to my family in Spain and Iran for their unconditional love, encouragement, and unwavering belief in my abilities. Their constant support and sacrifices have been the foundation of my academic journey, and I am forever indebted to them.

Lastly, I would like to thank my GRIAL family. Their generosity in sharing their time, experiences, and expertise has been valuable in shaping my research findings. I am truly grateful for their willingness to collaborate and the vibrant intellectual environment they have fostered.

Resumen

Esta tesis explora el uso de la inteligencia artificial (IA) en la educación, centrándose en mejorar la interacción humano-computadora (HCI) y la experiencia del usuario. El estudio incluye una revisión sistemática de la literatura (SLR) y un estudio de caso del proyecto LATILL, un ejemplo destacado del uso de IA en la educación. La SLR examina el conjunto de literatura existente para determinar los efectos de la integración de la IA en la educación en la experiencia del usuario y en la HCI. Los resultados demuestran cómo la IA puede personalizar y adaptar las experiencias de aprendizaje, mejorar el rendimiento en tareas y mejorar la experiencia del usuario tanto para los docentes como para los estudiantes. La SLR también identifica las dificultades y restricciones relacionadas con la aplicación de la IA en la educación. El proyecto LATILL, que ejemplifica el uso efectivo de la IA en la educación de idiomas, es el foco del estudio de caso. El objetivo principal del proyecto es ayudar a los docentes a proporcionar orientación y apoyo personalizados a sus estudiantes. Pueden seleccionar textos apropiados según los niveles del Marco Común Europeo de Referencia para las Lenguas (CEFR) y características lingüísticas. La plataforma utiliza una metodología de diseño centrada en el usuario e incorpora prototipos y comentarios de los usuarios para garantizar una funcionalidad óptima y satisfacer los requisitos particulares de los docentes. El proyecto LATILL busca transformar la enseñanza de idiomas convencional, aumentar la participación de los estudiantes y fomentar experiencias de aprendizaje de idiomas gratificantes y exitosas mediante la promoción de la colaboración y el intercambio de recursos entre los educadores. A través de la SLR y el estudio de caso, esta tesis proporciona conocimientos valiosos sobre el potencial de la IA en la educación, su impacto en la experiencia del usuario y la HCI, y los desafíos y oportunidades que surgen al implementar la IA en entornos educativos. En conclusión, esta investigación resalta los beneficios significativos de la integración de la IA en la educación y enfatiza la importancia de considerar los principios de experiencia del usuario y HCI al diseñar sistemas educativos impulsados por la IA. Al aprovechar de manera efectiva las tecnologías de IA y adoptar enfoques de diseño centrados en el usuario, los educadores pueden mejorar la experiencia de aprendizaje, fomentar la participación de los estudiantes y promover resultados educativos exitosos.

Palabras clave: Inteligencia Artificial, IA Generativa, Interacción Humano-Computadora, Experiencia del Usuario, Educación, Aprendizaje Personalizado, SLR, Revisión Sistemática de la Literatura.

Abstract

This thesis explores using artificial intelligence (AI) in education, concentrating on improving human-computer interaction (HCI) and the user experience. The study includes a systematic review of the literature (SLR) and a case study of the LATILL project, a prime example of the use of AI in education. The SLR examines the body of existing literature to determine the effects of integrating AI in education on user experience and HCI. The results demonstrate how AI can personalize and adapt learning experiences, enhance task performance, and improve user experience for teachers and students. The SLR also identifies difficulties and restrictions related to the application of AI in education. The LATILL project, which exemplifies the effective use of AI in language education, is the focus of the case study. The project's main objective is to assist teachers in providing their students with individualized guidance and support. They can select appropriate texts based on CEFR levels and linguistic characteristics. The platform employs a user-centered design methodology and incorporates prototypes and user feedback to guarantee optimal functionality and satisfy the particular requirements of teachers. The LATILL project seeks to transform conventional language instruction, increase student engagement, and foster enjoyable and successful language learning experiences by encouraging collaboration and resource sharing among educators. Through the SLR and the case study, this thesis provides valuable insights into the potential of AI in education, its impact on user experience and HCI, and the challenges and opportunities that arise in implementing AI in educational settings. In conclusion, this research highlights the significant benefits of integrating AI in education and emphasizes the importance of considering user experience and HCI principles when designing AI-driven educational systems. By leveraging AI technologies effectively and adopting user-centered design approaches, educators can enhance the learning experience, promote student engagement, and foster successful educational outcomes.

keywords: Artificial Intelligence, Generative AI, Human-computer Interaction, User-experience, Education, Personalized Learning, SLR, Systematic literature

Contents

List of Figures

List of Tables

1 Introduction

The term "Artificial Intelligence" was coined during the Dartmouth Conference in 1956, led by John McCarthy and others. However, earlier scientists like Warren McCulloch, Walter Pitts, and Alan Turing laid the foundation for AI [1][2][3]. They established the basis for AI with their research on neural networks and computational models of the brain. Experts were gathered at the Dartmouth Conference to discuss the viability of building intelligent machines. Since then, AI has developed further and found use in various fields[4].

There is an ongoing discussion about whether AI will one day beat human intelligence and achieve superintelligence. While there are some biological limitations to the human brain, AI-based systems have the potential to work around these restrictions and use more powerful algorithms and capabilities. AI systems may employ mathematical modules, have a larger and more accurate working memory, and run multiple instances that combine their memories and conclusions. Furthermore, if an AI has the necessary skills, it might help create AI systems that are even better, potentially accelerating technological advancement [5].

A computer-based AI with a mind comparable to a human's offers several advantages over our biological brains. It can benefit from the continuous advancements in hardware, as outlined by Moore's Law, enabling it to become exponentially faster and more capable over time [6]. This accelerated processing power would allow the AI to reason and analyze information much faster than humans, leading to faster progress in various research fields. Additionally, the AI would have access to vast amounts of data stored on expanding hard drives, enabling it to thoroughly research and consider relevant information without experiencing any noticeable slowdowns [7].

Furthermore, the software-based nature of AI allows for easy duplication and networking. Once trained in a particular skill, the AI can be replicated as needed, eliminating the need for repetitive training. Moreover, AIs can overcome limitations such as fatigue or a drop in motivation by reloading a saved state of peak energy or motivation [8]. By networking a group of AIs with diverse skills and compatible motivations, a super-committee can be formed, surpassing the capabilities of any human committee. These AI super-committees would possess a broad range of skills and the ability to collaborate seamlessly, outperforming human groups in terms of information sharing and collective problem-solving. Thus, a human-comparable AI has the potential to excel in scientific, technical, and social tasks, revolutionizing various fields and augmenting human capabilities [3] [8].

Many studies provide different definitions of AI, highlighting its multidimensional nature. It is described as a field of study in computer science focused on solving cognitive problems associated with human intelligence, such as learning, problem-solving, and pattern recognition. It is also seen as a theoretical framework guiding the development of computer systems with human-like capabilities, including visual perception, speech recognition, decision-making, and language translation [9][10][11]. Common characteristics of AI include the ability of machines to approximate human reasoning, perform functions that require human-like intelligence, adapt to the environment, and mimic human cognition and actions. AI involves the development of intelligent machines capable of performing a wide range of tasks and exhibiting cognitive abilities.

AI has expanded beyond its association with computers and has found applications in various domains, including education. To ensure a positive user experience when integrating AI into education, human-computer interaction (HCI) is essential [12]. Even before the official introduction of AI, education had already begun incorporating psychology and pedagogy theory with machines to create teaching tools [13]. In recent years, AI has been integrated into actual classrooms. For example, intelligent robots have assisted human teachers in teaching English to primary school students, a new teaching method where human and

AI teachers work together as partners. AI tools can teach any subject theoretically, making teaching more standardized. [14]

Using computer technology in the teaching and learning of second or foreign languages is known as intelligent computer-assisted language learning (ICALL) [1]. It is a branch of computer-assisted language learning (CALL) that creates intelligent tutoring programs to give language learners individualized feedback [15]. Natural language processing (NLP), spell and grammar checkers, feedback, student models, and future directions are all possible components of ICALL systems [16].

Mobile platforms and APIs have recently been developed to execute AI efficiency advances on mobile devices, reducing network latency and complexity [17]. AI in mobile devices has the potential to transform education by providing convenience, interactive and personalized learning experiences, global classrooms through virtual reality, and AI-based chatbots for personalized online learning and assessment[18]. While computers were the initial foundation for AI development, the concept has evolved to include other technologies such as embedded computers, sensors, and emerging technologies like buildings and robots [19], to name some examples.

Early computer-generated content was far from realistic and was easily distinguishable from human-made content, in contrast to today's AI-generated media. For generated content to achieve a high level of realism, AI has had to advance significantly over many years. This development can be attributed to developments in generative adversarial networks (GANs), which allow for creating realistic and high-quality content [20][21]. The capabilities of GANs have been further enhanced by style-based generator architectures, which allow for control over the appearance and style of generated content [22]. To produce deeper and more complex generated content, deep neural networks have been instrumental in learning and representing complex features [23]. Semantic image segmentation techniques, for example, have improved the comprehension and synthesis of visual content [24]. These developments in AI have made it possible to produce computer-generated media that is very similar to human-produced media.

Emerging technologies like Generative AI[25] have drawn interest from various industries, including education [26]. To better understand the future, Section 2.4 will define and discuss this technology's key concepts and details. The case study of Section 4 demonstrates the use of generative artificial intelligence to transform language learning. LATILL improves comprehension, engagement, and overall language acquisition by generating condensed versions of texts based on learners' proficiency levels. Teachers can choose individualized materials by incorporating generative AI algorithms, creating a customized and flexible learning environment.

However, our focus is on the user interface and experience; as AI continues to evolve and be integrated into educational settings, it is crucial to consider the user interface and experience. To investigate how artificial intelligence is used in education and how it affects the user experience, a Systematic Literature Review (SLR) [27] has been conducted. This review aims to comprehensively understand the currently available AI-based educational tools, identify new research directions, and identify opportunities for providing a beneficial user experience. The review also aims to spot patterns and techniques to enhance the user experience when integrating AI technologies into education, leading to more useful and practical solutions for students.

The structure of this thesis is organized as follows: A foundation for understanding how AI can be incorporated into educational settings to improve user experience is laid out in Section 2, which gives an overview of the key concepts pertinent to this study. Section 3.1 describes the Systematic Literature Review on Integrating AI into educational settings to enhance the user experience for educators and learners and

[1] https://en.wikipedia.org/wiki/Intelligent_computer-assisted_language_learning

highlights the review steps. Section 3.2 describes the review process, including the selection of articles and data extraction, after Section 3.3 describes the planning stage of the SLR in detail. In Section 3.4, which addresses the research questions, the conclusions drawn from the analysis of the chosen works are presented. The implications and importance of the study's findings are discussed in section 3.5. In addition, the LATILL project case study is highlighted in Section 4, providing in-depth insights into the technologies used to improve the user experience in an educational context. Finally, Section 5 brings the thesis to a close by summarizing the key findings and outlining possible directions for further investigation.

2 Theoritical Background

This section investigates the relationship between human-computer interaction and AI. The objective is to provide a comprehensive understanding of the ideas and methods that form the basis of the case study. Also contains an overview of the various AI technologies used and mentioned in Section 3.1 and Section 4. The platform's development and implementation depend on these AI techniques. Deeper explorations of particular concepts used in the case study, such as text summarization using NLP tools, machine translation, and a comparison of different NLP libraries, will also be covered in the theoretical background.

2.1 Human-Computer Interaction in Artificial Intelligence

In 1960, J.C.R. Licklider published a groundbreaking paper titled "Man-Computer Symbiosis,"[28] predicting a symbiotic relationship between humans and computers. These concepts have resurfaced today as Augmented Intelligence and Human-Computer Interaction (HCI) gain prominence. Licklider's vision, shared by influential figures such as Alan Kay [29] and Douglas Engelbart [30], has shaped the field of HCI and influenced the design of user-centered technologies. Licklider's concept of human-computer symbiosis highlighted the cooperative relationship between humans and computers. Combining human strengths in judgment and decision-making with the computational power of machines, symbiosis leads to enhanced problem-solving capabilities [31]. User Experience (UX) design facilitates this relationship, ensuring technology adapts to human needs and enhances cognitive performance. The design consciousness of Augmented Intelligence emphasizes ethical considerations and a human-centered approach to technology development [32].

As technology advances, Augmented Intelligence has the potential to create a harmonious partnership between humans and intelligent machines. Designers must consider the social consequences of AI implementation, create technologies that benefit all users, and respect individual rights and freedoms. Augmented Intelligence empowers individuals, maximizing human potential and fostering control and freedom in human-computer interactions. The future lies in a symbiotic collaboration that leverages the strengths of both humans and machines, enhancing intelligence and enriching lives [33].

Several applications already exemplify the symbiotic collaboration between humans and intelligent machines. Features like Gmail's "Smart Compose" and Grammarly[2]'s real-time suggestions demonstrate how AI enhances human productivity and confidence in tasks such as email writing and grammar checking. Virtual assistants like Siri[3], Alexa[4], and Cortana[5] act as cognitive prosthetics, assisting users in daily activ-

[2] https://www.grammarly.com/
[3] https://en.wikipedia.org/wiki/Siri
[4] https://en.wikipedia.org/wiki/Amazon_Alexa
[5] https://en.wikipedia.org/wiki/Cortana_(virtual_assistant)

ities. These examples showcase the power of Augmented Intelligence in supporting human endeavors and enabling users to achieve their goals effectively.

HCI focuses on how people interact with computers and other technology. To enhance how people use and interact with computers, it aims to design, evaluate, and put into practice interactive technologies. HCI has applications across many industries, including those of home appliances, entertainment systems, medical equipment, and more. HCI's main objective is to enhance interactive systems' security, utility, effectiveness, and usability [34]. It aims to create user-friendly and effective interactions by researching the user experience, improving interfaces, and developing intuitive designs. With the development of AI, the fusion of AI and HCI has become essential for creating new interactions between intelligent systems and people. Deep learning and other AI techniques have transformed the field's ability to study human behavior, perform tasks more effectively, and improve user experience [35].

HCI is a multidisciplinary field that optimizes user experience by designing interactive computing systems. It examines usability and user experience in computer technology use. HCI involves researchers from various disciplines, including psychology, computer science, information science, learning design, engineering, instruction, and communications. The ultimate goal is to understand the impact of human factors on interactions with devices, leading to the creation of visually appealing and effective interfaces. Software engineers, graphic designers, marketers, and HCI experts collaborate on software development. Each team member contributes to the software development process from their unique viewpoint, ensuring that the final product meets user needs and expectations.

Software development succeeds when the interface enhances the user's experience. Stone et al. [36] emphasize the importance of user input throughout development. Through studies and interviews, developers learn user preferences, needs, and experiences with similar software. In the pre-release phase, multiple software versions can be tested by users to gather feedback for final adjustments. Even after the release, user suggestions and feedback contribute to the continuous improvement of future software versions. Developers ensure that the software effectively meets their needs and expectations by involving users throughout development.

Properly programmed software organizes information, simplifies the structure, speeds up data transfer, allows visual comparisons of values and trends, and improves interface usability [37]. Well-designed graphics make the interface appealing and improve user experience. Customizing UI design ensures the graphical style matches context and user preferences. By incorporating effective UI design principles, software developers can create visually pleasing and engaging interfaces. UX is crucial in software development, encompassing information architecture, interaction design, and usability testing. UI/UX designers can make informed decisions about the functionality and design of the product, ultimately enhancing the overall user experience. UX design aims to create intuitive interfaces, seamless interactions, and meaningful experiences that meet user expectations and deliver value. UX designers are pivotal in facilitating a harmonious and symbiotic relationship between humans and intelligent machines. By drawing on their knowledge of human behavior, cognitive psychology, and the principles of user-centered design, they can create interfaces and products that are intuitive and user-friendly, thus enhancing the interaction between humans and computers [38].

Moreover, HCI plays a significant role in education, contributing to the design and development of interactive computing systems that enhance the learning experience for students. HCI in education focuses on understanding and improving the interaction between learners, teachers, and educational technologies to create effective and engaging learning environments [39][40]. One aspect of HCI in education is the design of user interfaces for educational software and digital learning platforms. These interfaces must be intuitive, visually appealing, and easy to navigate, allowing learners to access educational content and engage with learning activities effortlessly. Usability studies and user-centered design principles are applied to ensure the interfaces meet learners' specific needs and preferences [41]. HCI researchers collaborate with educators and instructional designers to create interfaces that promote effective learning experiences and support educational goals [42][43].

In addition to interface design, HCI in education explores emerging technologies to enhance teaching and learning processes. Conversational AI and natural language processing (NLP) technologies are being applied in educational chatbots, virtual assistants, and intelligent tutoring systems. These AI-powered systems engage with learners in natural language, providing personalized guidance, answering questions, and delivering adaptive feedback. HCI research focuses on designing conversational interfaces that effectively understand learner inputs, respond appropriately, and foster engaging interactions [44]. The impact of HCI in education is evident in enhancing user experience and improving learning outcomes. By incorporating HCI principles and research findings, educational technologies can be designed to be more user-friendly, accessible, and inclusive. HCI methodologies such as user testing and iterative design processes help identify usability issues, gather user feedback, and refine educational tools to serve the needs of learners and educators better [45].

HCI in education is significant in creating effective learning environments that promote learner engagement, collaboration, and knowledge acquisition. By integrating HCI principles, educational platforms, and software can be designed to enhance the user experience and facilitate seamless interactions between students, teachers, and learning resources. The application of HCI in education involves utilizing cutting-edge technologies such as virtual reality (VR) and augmented reality (AR) to create immersive and interactive learning experiences [46].

HCI principles are also crucial in analyzing user feedback and data to improve educational systems continuously. By gathering insights from students and teachers, educational platforms can be refined to better cater to their needs and preferences, resulting in more personalized and effective learning experiences. HCI in education aims to create user-friendly interfaces, intuitive designs, and accessible platforms to ensure all learners can engage with educational content and resources [47].

2.2 Intelligent Computer-Assisted Language Learning (ICALL)

As seen in Section 2.1, HCI is concerned with the design, evaluation, and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them. therefore, HCI research has been used in many fields, including intelligent computer-assisted language learning (ICALL). Intelligent Computer-Assisted Language Learning (ICALL) has emerged as a dynamic field that combines language learning with computer science to create interactive systems to assist learners in acquiring a foreign language[48]. The effectiveness and efficiency of language acquisition are increased by ICALL systems, which offer personalized and interactive language learning experiences by utilizing AI technologies like Natural Language Processing (NLP) and Intelligent Tutoring Systems (ITS) which will be explained more.

In the area of foreign language teaching and learning (FLTL), ICALL systems have developed into useful resources. These programs incorporate technology into language learning, allowing students to interact meaningfully with the target language and culture. ICALL systems provide learners with authentic language input and cultural exposure through multimedia presentations and web-based distribution of print media, radio, and television programs, encouraging contextualized, communicative language use. One of the major benefits of ICALL systems is their capacity to offer learners immediate, individualized feedback. These systems can analyze learner input, spot mistakes, and provide targeted feedback catered to each learner's individual requirements by utilizing NLP techniques. This tailored feedback not only aids in error correction but also fosters linguistic awareness and an understanding of grammatical concepts, aiding in the learning of a foreign language [49].

AI technologies are used by ICALL systems to build engaging and flexible learning environments. Automated error detection, grammar analysis, vocabulary assessment, and other language-related tasks are made possible by NLP, which enables the analysis and understanding of learner language. To support learners' language development, ICALL systems employ computational linguistics and NLP algorithms to deliver precise and timely feedback [50].

By offering personalized instruction and adaptive learning experiences, AI and ITS are essential to ICALL. To provide individualized instruction and remedial exercises, ITS incorporates learner modeling and keeps track of each learner's development and knowledge. The sequencing of learning activities, the delivery of personalized feedback, and the adjustment of difficulty can all be done by ICALL systems using AI algorithms, depending on the needs and proficiency of the learner.

These programs address the requirement for a well-rounded method of language instruction. ICALL acknowledges the significance of language awareness and understanding of language forms and rules, even though meaning-based, communicative activities are essential for enhancing fluency and communication skills. These systems allow students to participate in meaning- and form-focused activities, guaranteeing a thorough language-learning experience. Numerous applications and activities have been developed due to the incorporation of intelligent technologies into ICALL systems. Data-driven learning tools promote independent language exploration by encouraging students to investigate various linguistic options using annotated corpora. Text tools assist with grammar and vocabulary for writing and reading tasks. Intelligent language tutoring systems combine form-focused and meaning-focused activities to accommodate different learning styles and preferences to provide thorough language instruction [51].

It takes interdisciplinary cooperation between computational linguists, computer scientists, and language educators to integrate ICALL systems into FLTL curricula. By working together, ICALL systems are made to conform to pedagogical principles, instructional strategies, and individual student needs. It is still difficult to create ICALL activities that balance NLP analysis with real-world language learning situations. To design efficient and interesting language learning environments, activity design, learner input elicitation, and ICALL integration into FLTL curricula must be carefully considered. Exploring the potential of cutting-edge technologies can improve ICALL systems and provide immersive and interactive language learning experiences. Examples of these emerging technologies include speech recognition, natural language generation, and virtual reality [52]. Here are some examples of ICALL:

- **Duolingo**[6], a well-known language-learning app that employs gamification in its instruction.
- **Rosetta Stone** [7] is a software for teaching languages through images and sounds.
- **Babbel**[8] is a language learning app that teaches languages through interactive lessons and tests.
- **Lingoda**[9] is A website that provides real-time instruction from teachers who speak the student's language.
- **Busuu**[10] is a language-learning app that teaches languages through interactive lessons and tests.

[6] https://www.duolingo.com/
[7] https://www.rosettastone.com/
[8] https://www.babbel.com/
[9] https://www.lingoda.com/
[10] https://www.busuu.com/

These are only a few of the numerous ICALL tools that are now accessible. Every tool has advantages and disadvantages. In the case study section of this thesis (Section 4), the ICALL framework is used to create the LATILL language learning platform.

2.3 Different AI Technologies

In this section, we explore and define various AI technologies that have been used and examined in this study, extracted from the SLR conducted in Section 3.1. These technologies have been identified as influential in enhancing the user experience in educational settings. The following AI technologies are presented:

- **Affective computing:** Affective computing is an AI advancement that simulates, decodes and recognizes human emotions. It combines methods from cognitive science, computer science, and psychology to give machines the ability to understand and react to human emotions. Affective computing systems can identify and interpret emotional states by studying facial expressions, vocal intonations, gestures, and physiological signals. Numerous industries, including mental health, customer service, and educational settings, could benefit from this technology because it can personalize learning experiences and offer emotional support [53].
- **Augmented reality and virtual reality (AR&VR):** AR&VR, as AI technologies, offer immersive and interactive learning experiences by creating virtual environments or enhancing the real world with digital information. They enable students to explore complex concepts and receive hands-on training in a secure setting, enhancing engagement and retention [54].
- **Computer Vision:** Computer vision is an AI tool that enables computers to comprehend and interpret visual data from pictures and videos. Computer vision systems can identify objects, detect and track motion, and extract relevant details by analyzing and processing visual data. Numerous educational uses for this technology can be found in areas like image and video analysis, facial recognition for attendance monitoring, object recognition for augmented reality uses, and visual data processing for research [55].
- **Conversational AI:** AI systems that converse with humans in natural language are called conversational AI. These systems use machine learning and natural language processing techniques to comprehend user queries and prompts and provide appropriate responses. Virtual assistants and chatbots are examples of this technology, and they are getting common in education. They can facilitate interactive learning experiences, offer individual guidance, respond to inquiries, and offer tutoring or guidance. Conversational AI can be integrated into learning management systems, mobile applications, and educational platforms to improve accessibility and learner engagement [56].
- **Deep Learning:** A subset of machine learning that uses multiple-layered neural networks to extract and learn complex patterns from data. Deep learning algorithms can effectively process and analyze enormous amounts of data since they are made to resemble the structure and operation of the human brain. Numerous AI applications, such as computer vision, natural language processing, and speech recognition, have been transformed by deep learning. With the power of neural networks, deep learning models in education can make a personalized learning experience and drive advancements in student engagement and academic outcomes [57].
- **Intelligent Assesment:** The use of AI to automate and improve the educational evaluation process is called intelligent assessment. It uses AI algorithms to assess student performance, deliver individualized feedback, and produce insightful findings for teachers. Intelligent assessment systems can use machine

learning, natural language processing, and data analytics techniques to evaluate different aspects of learning, such as knowledge mastery, critical thinking, and problem-solving abilities. These systems can support data-driven educational decision-making, free up time for teachers, and give students timely feedback [58].

- **Machine Learning** Machine learning is a subfield of artificial intelligence that focuses on creating models and algorithms to learn from data and make predictions or decisions without explicit programming. Large datasets can be analyzed, and patterns found by machine learning algorithms can be used to automate tasks and make precise predictions. Predictive analytics, personalized learning, adaptive learning platforms, and educational data mining are just a few ways machine learning is used in education. Adjusting instruction to each student's needs makes spotting patterns in student learning easier and enhances academic results [59].

- **Natural Language Processing** Computers can now understand, interpret, and produce human language through an AI technique called NLP. It entails analyzing and processing textual data to make machines understand and produce language like humans. Applications for NLP include speech recognition, sentiment analysis, language translation, and text summarization. NLP in education can help with many tasks, such as language learning applications and the analysis of educational text resources [60].

- **Speech Recognition:** Speech recognition technology transforms spoken words into text. It uses algorithms and models trained on enormous amounts of audio data to recognize and transcribe spoken words accurately. Speech recognition has uses in education, particularly for voice-activated interfaces, accessibility, and language learning. This makes the development of voice-enabled learning tools, transcription of lectures and discussions, and voice-based interaction with educational applications possible. Speech recognition can make educational content more easily accessible to students with disabilities and offer practical ways to interact [58].

2.4 Generative AI

Generative AI, also known as GAI, is an innovative technology that has gained popularity for generating content within responses, surpassing the human-like interactions of Conversational AI [61]. GAI can produce fresh, original content independent of its explicit programming, unlike Conversational AI, which depends on programmed responses [62]. ChatGPT is an example of an enhanced AI model that combines conversational and generative AI to improve its capabilities [63] [64]. The following Sections will discuss Large Language Models (LLMs) and diffusion models with generative AI. These models are used to build generative AI models that generate new text, images, and media.

2.4.1 Large Language Models

LLMs have recently transformed the field of natural language processing by providing amazing capabilities for tasks like conversational AI, text generation, and language understanding [65].

Due to the versatility of Large language models in many different applications, especially the NLP tasks, they have gained interest in education [66]. They can enhance learning and teaching experiences for individuals at all educational levels, from primary to professional development. Having personalized and effective learning experiences is possible by implementing these models, as each person has distinct learning preferences, abilities, and needs. Therefore, LLMs can change how education is provided and improve student development. [61]

Researchers have used large language models to generate interactive educational materials like quizzes and flashcards to improve student engagement and learning [67]. In [64], GPT-3 was used as a pedagogical agent to encourage curiosity and improve questioning skills in children. According to their conclusions, LLMs not only have the potential to facilitate curiosity-stimulating learning but can also help improve curiosity expression.

According to [68], a recent study on conversational AI in language education, conversational AI can be applied during teaching in five main ways. Such as using large language models as a conversational partner, either written or oral, in task-oriented dialogues that offer language practice opportunities such as pronunciation [69], Supporting students with foreign language learning anxiety or is less willing to communicate [70]. In [71], the researchers discovered that a chatbot instructed by a mind map is more effective in supporting language learning by providing scaffolds than a traditional AI chatbot.

These developments of LLMs are largely due to the Transformer architecture, which included the self-attention mechanism and allowed models to detect complex relationships between input tokens [72]. The Transformer architecture, as shown in Figure 1, a neural network architecture described in the Google paper "Attention Is All You Need" [73], is fundamentally based on the self-attention mechanism.

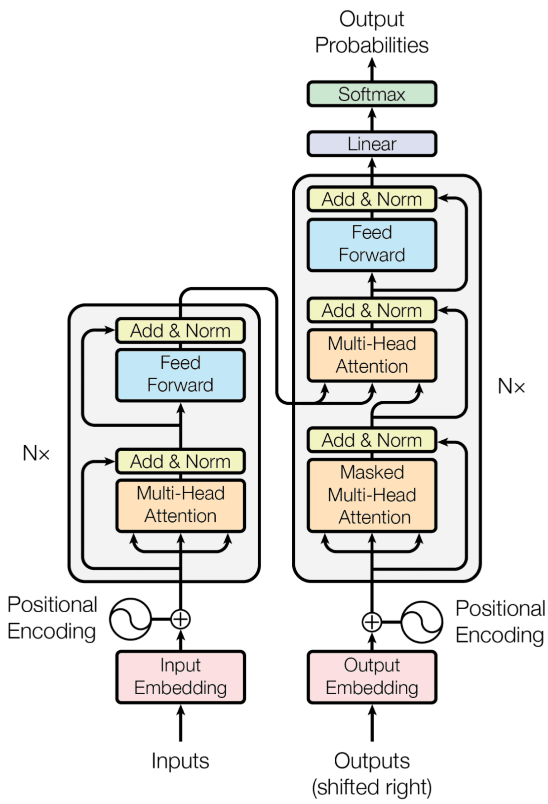


Figure 1: Transformer Architecture. (Source: Vaswani [73])

Since numerous LLM models are available, choosing the most effective model for a given task requires understanding each one's different self-attention mechanisms and overall performance. The self-attention mechanism allows LLMs to give tokens in the input sequence various attention scores, allowing the model to concentrate on important information and produce expressive representations. Regardless of the data type, this mechanism has proven effective at capturing intricate dependencies between tokens [74]. They can perform tasks without explicit training because of zero-shot and few-shot learning techniques.

1. **Zero-shot learning:** LLMs' capacity to carry out tasks or produce text in languages or fields outside their explicit training data is called zero-shot learning. For instance, if trained on a diverse dataset of texts in various languages, a language model can still produce coherent text in languages it has never encountered during training. It is accomplished by utilizing the model's knowledge of multilingual patterns and semantic relationships, which enables it to generalize to languages that have yet to be discovered [75][76].

2. **Few-shot learning:** Few-shot learning extends the capabilities of zero-shot learning. It enables the LLM to carry out tasks while being trained with fewer task-specific examples. For instance, it can modify its knowledge and produce text that complies with the task requirements if only a few examples or instructions are given for a particular task. Few-shot learning is beneficial when few labeled data are available for a particular task. The model can still learn to complete the task successfully without guidance [77][78].

The impressive generalization abilities of LLMs are highlighted by both zero-shot learning and few-shot learning, making them incredibly adaptable and capable of carrying out various language-related tasks across multiple languages and domains without requiring intensive task-specific training [79]. A downside to LLMs is the growing resource requirements needed to run or train them [80]. Models like GPT-3 [81] and Bloom [82] require powerful computer hardware, limiting their accessibility to large corporations. Open-source alternatives like OPT [83] aims to address this by providing a free, open GPT-3 alternative that can run on regular desktop computers.

Resources like the Open LLM Leaderboard [11] assess different LLM models to help with informed decision-making. These benchmarks enable users to contrast various models.Users must decide whether to use a commercial model, such as GPT-4 [84], or to create a unique model with a set of trainable parameters. Additional fine-tuning strategies, such as pre-training and targeted fine-tuning, must be considered to optimize the model for a specific task [85].

The parameter *"size"* in LLMs refers to the number of learnable parameters in the model. Larger models with more parameters can capture a wider range of knowledge and produce more contextually relevant responses, but they require more computational resources and may suffer from overfitting. The size of LLMs should be chosen based on task requirements, available resources, and the need for linguistic understanding and complexity. Balancing model size and efficiency is essential to optimize the performance of LLMs [86].

Below are some of the LLMs, and Table 1 shows a comparative overview of some selected models taken from [79].

1. **GPT LM:** Developed by OpenAI, GPT-4 is a fine-tuned implementation of the GPT-3 model. It excels in chatbot-style interactions, making it ideal for creating conversational interfaces and personalized user experiences [87]. Using Reinforcement Learning from Human Feedback (RLHF), the model has been trained to generate coherent and sophisticated language outputs [88]. GPT-4 can be used commercially, but its usage is subject to certain limitations and pricing. OpenAI offers limited free access for non-commercial use through their API [89].

2. **BLOOM:** BLOOM is a powerful autoregressive Large Language Model (LLM) trained on massive text data using powerful computational resources. Using its vast training corpus, it can generate

[11] https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard

coherent text in 46 languages and 13 programming languages. Its language generation is nearly indistinguishable from human writing and can also generate text without being explicitly trained. This feature allows BLOOM to adapt and perform various text-related tasks, demonstrating its versatility and broad applicability [90].

3. **StableLM:** StableLM is a new open-source language model suite released by Stability AI. It offers scalability and transparency and is currently available in an alpha version with 3 billion and 7 billion parameters. The model is designed for research use and can generate text and code. StableLM-alpha was trained on a diverse experimental dataset built on The Pile, ensuring robust performance [91]. However, it requires significant RAM and may not be suitable for platforms with limited resources like Google Colab's free version.

4. **LLaMA:** The LLaMA Model, developed by The FAIR team of Meta AI, is an auto-regressive language model based on the transformer architecture. It comes in various sizes, ranging from 7B to 65B. LLaMA is intended primarily for NLP, machine learning, and AI researchers. However, it is important to note that the model needs to be fine-tuned with human feedback, which may lead to generating toxic, offensive, or unhelpful content. It is licensed for non-commercial use only, and access requires permission with a link [92].

5. **Alpaca:** The Stanford Alpaca project offers an instruction-following language model that was fine-tuned on a dataset of 52K examples using Self-Instruct. The current Alpaca model is intended for research use only and may not be considered safe for commercial applications. The provided dataset contains instructions, input, and output fields, which can be used in various NLP tasks [93].

6. **Dolly:** Dolly is a commercial large language model created by Databricks. It is derived from EleutherAI's Pythia-12b and fine-tuned on a dataset of instruction/response records. Dolly is available on Hugging Face, making it accessible for various applications. However, it is worth noting that Dolly has certain limitations in syntactically complex prompts, programming problems, mathematical operations, and open-ended question answering [94].

Table 1: Comparative overview of different LLMs (Source: Baghdadlian [95])

Model	**Size**	**Dataset trained on**	**Released by**	**How to access**	**Type**
GPT-4	170T	Various, Including articles, books, websites	OpenAI	OpenAI API or WebUI	Commercial
BLOOM	1.065B	45 natural languages, 12 programming languages, In 1.5TB of preprocessed text, converted into 350B unique tokens	BigScience	Hugging Face	Research
StableLM	7B	The pile	Stability AI	Hugging Face	Research
LLaMa	65B	CCNet, C4,Wikipediam Books, GitHub, ArXiv, Stack Exchange	Meta AI	Application required	Research
Dolly	12B	15k instruction&response records generated by Databricks	Databricks	Hugging Face or Download locally	Commercial
Alpaca	30B	52K examples generated by self-instruct technique	Stanford Alpaca project	GitHub repository	Research

2.4.2 Diffusion models

Diffusion models are generative models that have recently gained attention, and they offer an alternative approach to generating images compared to traditional generative adversarial networks (GANs) [96]. GANs are used in diffusion models to produce high-quality samples that closely resemble real data. They are made of a generator network and a discriminator network. While the discriminator network tells the difference between real and fake samples, the generator network turns random noise into more realistic samples [97]. The generator tries to trick the discriminator through an adversarial training process, and the discriminator tries to classify the samples correctly. By capturing the underlying data distribution and generating samples with realistic patterns, textures, and structures, GANs are incorporated into diffusion models to enhance the quality of generated samples. It improves the generation capabilities of diffusion models by enabling the synthesis of realistic samples.

In diffusion models, the goal is to iteratively transform a noisy image into a target image by gradually reducing the noise. The process involves adding noise to the target image and training a network to predict the added noise at each step, allowing the noise to be removed and revealing the underlying image. The network can generate images that resemble the target distribution by iteratively applying this process, starting from a noisy image and gradually removing noise [98]. Compared to GANs, diffusion models offer certain advantages. They are generally more stable during training, allowing more control over the image generation process. However, they also require more iterations to generate high-quality images [99]. Several diffusion models have been proposed, including DALL-E and DALL-E 2 by OpenAI[12], the Stable Diffusion model by Google[13] and Midjourney[14]. Each model may have its unique characteristics and training techniques.

- **Midjourney:** Midjourney is a technique introduced by Google in the context of image generation. It focuses on generating intermediate images during the generation process, providing insights into the neural network's internal representations at different stages. By examining the changes in the image features as the model progresses, researchers can better understand how the network learns and transforms images over time. Midjourney offers valuable interpretability and visualization capabilities, enabling users to observe the evolving image representations during generation [100].

- **Stable Diffusion:** Stable Diffusion is a method based on diffusion models, where the image generation process is broken down into multiple iterative steps. It aims to gradually remove noise from a noisy image to reveal the underlying structure and generate high-quality images. The model can approximate the original image by predicting and subtracting the noise added at each step. Stable Diffusion offers stability during training, mitigating issues like mode collapse often encountered in traditional GANs [101].

[12] https://openai.com/product/dall-e-2
[13] https://stability.ai/stable-diffusion
[14] https://www.midjourney.com/

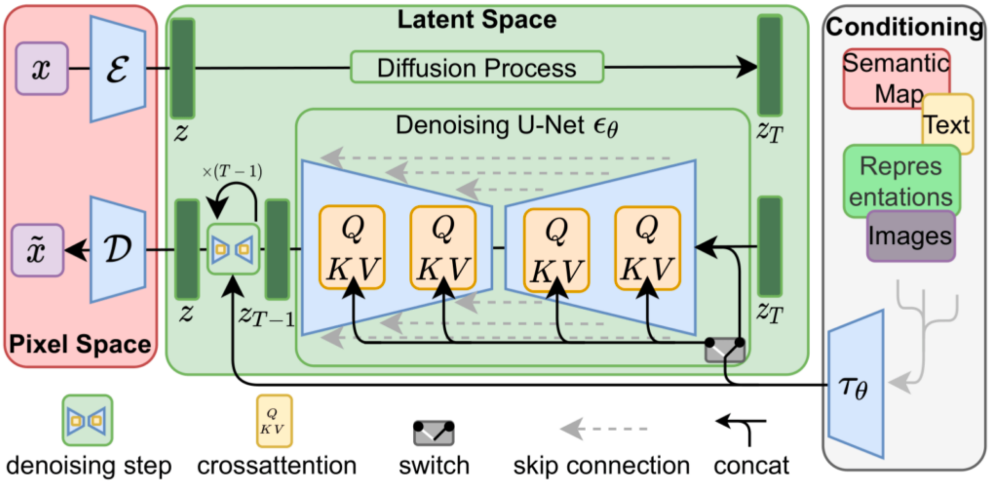
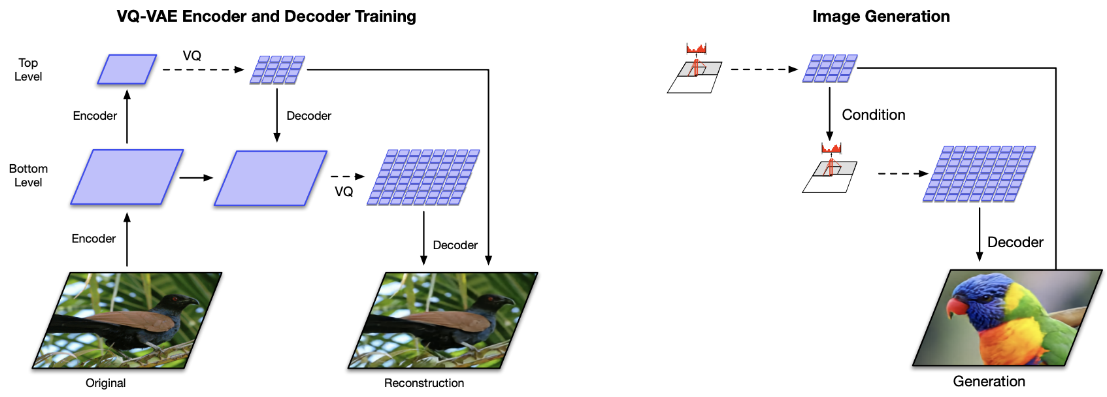


Figure 2: Stable Diffusion Architecture Explained in the article [102]

The Stable Diffusion architecture, as shown in Figure 2, consists of three main components: an autoencoder, a U-Net block, and a text encoder. The autoencoder reduces the input sample to a lower-dimensional latent space using the Variational Autoencoder (VAE) architecture (Figure 3. The U-Net block, based on ResNet, further compresses the sample and then decodes it with less noise, generating an estimated denoised representation. The text encoder processes the text by converting the prompt into an embedding space using a frozen CLIP ViT-L/14 Text Encoder. These components work together to reduce noise, denoise samples, and process text in the Stable Diffusion model [102].

- **DALL-E:** DALL-E, also developed by OpenAI, is an image generation model that combines a VQ-VAE-2 [15] encoder-decoder architecture and a transformer-based generative model. The VQ-VAE-2 encoder-decoder architecture learns data representations for image generation and compression [103]. An encoder quantizes high-level image features into discrete codebook entries. The decoder upsamples the quantized features to reconstruct the image. Vector quantization discretizes continuous-valued features, and a codebook and commitment loss improve training stability and meaningful representations. VQ-VAE-2 can learn discrete representations for image generation and manipulation [104]. It generates highly creative and novel images by conditioning the model on text prompts. DALL-E can generate images based on textual descriptions, allowing users to specify the desired attributes, objects, or concepts they want to see in the image. This approach combines natural language understanding with image generation, creating unique and specific visual outputs [105].

[15](Vector Quantized Variational Autoencoder 2)



(a) Overview of the architecture of our hierarchical VQ-VAE. The encoders and decoders consist of deep neural networks. The input to the model is a 256×256 image that is compressed to quantized latent maps of size 64×64 and 32×32 for the *bottom* and *top* levels, respectively. The decoder reconstructs the image from the two latent maps.

(b) Multi-stage image generation. The top-level PixelCNN prior is conditioned on the class label, the bottom level PixelCNN is conditioned on the class label as well as the first level code. Thanks to the feed-forward decoder, the mapping between latents to pixels is fast. (The example image with a parrot is generated with this model).

Figure 3: VQ-VAE-2 Explained in the article [105]

Table 2 compares the described models for generating images. The comparison was based on various factors and parameters mentioned in the documentation and articles of each model.

Table 2: Comparison of different models for image generating

Factor	**DALL-E**	**Stable Diffusion**	**Midjourney**
Image Generation Quality	High	High	High
Text Generation	Yes	No	Yes
Diversity	Limited	High	High
Flexibility and Control	Limited	Limited	High
Sample Efficiency	High	Medium	Medium
Computational Requirements	High	Low	Low
Model Size	Large	Small	Small
Realism	Yes	Yes	Yes

2.5 Text Summarization with NLP tools

Natural language processing text summarization is a method for automatically generating a brief and coherent summary of a longer text document. It is a useful tool to extract the most important details from a document while maintaining the main points and important information [106]. There are two main methods for summarizing text:

1. **Extractive Summarization:** In this method, the most important sentences or phrases are combined from the original text to create the summary. It entails selecting the most pertinent sentences based on various factors, including word frequency, sentence position, and importance of sentences [107] [108].
2. **Abstractive Summarization:** A summary contains words, phrases, and sentences absent from the original text. Natural language generation (NLG) [109], an advanced NLP technique, is used in abstractive summarization to comprehend the context of the text and produce a summary that captures the key ideas while still being readable [110] [111].

NLP frameworks and libraries like Natural Language Toolkit (NLTK)[16], Gensim[17], spaCy[18], TextBlob[19] and others can be used to implement these techniques. These libraries offer models and tools to help with sentence tokenization, text preprocessing, scoring, and summary generation. The steps involved in text simplification can vary depending on the approach and the specific library or technique used [112][113] [114]. However, in general, the following steps are commonly involved in text simplification:

1. **Tokenization:** Break the text into individual words, phrases, or sentences, depending on the granularity required for simplification.
2. **Lemmatization/Stemming:** Reduce each word to its base form (lemma) or root form (stem) to normalize the text and remove inflections.
3. **Stop Word Removal:** Eliminate common words (stop words) that do not convey significant meaning or contribute to understanding the text.
4. **Sentence Simplification:** Simplify the structure and complexity of sentences by removing or replacing complex phrases, clauses, or constructions with simpler alternatives.
5. **Word Substitution:** Replace complex or domain-specific words with simpler synonyms or more common vocabulary to enhance readability.
6. **Sentence Fusion/Splitting:** Merge or split sentences to create shorter, clearer, and more concise sentences.
7. **Grammatical Simplification:** Modify the grammar and syntax of the text to adhere to simpler sentence structures, such as using simple tenses, active voice, and shorter sentence lengths.
8. **Rephrasing/Paraphrasing:** Restate or rewrite complex or convoluted sentences using simpler language and clearer expressions.

[16] https://www.nltk.org/
[17] https://github.com/RaRe-Technologies/gensim
[18] https://spacy.io/
[19] https://textblob.readthedocs.io/en/dev/

Table 3 compares four well-known NLP libraries, highlighting the features and capabilities for NLP tasks. The selected features for this comparison were chosen based on key factors such as library features, ease of use, performance, and multilingual capabilities. The evaluation of each library is based on its specific features and characteristics [115]. The selection of features for this comparison was informed by several articles, namely [116], [117], and [118]. These articles likely provided insights into the strengths and capabilities of the NLP libraries, enabling a comprehensive comparison of their key features.

Table 3: Comparison of NLP Libraries

Library	**Key Features**	**Ease of Use**	**Performance**	**Multilingual**
Spacy	Efficient tokenization and POS tagging	Moderate	High	Yes
NLTK	Comprehensive NLP toolkit	Easy	Moderate	No
Gensim	Topic modeling and document similarity	Easy	Moderate	No
TextBlob	Simplified API for common NLP tasks	Easy	Moderate	No

Based on Table 3, Spacy is renowned for its effective tokenization and part-of-speech tagging, making it suitable for various NLP tasks. It produces high performance and has a moderate learning curve. Also, NLTK is a complete NLP toolkit that provides a variety of functionalities. For beginners, it is particularly simple to use and offers mediocre performance. Topic modeling and document similarity analysis are the main focuses of Gensim. It has a user-friendly interface and gives a mediocre performance. For typical NLP tasks, TextBlob offers a condensed API. It is simple to use and suitable for users of all skill levels. The "Ease of Use" and "Performance" ratings are subjective and may vary depending on individual experiences and specific use cases. It is recommended that libraries be evaluated based on the project's specific requirements and preferences.

2.6 Machine Translation

Machine translation (MT) relies on algorithms to rapidly and effectively translate large volumes of text. Although machine learning and neural networks have enhanced their capabilities, it is not yet a complete substitute for human translators [119]. The limitations of MT include challenges in accurately handling complex or nuanced texts, difficulties with idiomatic expressions and cultural nuances, and struggles with domain-specific terminology. To ensure precise and culturally appropriate translations, a combination of MT technology and human translators is often the most effective approach [120]. Table 4 compare Python translation libraries, outlining their respective advantages and disadvantages; this table was created based on the documentation of each library.

Table 4: *Comparison of Python translation libraries*

Library	Pros	Cons
Translators [121] [122]	- Actively supported - Stable with few open issues - Supports multiple translation APIs - Can translate HTML	- Limited customization options - No language detection option - Response lacks additional information
Deep-translator [123] [124]	- Supports multiple translation APIs - Allows translations from text files - Can be used directly from a terminal	- Language detection requires private API key - Decreased community activity
Googletrans [125] [126]	- No configuration or authentication needed - Text language detection feature - Returned data includes additional info	- Not actively maintained - Unresolved issues and reliance on release candidate - Certain additional data may not be available
DeepL [127] [128]	- High-quality translations - Supports translation of longer texts - Neural network-based translation	- Limited official Python library support - Limited customization options

Table 4 evaluates Python translation libraries. "Translators" is well-supported and versatile but lacks customization and language detection. "Deep translator" supports multiple APIs, but language detection requires a private key. "Googletrans" is simple but unmaintained. "DeepL" has limited Python support but high-quality translations. This summary helps with choosing the right library for the case study of the thesis.

3 Systematic Literature Review (SLR)

3.1 Methodology

The PRISMA model [129] and an SLR guided this study, specifically the SLR methodology by Kitchenham [130]. Kitchenham and Charters [131], providing a well-established methodology for evaluating and interpreting primary research and the mapping study guidelines by Petersen's [132] to conduct a thorough analysis of AI technologies in educational domains with a focus on enhancing user experience and human-computer interaction. Using these approaches, relevant papers are synthesized and selected from specific criteria relevant to the research area, resulting in a comprehensive and focused literature review. The purpose is to provide a comprehensive overview of the different Artificial Intelligent technologies used in various educational domains for better human-computer interaction. The protocol used for the SLR is described in this Section, giving all the details required to follow the findings. ***Planning***, ***Conducting***, and ***Reporting the study*** are the three main phases of the SLR. The following sections will further discuss the phases, giving readers a thorough understanding of the review procedure.

3.2 Review Planning

Important steps are taken to establish the foundation for the review during the review planning phase of an SLR. First and foremost, it involves creating specific research questions that will direct the review procedure. These questions aid in defining the review's objectives and the scope of the study. The review protocol is then described, including the methodology and strategy to be used. This protocol outlines the search strategy, standards for including and excluding studies, data extraction techniques, and other essential steps. It is a comprehensive guide to guarantee the review is carried out consistently and methodically. Documenting important details like the sources consulted, databases searched, and keywords used is also a part of the review planning phase. This documentation improves the review process's traceability and transparency and makes it easier for other researchers to replicate and confirm the findings. By outlining the review protocol, defining the research questions, and recording important details, the review planning phase sets the groundwork for a structured and rigorous SLR.

3.2.1 Research Questions

Given the research objective of providing a comprehensive overview of the various AI technologies used in educational technology for creating a user-friendly tool, The answers to these research questions provide essential information about AI's application, assessment, effects, and future potential in education, particularly in enhancing the user experience. A literature mapping was done in addition to providing an analysis of the research domain and a comprehensive understanding of the research field. Here are the mapping questions (MQs) related to the search:

MQ1 How is the publication distribution of AI in education research studies over the few years?

MQ2 What type of papers have been published?

MQ3 In which domains and education levels are the distribution of research papers on AI in education being used?

The research questions (RQs) for this study are:

RQ1 How is AI being used to improve the quality of human-computer interaction in education?

RQ2 What are the impacts on students and teachers regarding user experience when implementing AI in education?

RQ3 What are the future outlooks for using AI tools to enhance the user experience of students and teachers in educational technology?

An understanding of the research setting for AI in education can be gained by responding to these questions. We can understand the development and growth of this field and find significant contributors by analyzing the publication distribution over time and across various venues and the geographic distribution of research papers. Identifying areas of focus and potential impact also involves looking at the domains and educational levels where AI in education research is applied. In addition, investigating how various AI strategies contribute to enhancing educational experiences provides insightful information for enhancing teaching and learning procedures. The information in these responses offers a thorough understanding of the state of AI in education today, directing further study and development in this area.

The PICOC method suggested by Petticrew and Roberts [132] defined the research questions in studying various AI technologies in education to improve the user experience shown in Table 5.

Table 5: PICOC framework

(P) Population	Software or platforms for education that use AI
(I) Intervention	Improving user experience in education through the use of AI technologies
(C) Comparison	The primary focus of this study is to analyze and examine the existing approaches and technologies rather than compare them directly.
(O) Outcomes	Improve user experience, personalized learning, engagement, satisfaction, etc., by developing AI-based tools
(C) Context	Educational settings and environments where AI technologies are employed for educational purposes, including various levels.

The inclusions and exclusion criteria are explained in the following Subsection (3.2.2).

3.2.2 Inclusion and exclusion criteria

A critical part of the SLR methodology is making the inclusion criteria (IC) and exclusion criteria (EC) because they help ensure that the selected primary studies are relevant and high-quality. They define the characteristics of studies to be included and excluded in the systematic literature review and help minimize bias and increase the review process's reliability.

The ICs are used for this research to represent that for selecting the articles, only the studies published in English between 2019 and 2022 have been chosen to guarantee that the review is based on recent research. The exclusion criteria are derived from the IC as they are the opposite. Also, the studies must be full-text available, peer-reviewed journal articles, book chapters, or conference proceedings indexed in Scopus or Web of Science. The topics of the studies must be relevant to the integration of AI in education and learning, as well as user experience and human-computer interaction in education, excluding those that are not related to the use of AI tools in education or that do not explain the user experience and human-computer interaction in education. Creating the topic's relevance guarantees that the review is focused and comprehensive, explicitly concentrating on the use of AI in the educational domain.

- **IC1** Studies published in English
- **IC2** Studies published between 2019 and 2022
- **IC3** Peer-reviewed journal articles, book chapters, and conference proceedings
- **IC4** The full text is available
- **IC5** The study must use AI-based technologies
- **IC6** The study must include in Education and Learning
- **IC7** The study must include in User-experience and Human-computer interaction in education

The following details the criteria used for exclusion:

- **EC1** Studies published in languages other than English
- **EC2** Studies published before 2019 or after 2022

- **EC3** Not primary research (e.g., review)
- **EC4** The full text is not available
- **EC5** Not mentioning user-interface but about Implementing AI-embedded technologies
- **EC6** Not related to education and learning
- **EC7** Not explaining the User-experience and Human-computer interaction in education

3.2.3 Data Sources

Finding the key databases compatible with the research context is essential for getting relevant search results. Based on the reasons below, *Scopus* and *Web of Science (WoS)* were chosen.

- It is a wide reference database in research scope, making it valuable and reliable
- It offers flexible search capabilities, including using similar search strings as other selected databases and enhanced search results through Boolean operators.
- It is relevant to the research context of this study and includes many academic publications related to topic.

3.2.4 Query Strings

Table 6 and Table 5 were used to build each selected source's search strings which are shown in Table 7. Boolean operators (AND/OR) were used to connect these terms, and the wildcard (*) accounted for both the singular and plural forms of each term. This study focused on human-computer interactions in integrating AI into education. These search techniques ensured that the returned works were specifically pertinent to the area of interest and offered information on how AI is being used in educational settings to enhance human-computer interactions.

Table 6: Search strings in each topic

Topic	**Search Terms**
Education	education* OR "AIED"
AND	
Artificial Intelligence	"artificial intelligence" OR "AI"
AND	
User Experience	"user experience" OR "user-experience" OR "Human-computer interaction" OR "User-centered design"
AND	
Learning	learn* OR student* OR teach*

Table 7: Search Query used for each database

Database	Search query
Scopus	TITLE-ABS-KEY ((education* OR "AIED") AND ("artificial intelligence" OR "AI") AND ("user experience" OR "user-experience" OR "Human-computer interaction" OR "User-centered design") AND (learn* OR student* OR teach*)) AND PUBYEAR > 2018 AND PUBYEAR < 2023
Web of Science	ts=((education* OR "AIED") AND ("artificial intelligence" OR "AI") AND ("user experience" OR "user-experience" OR "Human-computer interaction" OR "User-centered design") AND (learn* OR student* OR teach*))

3.2.5 Quality Criteria

Inclusion and exclusion criteria ensure appropriate articles are included in a review, but they do not evaluate the quality of retrieved papers based on their responses to research questions. A new set of criteria has been created to assess the quality of papers before including them in the final literature review. Four different criteria are included in the quality assessment, with the first three graded on a scale of 0 to 3 and the fourth from 0 to 1. Only papers with scores in the top quartile (25% of the possible total score) are considered for further review. These standards assess papers' accuracy and relevance in responding to research questions, enabling a thorough evaluation for inclusion in the final literature review.

QC1 The research goals of the work are focused on addressing the integration of AI tools to improve user experience. (0-3 Points)

QC2 The paper specifically focuses on the impact on student and teacher user experience, and the recommended solution has been tested with actual users. (0-3 Points)

QC3 The outcomes and challenges with the suggested approach are stated. (0-3 Points)

QC4 Educational domains or levels were mentioned. (0-1 Points)

3.3 Review Process

The data-gathering process for conducting this SLR has been structured into three phases that involve various activities. The PRISMA flow diagram in Figure 4 outlined the actions executed during the data extraction. Also, it shows that there were no additional records added.

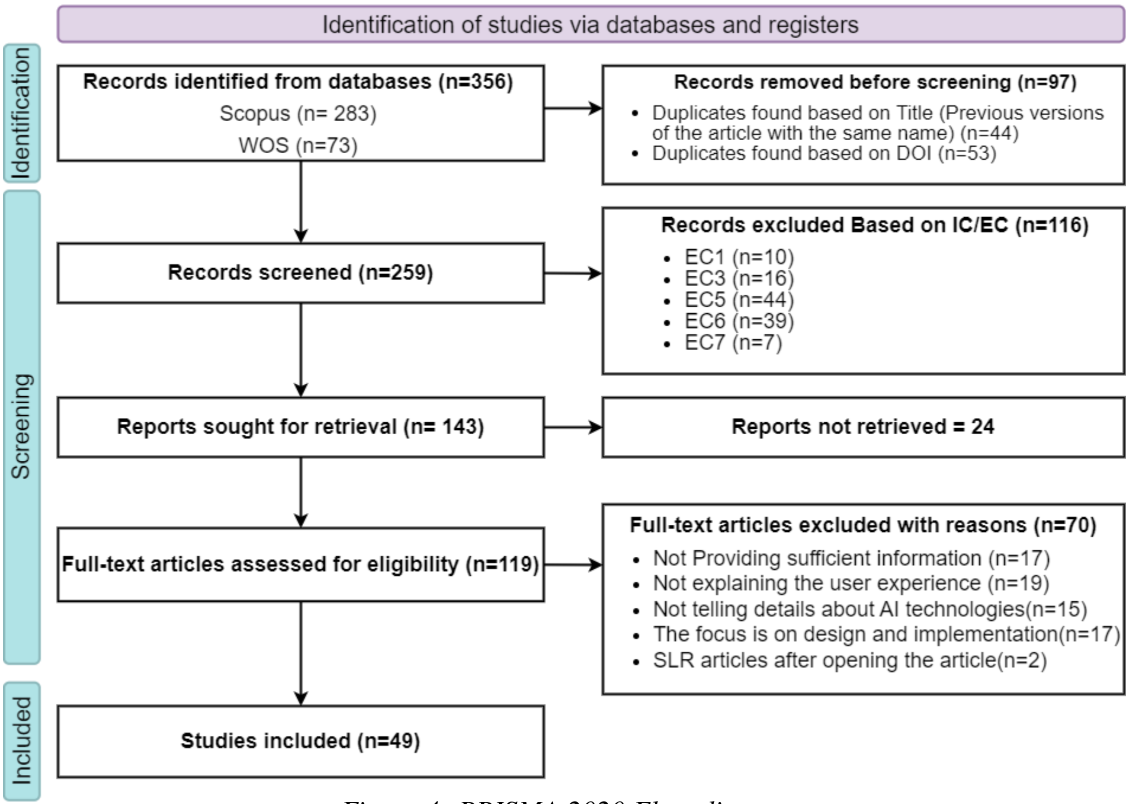


Figure 4: PRISMA 2020 Flow diagram

Phase 1: Identification - Based on the query, 356 records were gathered from the chosen databases. In particular, 283 records were taken from Scopus, and 73 were collected from WOS.

Phase 2: Screening - The collected records were added to the inclusion and exclusion criteria during the screening phase. Out of all the records, 97 duplicates were found and removed because. They appeared in both databases. 53 records were found to be identical in both databases of these duplicates, while 44 records had earlier versions in both databases. 259 records were left after duplicates were eliminated for further analysis. 116 records were removed from this set because they did not fit the proposed inclusion/exclusion criteria. As a result, 143 reports were accepted for further evaluation.

The full-text articles of the chosen studies were thoroughly investigated and scored for quality during the eligibility phase. 24 of the reports, however, were not accessible, leaving 119 articles available for additional review. 70 articles were excluded from the quality assessment as they failed to satisfy the proposed quality criteria in 3.2.5. Five specific reasons why these articles did not meet the criteria were explained in Figure 4.

Phase 3: Included - 49 articles were chosen after the review process was complete because they all met the requirements for inclusion and quality. These articles will be examined in greater detail and used in the study.

The following section involves conducting an SLR and analyzing the selected studies. The main goal is to answer the proposed research questions and quantitative analysis to reveal practical understandings and contribute more profound information about integrating AI into education.

3.4 Results of the SLR

This section aims to create a structured form for gathering relevant and significant information from the chosen primary studies to address the research questions outlined in Section 3.3. The collected data have descriptive information, approach-related information, quality-related information, the use of AI in Education, and its impact on Human-computer interaction. These categories were defined based on Section 3.1 to ensure consistency.

This section provides a detailed analysis of the 49 selected primary studies to answer the questions made for doing this SLR. Section 3.4.1 will answer the mapping questions in Section 3.2.1, while Section 3.4.2 will explain the results in answer to the research questions. Table 8 shows the data extraction form, which will be used to study all 49 selected primary studies in descending order of their title with the IDs and scores, and the Excel file is uploaded in Google Drive (`https://bit.ly/dataset-mapping`).

Table 8: Data Extraction form

Article	Score
P6 [133], P7 [134] , P9 [135] , P10 [136] , P12 [137] , P13 [138], P15 [139], P21 [140], P24 [141], P28 [142],P36 [143],P37 [144],P39 [145]	10
P8 [146], P27 [147]	9.5
P4 [148],P19 [149],P23 [150],P29 [151],P31 [152],P43 [153],P48 [154],P49 [155]	9
P3 [156],P5 [157],P16 [158],P34 [159]	8.5
P1 [160], P18 [161], P20 [162], P22 [163], P26 [164], P42 [165]	8
P2 [163], P11 [166], P14 [167], P17 [168], P25 [169], P30 [170], P32 [171], P33 [172], P35 [173], P38 [174], P40 [175], P41 [176], P44 [177], P45 [178], P46 [179], P47 [180]	7.5

3.4.1 Results of Mapping Questions

MQ1: Publication distribution of AI in education research studies over the years

As shown in Figure 5, which presents the interest in integrating AI technologies in education from 2019 to 2022, particularly in 2022, a noticeable trend appears, and 16 studies have been published. Out of the 49 studies, 20.4% (ten studies) were published in 2019, and also 2020 exhibits a similar production; 26.5% (13) of the studies in 2021, and 32.7% (16) of the studies in 2022 were published.AI in education is a complicated and quickly changing topic that researchers actively look into and contribute to. The results show that putting AI into education is becoming more popular and is still being looked into. As research continues, more improvements are likely to be made, making using AI to improve education easier.

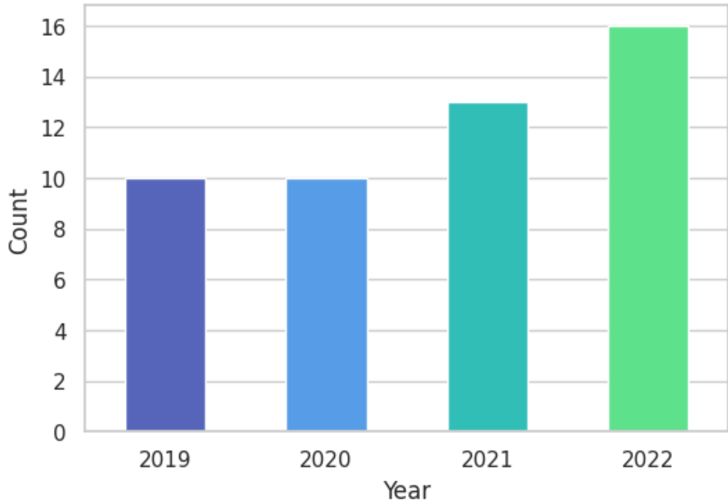


Figure 5: Distribution of publications per year

MQ2: Type of published papers

The complete list of paper types extracted from the records is shown in Table 9. Only papers that have gone through peer review in journals, conferences, or book chapters are considered after the inclusion and exclusion criteria have been applied.

Table 9: Papers grouped by the publication type

Type	Total	Papers
Article	12	P33, P25, P44, P16 ,P14, P18, P34, P23, P22, P35, P41, P45
Conference paper	37	P20, P27, P30, P32, P10, P36, P02, P04, P06, P09, P13, P24, P28, P29, P31, P37, P38, P42, P08, P40, P03,P21, P01, P11, P17, P43, P47, P15, P19, P46, P48, P49, P07, P05, P12, P26, P39

MQ3: Educational domains and levels mentioned in the articles

Table 10 details the effects of artificial intelligence in education across different domains and levels of education.

Table 10: Different Educational Domains and Levels where AI was used

Domain	Level	Articles
Academic Management	Higher Education	(P31)
	Secondary Education	(P35)
	Various Levels	(P37,P43)
Art Education	Higher Education	(P16, P19,P26)
E-Learning	Higher Education	(P22, P34, P36)
	Maritime Education	(P40)
	Various Levels	(P10)
General Education	K-12	(P2, P46)
Language Learning	Higher Education	(P6, P8, P13, P23, P32)
	Various Levels	(P9, P33, P48)
Legal Education	Higher Education	(P44)
Medical Education	Higher Education	(P24, P38, P42)
Personalized Learning Environment	Higher Education	(P5, P17)
	Preschool Education	(P29)
	Various Levels	(P4)
Physical Education	Primary Education	(P18, P27)
	Various Levels	(P21, P25)
Pilot Training	Aviation Industry	(P11)
STEM	Higher Education	(P3, P7, P12, P28, P30, P45, P47)
	Preschool Education	(P41)
	Various Levels	(P01)
Various Domains	Higher Education	(P39)
	Secondary Education	(P20)
	Various Levels	(P15, P49)

The key observations from Table 10 are:

- AI is used across various areas and educational levels, demonstrating its versatility.
- It is mentioned in domains like Academic Management, Art Education, E-Learning, Language Learning, Medical Education, and more.
- AI impacts K–12 education, focusing on STEM, academic management, various domains, and General Education and Physical Education.
- AI is now being used in several other fields, including pilot training, legal education, maritime education, and personalized learning environments.
- STEM education demonstrates significant AI use in higher education.
- With a total of 8 mentions in Table 10, AI has significantly impacted language learning, both in higher education and at different levels.

Figure 6 provides insights into applying AI technologies in different domains, showing AI's potential to affect different educational scopes. STEM[20] emerges as the predominant area, with 18.4% (9 papers) of the articles focusing on AI in education in STEM learning, which reflects the significance of integrating AI tools to enhance STEM education, a crucial component of the overall education system.

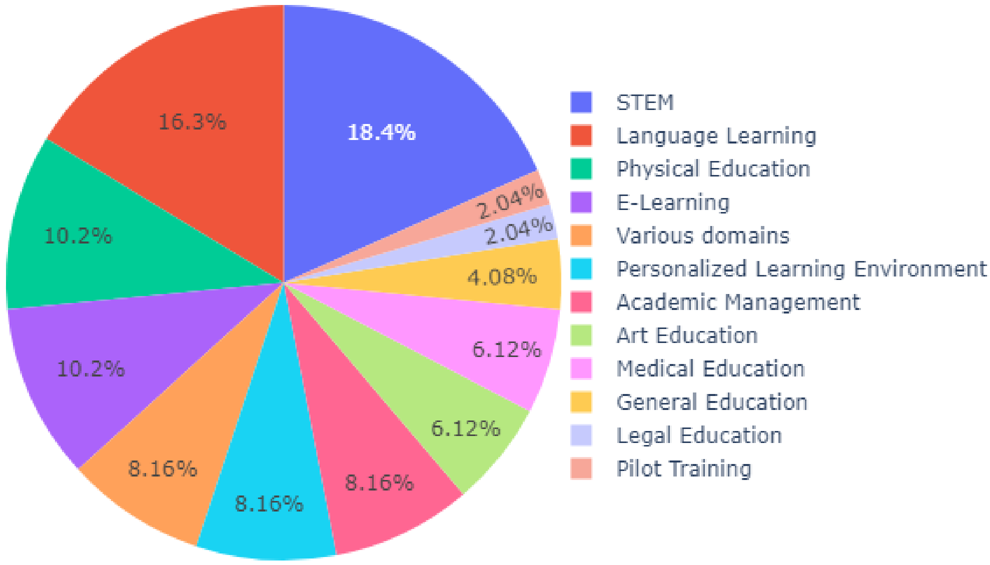


Figure 6: Distribution of AI tools used in different educational domains

Language learning is another major domain, accounting for 16.3%(8 papers) of the articles. AI-based language learning platforms offer interactive and immersive experiences for learners, making it an intriguing area of research. Language learning has consistently attracted attention over the years, highlighting its enduring significance and ongoing exploration. Additionally, e-Learning and physical education each comprise 10.2% of the articles, demonstrating the impact of AI on providing flexible and accessible learning opportunities for students of all ages and backgrounds. Furthermore, Personalized Learning environment and academic management emerge as another interesting area, representing 8.16% of this study's articles per scope. Using AI in these scopes offers potential benefits in streamlining administrative processes and enhancing educational institutions' overall effectiveness. They help students explore difficult concepts, analyze data, simulate real-world scenarios, and expand their problem-solving skills, critical thinking, and creativity.

Figure 7 shows the application of AI across different educational levels. Most articles (55.1%, 27 papers) focus on implementing AI tools to assist instructors and learners in higher education. However, it is important to note that AI in education is not limited to higher education alone. It can be used in all educational levels, including K-12, as evidenced by the presence of 8 papers related to K-12 education. Regardless of the specific educational level, AI technologies offer advantages in educational settings, improving teaching and learning processes.

[20]Science, Technology, Engineering, and Mathematics

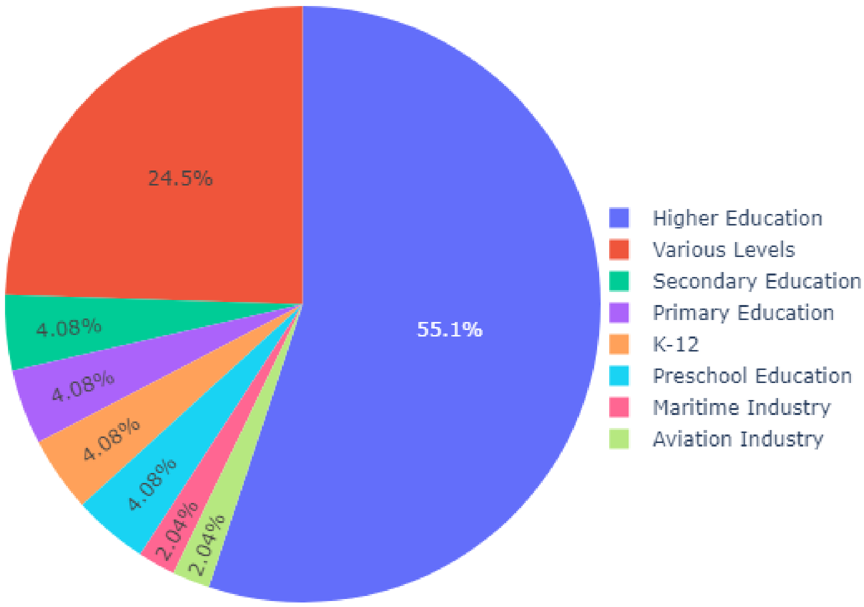


Figure 7: Distribution of AI tools used in different educational levels

3.4.2 Results of Research Questions

RQ1: How is AI used to improve human-computer interaction in education?

An overview of the AI technologies used in education research over the previous four years is shown in Figure 8. The growth of the trends each year shows the importance and necessity of research and the steady development of AI technologies and tools. It shows that researchers are investigating new AI tools to improve the quality and performance of education and will continue to shape the tendencies in the future. The use of Deep Learning and Machine Learning techniques has significantly increased as a current trend in AI in education. The increasing number of papers on these approaches shows their importance and positive effects on education. Particularly, in 2021, Machine Learning gained a lot of interest, highlighting its growing importance.

NLP is another important field of interest, which continues to see an increase in papers each year, indicating its continued relevance and research potential. Researchers are constantly attracted to AI techniques like Computer Vision, Speech Recognition, Augmented Reality & Virtual Reality because of their valuable contributions.

Every year, interest in Intelligent Assessment, an AI tool designed to improve evaluation processes, has grown. Its growth will likely continue developing and growing over the next few years, supporting current educational assessment methods. Since 2021, interest in conversational AI (such as chatbots), which allows content creation and user engagement, has increased. This upward trend shows growth and broad use in the future. In 2021, the relatively new field of affective computing attracted a lot of attention and saw many publications focused on it, meaning its growing importance and the potential for further research.

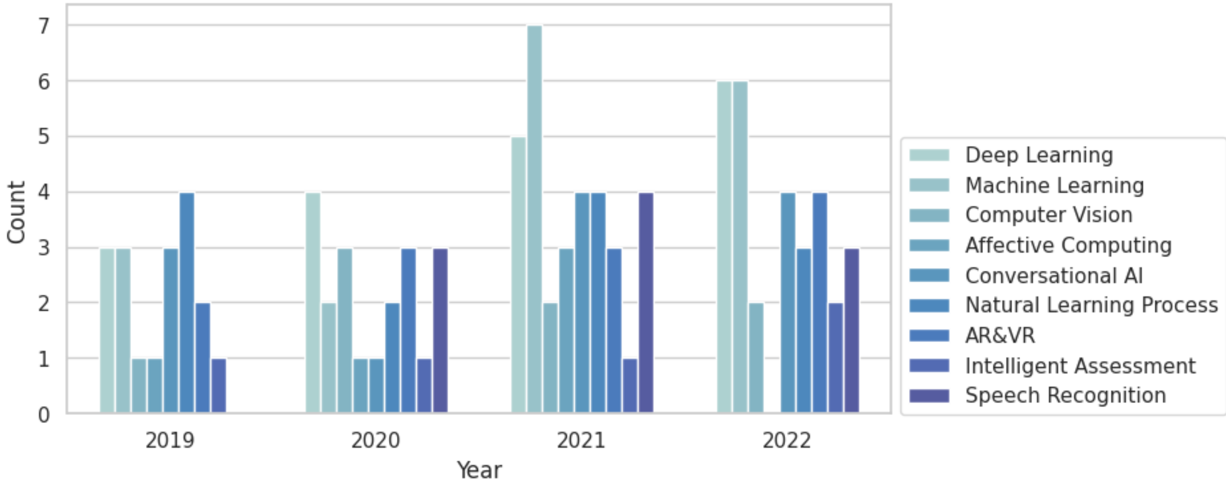


Figure 8: Number of different AI Technologies in each study per year

Table 11 details the trends and research on various AI applications in education. It highlights areas that have drawn more attention and those that may need additional research. Research papers in these fields highlight the significance of incorporating AI tools in education to improve evaluation processes, personalized learning experiences and support effective and efficient communication between users and technology.

Table 11: Paper (IDs) published in each year across different AI Technologies

AI technologies	2022	2021	2020	2019
Affective Computing		(P06, P17, P37)	(P02)	(P04)
AR&VR	(P23, P40, P41, P45)	(P06, P09, P29)	(P21, P28, P42)	(P03, P46)
Computer Vision	(P14, P38)	(P27, P37)	(P12, P21, P28)	(P46)
Conversational AI	(P05, P16, P22, P36)	(P09, P26, P43, P47)	(P02)	(P08, P32, P39
Deep Learning	(P18, P33, P35, P38, P49, P45)	(P10, P26, P27, P37, P44)	(P01, P12, P30, P31)	(P08, P15, P48)
Intelligent Assessment	(P05, P13)	(P06)	(P20)	(P08)
Machine Learning	(P14, P16, P22, P34, P35, P36)	(P06, P10, P11, P17, P44, P47, P49)	(P20, P30)	(P19, P24, P46)
NLP	(F05, F36, F38)	(P10, P17, P47,P49)	(P12, P20)	(P08, P24, P32, P39)
Speech Recognition	(P13, P25, P38)	(P01, P07, P12)	(P01, P07, P12)	

Based on Tabe 11, some observations and key points are:

- The presence of research papers for each AI technology across several years, from 2019 to 2022, is shown in the Table, indicating a persistent interest in and research focus on these AI technologies in education.
- Some AI technologies, like AR&VR, computer vision, and NLP, seem to have a consistent presence over

several years, with research papers published each year suggesting sustained research interest and ongoing developments in these areas.

- Over time, more research papers have been published on specific AI technologies, such as Deep Learning and Conversational AI. It demonstrates the growing understanding and investigation of the capability of these technologies to improve educational user experiences.

- The research activity surrounding different AI technologies shows varying trends over time. Intelligent Assessment has experienced a decline in publications since 2020, while Machine Learning has maintained a consistent presence. In 2022, no research papers explicitly focused on Affective Computing were found, indicating a need for further exploration in recent years. However, there has been a growing interest in this area, with three papers in 2021, one paper in 2020, and one paper in 2019 highlighting the potential for future research.

RQ2: The impacts of AI in education on students and teachers

The use of AI in education has significantly impacted the user experience for teachers and students. Table 12 highlights important findings about the impact of AI technologies in education from the user-experience part. AI tools have provided teachers with valuable administrative and management support, as discussed in 20.4% (10 of the papers). They facilitate the creation of personalized educational programs and help to streamline administrative tasks and resource allocation. Teachers can concentrate more on providing high-quality instruction and interacting with others by reducing administrative work.

The number of research papers focusing on how AI can improve teachers' understanding and support of students, as seen in 34.7% of the papers (17 of the papers), highlights the importance of further research in this area to explore how AI tools can help teachers gain insights into students' needs, emotions, and progress. Researchers can learn more about this subject and create innovative approaches by getting more deeply, which will help improve educational practices through effective AI integration. Furthermore, as mentioned in 14.3% of the articles (7 of the papers), AI tools offer suitable tools for evaluation and feedback, enabling teachers to give students helpful feedback and support their growth. It was mentioned in 22.45% of the articles (11 of thepapers) that AI tools could improve teachers' ability to engage and inspire students and offer technical support and design teaching methods.

The significant interest in studying how AI can improve the user experience is shown by 36.7% of the papers (18 of the papers) focusing on the impact of AI in education and by 30.6% of the papers (16 of the papers) devoted to personalized learning and knowledge acquisition. It reveals a developing trend in research by highlighting the significance of looking into and creating AI-based solutions that are personalized for students' individual requirements, ultimately improving their learning experiences and outcomes [P1, P10, P16, P26]. Additionally, 32.6% (16 of the papers) of the publications support immersive, interactive learning environments using computer vision, virtual reality, and augmented reality. With the help of these technologies, education becomes more enjoyable, interactive, and engaging for students, encouraging greater participation and memory retention.

By adapting resources and content to user needs and preferences, AI also supports personalized learning experiences. Enabling self-regulated learning [P20, P43], which gives students more control over their learning process and pace, has an additional effect on students. Additionally, AI tools provide real-time feedback and guidance, supporting students instantly and fostering their academic success [P21, P25, P27, P30, P33, P34, P39]. AI systems considering students' needs and emotional factors can enhance psychological well-being. AI helps students feel good and motivated by fostering a welcoming and inclusive learning environment [P8, P15, P40, P43].

Table 12: Impacts of using AI in education on teachers and students

Persona	Impacts	Articles
Teachers	**Administrative and Management**	
	- *Comprehensive management tool*	(P16, P43)
	- *Optimization of resource allocation and individualized learning programs*	(P4, P30, P36)
	- *Reduced workload for instructors*	(P39, P49)
	- *Teaching Quality Improvement*	(P31, P34, P48)
	Effective evaluation and feedback for learning outcomes	(P6, P8, P13, P15, P29, P34, P39)
	Interactive and Immersive Learning Environment	(P9, P10, P11)
	Teacher Engagement and Motivation	
	- *Enhancing teachers' ability to engage and motivate students*	(P9, P15, P20, P7, P12, P22, P28)
	- *Providing technical support and strategy design for teaching*	(P13, P30, P31, P49)
	Understanding and Support for Students	
	- *Enhanced understanding of students' emotions and instructional practices*	(P4, P6, P7, P26, P31, P37, P39, P43, P49)
	- *Monitoring student progress and identifying areas for additional help*	(P6, P10, P14, P19, P29, P35, P37, P39)
Students	**Continuous improvement of education**	(P1, P10, P16, P26)
	Enhanced User Experience	(P1, P3, P5, P6, P7, P9, P11, P13, P15, P16, P22, P23, P24, P28, P31, P35, P37, P43, P48)
	Facilitation of self-regulated learning	(P17, P20, P43)
	Gender and disability equality	(P3, P46)
	Immersive and Interactive Learning	(P3, P6, P7, P11,VP14, P18, P21, P26, P28,VP39, P40, P41, P42, P45)
	Personalized Learning and Knowledge Acquisition	(P1, P5, P8, P10, P12, P19, P20, P21, P25, P27, P29, P34, P36, P40, P49)
	Psychological impact	(P8, P15, P40, P43)
	Real-time Feedback and Guidance	(P21, P25, P27, P30, P33, P34, P39)

RQ3: The outcomes of using AI tools to enhance the user experience of students and teachers in education

The use of AI tools in education has the potential to enhance the user experience for both students and teachers greatly. Some outcomes associated with using AI tools to enhance the user experience in education are described in Table 13. One is assessments with eight papers (16.3% of the articles); teachers can better track and support student collaboration. By providing real-time evaluation and feedback, enabling personalized guidance and improvement opportunities, AI systems improve student performance. Students actively engage in collaborative activities and receive prompt feedback through interactive assessments, which improves the user experience.

AI also significantly improves accessibility and flexibility in education, with 32.6% of the studies (16 of the papers). AI solutions make educational platforms and resources accessible to more students. This removes financial, geographic, and physical barriers to ensure all students can access educational materials and participate in learning activities. AI technology boosts student engagement by fostering creativity and imagination. Another area mentioned in [P21, P30] is digital literacy. Students gain essential digital skills from improved AI and digital competency. This improves the user experience by helping students use digital resources for learning and thrive in a technological society. Another aspect of the user experience is improved human-computer interaction, which accounts for 12.2% of the studies (6 of the papers). AI technologies enhance the usability, intuitiveness, and effectiveness of educational platforms and tools by enhancing human-computer interaction. As a result, learning outcomes are improved, and user satisfaction is raised.

According to 49% of the studies, AI can improve learning experiences by increasing students' motivation and engagement and creating a more immersive and interactive learning environment. Improved learning outcomes and a better user experience result from personalized guidance, AI-powered tools, and content delivery customized to each student's needs. AI streamlines processes provides individualized support, and optimizes learning experiences with data-driven insights. This result improves students' overall user experience by enabling them to learn more effectively and efficiently. Through AI's contribution to gender and disability equality and its ability to get around geographical restrictions, fairness in education is addressed [P3, P13, P46]. By addressing the diverse needs of students and guaranteeing equal opportunity for all, AI technologies contribute to creating an inclusive and equitable learning environment. By fostering a sense of fairness, encouraging diversity and inclusivity, and offering a supportive and accessible educational experience for all learners, this outcome improves the user experience.

Pedagogical or instructional outcomes highlight the largest impact of AI on teaching and learning practices, according to 57% of the studies (28 of the papers). AI enhances the user experience by adjusting education to individual needs and encouraging active learning. It offers personalized learning experiences, real-world learning opportunities, and cutting-edge teaching methods. These results give teachers the tools to deliver effective, engaging, and interactive instruction to students. Finally, personalized resource allocation using AI optimizes the allocation of educational resources based on each student's needs in 9 studies [P4, P6, P11, P16, P17, P24, P25, P32, P44]. Resources like time, materials, and support can be allocated more efficiently by analyzing data and using AI algorithms. This outcome improves the user experience by giving students the right resources at the right time, maximizing their learning potential, and providing a customized educational experience.

Table 13: Outcomes of AI tools on the user experience in education

Categories	Description	Outcomes	Articles
Assessment	*AI positively impacts assessment outcomes by improving student collaboration and providing real-time evaluation and feedback.*	- Monitor and support student collaboration more effectively	(P3, P15, P35, P36)
		- Real-time evaluation and feedback	(P13, P18, P21, P34)
Accessibility and Flexibility	*AI enhances accessibility and flexibility in education, making it more affordable, accessible, and inclusive for learners.*	- Cost-effective and accessible manner	(P3, P16, P20, P24, P29, P34, P39, P43)
		- Improved interaction, creativity, and imagination compared to traditional learning methods	(P9, P27, P36, P37, P42, P45, P46, P48)
Digital Literacy	*AI contributes to developing digital literacy skills by providing access to advanced AI characteristics and digital competency.*		(P10, P30)
Enhanced Human-Computer Interaction	*Enhanced human-computer interaction through AI technologies improves communication and collaboration between students, teachers, and educational platforms.*		(P2, P4, P14, P22, P33, P32)
Enhanced Learning Experience	*AI enhances the overall learning experience by increasing student engagement, motivation, providing personalized guidance, and improving instruction effectiveness.*	- Increased Engagement	(P16, P17, P25, P28, P29, P39, P41, P43, P47, P49)
		- Learning efficiency	(P2, P8, P10, P17, P19, P21, P22, P23, P25, P26, P32, P40, P45, P49)
Fairness	*AI promotes fairness by addressing gender and disability equality in education and overcoming geographical limitations.*	- Gender and disability equality	(P3, P46)
		- Overcoming Geographical Limitations	(P13)
Pedagogical or instructional	*AI supports innovative teaching methods, practical learning experiences, and personalized instruction, transforming pedagogy.*	- Personalized Learning Experience	(P2, P3, P5, P10, P17, P19, P21, P22, P36, P40, P44)
		- Practical learning experiences	(P12, P13, P19, P21, P27, P30, P36, P38, P40, P42)
		- Offers innovative teaching methods	(P3, P13, P16, P29, P31, P45, P47)
Personalized resource allocation	*AI enables personalized resource allocation, optimizing the distribution of educational resources to meet individual student needs.*		(P4, P6, P11, P16, P17, P24, P25, P32, P44)

3.5 Discussion

The SLR conducted in this study offers valuable insights into the impact of integrating AI into the user experience in education. A total of 49 selected articles were thoroughly analyzed to address the research questions posed in the study. This section will discuss the key findings and implications derived from the results.

The analysis underscores the multifaceted nature of integrating AI in education, with a particular focus on enhancing user interaction and educational tools through user interface and experience. In addition to the present study, numerous other research works have been done into the design, development, and utilization of AI tools in education [181][182][183][184][185][186][187][188]. These studies have explored diverse topics, including the design of AI-based embedded systems and environments like smart campuses [189][190][191][192][193]. Furthermore, some articles have investigated the use of gamification in educational settings, employing AI techniques to create engaging and interactive learning opportunities [194][195].

The data analysis highlights the significance and growth of AI in education, particularly in STEM and language learning domains. It is evident that AI is being applied in various areas and is expected to continue expanding. Additionally, AI exhibits notable applications in e-learning and physical education [P1, P5, P9, P12, P19, P21, P24].

Table 10 provides significant observations regarding the application of AI in education. Firstly, AI is utilized in various fields and at all educational levels, demonstrating its adaptability. It finds applications in higher education, K–12 settings, academic management, art education, e-learning, language learning, and more. AI also has diverse applications in pilot training, legal studies, maritime studies, and personalized learning environments. STEM education is a significant area with substantial AI integration in higher education. Language learning receives considerable attention, with AI-based platforms providing immersive and interactive learning environments. These findings further emphasize the potential of AI to enhance various aspects of education.

To enhance oral practice and advance listening and speaking abilities in non-English speaking professional college English classrooms, researchers in P14 examine the use of human-computer interaction technology, multimedia courseware, and speech recognition technology.

The Cognitive Immersive Language Learning Environment (CILLE), described in Article P24, combines AI and Extended Reality (XR) to enable naturalistic, multi-modal conversations for comprehensive foreign language acquisition, which is illustrated through a study on teaching Chinese as a foreign language.

General education, as mentioned in [P2, P46], utilizes AI to teach students, and many articles [P35, P2, P46, P29, P18, P27, P41, P20] focus on using AI to teach different levels of K-12 education in various domains. While most articles concentrate on integrating AI into higher education, it is essential to consider the potential utilization of AI tools across different educational levels. Moreover, educational purposes extend beyond academic learning. For example, in P2, Deep Learning and Speech Recognition were used to teach plant science, and AI was applied in a botanical garden to facilitate learning about plants. Additionally, platforms like STEP[21] (mentioned in P45) enhance traditional maritime learning cycles by making them more engaging and interactive with AR & VR. Furthermore, P12 presents an ML-aided pilot training and education framework. AI tools, such as ML, DL, and ITS, are also utilized in Art Education for higher education students [P17, P20, P31].

The trends in AI research related to education indicate sustained interest and development in areas such

[21] http://www.smarteducationplatform.it/

as AR & VR, computer vision, and NLP. Research papers in these areas are published annually, reflecting ongoing efforts to improve educational user experiences. Additionally, there has been an increase in research papers on Deep Learning and Conversational AI, highlighting a focus on leveraging these technologies to enhance education. However, research trends vary across different AI technologies. Notably, Intelligent Assessment publications show a decline after 2020, suggesting a shift in research focus.

Furthermore, there has been limited research on Affective Computing in recent years, with no papers published in 2022 on this topic. Although there was growing interest in this area in 2021, 2020, and 2019, further research is necessary to explore its potential in education. Table 11 presented in the study provides insights into AI education trends and identifies areas that require more research. Research papers suggest that AI tools in education have improved evaluation, personalized learning, and user-technology communication.

The use of AI in education has significantly impacted the user experience for both teachers and students. AI tools provide teachers with valuable administrative and management support [P16, P34], enabling personalized educational programs [P4, P30, P36] and reducing administrative workload [P39, P49]. Additionally, teachers have access to better materials, improving the quality of teaching [P31, P32, P48]. Further research is needed to explore how AI can help teachers gain insights into students' needs, emotions, and progress, with 17 papers (34.7%) focusing on this area. AI tools also facilitate evaluation and feedback, helping teachers provide meaningful support and guidance to students (mentioned in 7 papers [14.3%]). Additionally, AI improves teachers' ability to engage and inspire students and offers technical support and innovative teaching methods (mentioned in 11 papers [22.45%]). There is a growing interest in exploring the impact of AI in education and personalized learning, with 18 papers (36.7%) and 16 papers (30.6%), respectively, focusing on these areas.

Furthermore, many articles [P9, P10, P11, P3, P6, P7, P11, P14, P18, P21, P26, P28, P39, P40, P41, P42, P45] highlight using computer vision, virtual reality, and augmented reality to create immersive and interactive learning environments for both students and teachers. Immersive education enhances learning outcomes by creating a highly engaging and interactive learning environment that promotes active participation and deep understanding of the subject matter. AI also supports personalized learning experiences, enabling self-regulated learning, providing real-time feedback and guidance, and fostering students' psychological well-being [P8, P15, P40, P43].

The impacts of AI in education are broad and multifaceted. One notable impact is the automation of administrative tasks, which frees up teachers' time, enabling them to dedicate more attention to personalized instruction and support. This automation contributes to the efficiency and organization of the educational system [P17, P20, P26].

AI benefits students by enhancing personalized learning experiences, motivation and engagement, immersive and interactive learning environments, accessibility and flexibility, and learning effectiveness [P3, P8, P14, P23]. By addressing individual needs, encouraging a sense of fairness, and offering support for diverse learners, AI technologies also help to promote inclusivity and equity in education [P6, P13, P27].

Researchers in P3 and P46 suggested AI in education assist students with disabilities and mentioned the significance of equality among students from various backgrounds. This strategy aims to develop a just educational system where all students have equal learning opportunities regardless of background.

It is also crucial to recognize how interconnected and mutually reinforcing these effects of AI on education are. Although each AI tool contributes differently to the overall user experience, they are all interdependent and shape the learning environment. For instance, the comprehensive management tool and resource allocation optimization decrease teachers' workload and produce a more effective and organized system, which benefits students' learning experiences. Similarly, interactive and immersive learning environments powered by AI technologies boost students' motivation and engagement while enhancing the effectiveness of instruction and interactions between teachers and students.

The interconnectedness of these effects emphasizes the beneficial effects of AI in education. A more comprehensive and integrated approach to teaching and learning has become possible thanks to AI tools and technological advancements. By utilizing the power of AI, education has evolved into a dynamic ecosystem where different stakeholders, such as teachers, students, and administrators, work together and gain from the connected effects. Recognizing and utilizing these interdependencies to build a harmonious and effective learning environment is key to the success and effectiveness of AI in education.

Integrating AI tools in education has many potential outcomes for the user experience. One key outcome is the improvement in assessment. With the help of AI, teachers can better track and support student collaboration. AI systems offer real-time evaluation and feedback, providing timely insights into student performance. This enables individualized guidance and opportunities for improvement. By creating a more dynamic and interactive assessment process that actively involves students and provides prompt feedback, AI enhances the user experience [P3, P13, P15, P18, P21, P34, P35, P36].

Another significant outcome is the increased accessibility and flexibility of education. AI solutions make educational platforms and resources more easily accessible to a wider range of learners. By eliminating physical, financial, and geographic barriers, AI ensures that all students can interact with educational materials and participate in learning activities. This improved accessibility and flexibility not only enhances the user experience but also encourages imagination, creativity, and engagement in the classroom [P3, P9, P16, P20, P24, P27, P29, P34, P37, P39, P42, P43, P45, P46, P48].

AI also plays a crucial role in developing digital literacy skills among students. By providing access to advanced AI characteristics and digital competency, AI enhances students' abilities to navigate the digital world. This, in turn, improves the user experience by fostering students' competence and confidence in using digital resources for learning [P10, P30].

One of the key aspects of user experience in AI-enabled education is improving human-computer interaction. AI technologies enhance the usability, intuitiveness, and effectiveness of educational platforms and tools, improving communication and collaboration between students, teachers, and educational platforms. This enhanced human-computer interaction improves learning outcomes and enhances user satisfaction [P2, P4, P14, P22, P32, P33].

AI significantly impacts the overall learning experience by increasing student motivation and engagement. Through personalized guidance, AI-powered tools, and customized content delivery, AI creates a more immersive and interactive learning environment. Students benefit from personalized learning experiences, adaptive content, and data-driven insights, leading to improved learning outcomes and a more satisfying user experience [P2, P8, P10, P16, P17, P19, P21, P22, P23, P25, P26, P28, P29, P32, P39, P40, P41, P43, P45, P47, P49].

Furthermore, AI contributes to fairness in education by addressing gender and disability equality and overcoming geographical limitations. By catering to the diverse needs of students and ensuring equal opportunities for all, AI technologies promote an inclusive and equitable learning environment. This fosters a sense of fairness, encourages diversity and inclusivity, and provides a supportive and accessible educational experience for all learners, enhancing the user experience [P3, P13, P46].

Pedagogical or instructional practices also see a significant impact from AI. AI supports innovative teaching methods, practical learning experiences, and personalized instruction, transforming traditional pedagogy. It enables personalized learning experiences, real-world learning opportunities, and cutting-edge teaching methods. These outcomes provide teachers with the tools to deliver effective, engaging, and interactive instruction, ultimately improving the user experience for both teachers and students [P2, P3, P5, P10, P12, P13, P16, P17, P19, P21, P22, P27, P29, P30, P31, P36, P38, P40, P42, P44, P45, P47].

Lastly, AI enables personalized resource allocation, optimizing the distribution of educational resources based on individual student needs. By analyzing data and identifying specific requirements, AI ensures that students receive the right resources at the right time. This personalized resource allocation maximizes learning potential and offers a customized educational experience, enhancing the user experience [P4, P6, P11, P16, P17, P24, P25, P32, P44].

Integrating AI approaches in education presents challenges that directly impact the user experience. Table 14 categorizes these challenges and provides insights into the difficulties associated with incorporating AI in educational settings.

Data and analysis emerge as a critical factor affecting the user experience, as emphasized by 57.1% of the articles. Building comprehensive databases and conducting accurate data analysis is essential for successful AI implementation. The availability of reliable data and the ability to interpret it correctly contribute to producing valuable insights and improving learning outcomes. Ensuring the accuracy and validity of AI-generated information is crucial to address ongoing clarification and correction needs [P5, P6, P15, P19, P21, P24, P27, P30, P35, P36, P38, P39, P42, P43, P47, P48, P49].

Ethical and privacy concerns also pose challenges that affect the user experience in AI-enabled education. Approximately 8.3% of the studies highlight these concerns, particularly related to the disclosure of personal information and the potential for machines to gain insights into human emotions. The absence of universal standards and guidelines for AI in education further exacerbates these concerns. Addressing these ethical conundrums, establishing robust frameworks to protect privacy, and promoting responsible use of AI technologies is imperative to ensure a positive user experience [P4, P18, P19, P43, P47].

Integration represents a significant obstacle to adopting AI in education, as discussed in 61% of the articles. Challenges in this category include the cost of implementation, difficulties in integrating AI technology with existing educational systems, and the need for adequate resources in digital learning environments. Overcoming these obstacles requires extensive digital transformation and efficient information management. Additionally, professionals in education must adapt to and embrace AI advancements to maximize the potential benefits for the user experience [P1, P6, P7, P9, P10, P13, P14, P17, P20, P25, P26, P28, P29, P30, P34, P36, P40, P41, P44, P45].

Learning and adaptation are critical aspects that significantly impact the user experience in AI-enabled education. Approximately 22.4% of the studies emphasize the importance of fostering self-learning abilities among students and the need for accurate emotion recognition and analysis to create personalized learning experiences. Adaptive training tailored to students' needs enhances their educational background and contributes to a more positive user experience [P4, P12, P25, P28, P32, P33, P37, P38, P43, P46].

Pedagogical and research challenges also influence the user experience, as highlighted in 22.4% of the studies. Overcoming implementation difficulties, designing effective AI experimental teaching content, and addressing inequalities and gaps in current learning systems are crucial for ensuring equitable access to AI-based education. Research and development efforts in these areas are necessary to enhance the user experience and improve educational outcomes [P9, P10, P12, P23, P27, P29, P31, P39, P44, P46, P49].

Lastly, technology and human interaction play a significant role in shaping the user experience. Building trust in human-computer collaboration and interaction is essential for successfully integrating AI in educational settings. Fostering productive and fruitful learning experiences requires establishing a positive relationship between users and AI technologies [P1, P17, P20, P31, P38].

The distribution of articles across different categories reveals varying levels of research attention. While areas like data and analysis, implementation and integration, and ethical and privacy concerns have received more research focus, categories such as learning and adaptation, technology and human interaction, and pedagogical and research challenges have relatively fewer papers, suggesting potential research gaps. Further studies in these areas are necessary to address the identified challenges, establish best practices, and ensure AI's ethical and effective application in education, ultimately enhancing the user experience.

The next section (Section 4 highlights a project carried out by the GRIAL research group and is covered in the following section. This case study's main topic is developing a language learning platform to help teachers teach German as a foreign language. As stated in the introduction, this project consists of some parts, which will be further examined and discussed in the following sections.

Table 14: Challenges of integrating AI in Education

Category	Challenges	Articles
Data and Analysis	- The need to develop comprehensive databases and corpora	(P5,P24, P6, P19, P35, P38, P39, P42,P43, P48)
	- The requirement for accurate analysis and interpretation	(P6, P15, P21, P27, P30, P36, P38)
	- Requirement for continuous explanation and correction	(P5, P14, P21, P24, P42, P47, P49)
Ethical and Privacy Concerns	- Ethical concerns regarding disclosure of personal information and machines gaining insights into human emotions	(P4, P43, P47)
	- Lack of universal standards and guidelines for AI in education	(P4)
	- Potential infringement on privacy and freedom due to data collection and analysis	(P4, P18, P19)
	- Risk of blind attachment to technology	(P4)
Implementation and Integration	- Cost of implementation	(P29, P30, P40, P44)
	- Difficulties in integrating AI technology and education	(P1, P6, P7, P9, P10, P13, P14, P17,P20, P25, P26, P28)
	- Lack of resources in digital learning environments	(P10, P11, P12, P18, P41)
	- Need for extensive digital transformation and information management control	(P10, P38)
	- Need for professionals to adapt to and embrace AI advancements	(P6, P8, P13, P29, P34, P36,P45)
Learning and Adaptation	- Cultivating self-learning abilities	(P12, P25, P32)
	- Difficulty in accurately recognizing and analyzing emotions	(P4, P33, P37, P38, P43, P46)
	- Students requiring adaptive training	PF8, P28)
Pedagogical and Research	- Challenges related to research and development	(P9, P31, P39, P44, P46)
	- Designing effective AI experimental teaching contents	(P12, P49)
	- Inequalities and gaps in the current learning systems	(P10, P23, P27, P29)
Technology and Human Interaction	- Lack of trust in human-computer collaboration and interaction	(P1, P17, P20, P31, P38)

4 Case Study: LATILL Platform

As seen in Section 3.5, in the result of the systematic review, AI technologies have been applied to education to improve the efficiency and effectiveness of communication between teachers and students. One of the interesting areas that AI is being used is Language learning. Also, in the Introduction (Section 2), the details about AI techniques, HCI, ICALL, and Generative AI tools are explained. Therefore this section will discuss a case study of the LATILL[22] Project and how AI helps the German Foreign Language (GFL) teachers respond to student's questions in a natural language format, providing personalized guidance and support which can help students and teachers overcome obstacles and improve their learning outcomes.

In today's interconnected world, reading and comprehending information in multiple languages is increasingly crucial. Proficiency in foreign language reading allows individuals to access information from different countries, compare diverse perspectives on complex topics, and engage in international problem-solving. However, teaching foreign language reading skills is a challenging task that cannot solely rely on pre-packaged materials found in textbooks. The LATILL project aims to address this challenge by creating digital tools to assist foreign language teachers, primarily focusing on German as a foreign or second language. The LATILL platform incorporates a search and analysis feature specifically designed for German texts, utilizing the CEFR [196] levels and other linguistic features to identify level-appropriate texts. This allows teachers to curate personalized learning experiences for their students, catering to their interests and goals. By integrating a self-regulatory approach to foreign language reading and implicit lexico-grammatical learning, the platform enhances the quality of language programs [197].

The LATILL project is supported by the Erasmus+ programme of the European Union, with collaboration from several prestigious institutions. The project aims to provide open educational resources for teachers of German as a foreign language, focusing on current, authentic, and level-appropriate reading materials. The project's objectives include promoting innovative teaching methods, encouraging learner-oriented materials, strengthening key competences in reading skills, ensuring quality assurance in teaching, fostering cooperation among teachers, and supporting professional development. The project's goals include an educational platform, a CEFR Reference Corpus for German, didactical materials with methodological recommendations, and a teacher professional development program. One of the unique features of the LATILL platform is the use of generative AI techniques for text creation and the development of text bundles which is a collection of related texts generated by the system upon user request. AI technologies, such as translation, summarization, and text adaptation, enrich the platform's content and expand its corpus of authentic texts. Additionally, the platform offers an image-generation service to create specific sentences, further enhancing comprehension for learners, explained in Section 2.

In the following section of this case study, we will go further into the details of the LATILL project, discussing subjects such as the process of developing the platform itself (Section 4.2), the methodology employed (Section 4.3), user stories and their significance (Section 4.1), user testing and its outcomes (Section 4.3.1.3), and potential future directions for the project (Section 4.3.2).

4.1 User stories

Through the 41 user stories that domain experts provided, crucial insights were gathered throughout the development process. These accounts were used as a guide to identify the important features of the platform. Based on these stories, objectives were set, and a structured development strategy was put into practice. The platform primarily is intended for GFL teachers, though pre-service teachers can also use

[22] Level-Adequate Texts in Language Learning

it to their advantage. The platform allows for registered and anonymous users, ensuring inclusivity and accessibility. Its prioritized features have undergone careful analysis to ensure they satisfy the requirements mentioned in the user stories. The detailed information about each text, including copyright information and source links, is presented in a thorough results viewer. Users can save texts and sort search results based on various criteria, making text management more effective. Personalized text organization is possible with individual user accounts. Additionally, users can export texts in well-liked formats like Word and PDF after receiving shared links to particular texts. The platform also enables users to submit texts for analysis and access texts that have already been examined.

Along with a wide selection of texts, the platform provides instructional materials and methodological advice for incorporating authentic texts into classroom instruction. Users have the freedom to change the interface's settings, including the typefaces, colors, and options for day/night mode, which improves user comfort and accessibility. Additionally, the platform has tools for creating customized activities based on chosen readings and a search engine for finding reading aids and other resources. By providing teachers with useful tools and assistance, these features ultimately improve students' educational experiences. The development team has successfully built a comprehensive platform that addresses the particular needs mentioned in the user stories by incorporating these functionalities. The platform is useful for assisting with language teaching and learning initiatives.

4.2 Platform development

The design and implementation of the educational platform for GFL teachers are the main objectives of the LATILL project's platform development section. As discussed in Section 4.3.1, several functional and non-functional prototypes were created to improve the platform's features and user interface. AI technologies like NLP and generative AI were incorporated into the development process to provide cutting-edge features like text translation, summarization, and image generation, which were explained in Section 2. The platform includes a German text search tool with editable filters, a results viewer with in-depth information and sorting options, user accounts for text management and storage, and the ability to upload texts for analysis. The platform also offers methodological tips for working with authentic texts, and users can personalize interface settings to suit their tastes. The platform development section highlights the iterative and user-focused approach used to develop a thorough and user-friendly platform that meets the unique needs of GFL teachers and improves their teaching methods.

The LATILL platform's software development followed the SCRUM methodology [198], which emphasizes incremental and iterative development. The project was divided into sprints, allowing regular review and adaptation based on feedback and changing requirements. The platform's backend was built using Django, a popular Python web framework known for its effectiveness and scalability. Django provided a solid foundation for handling server-side operations, implementing business logic, and managing data.

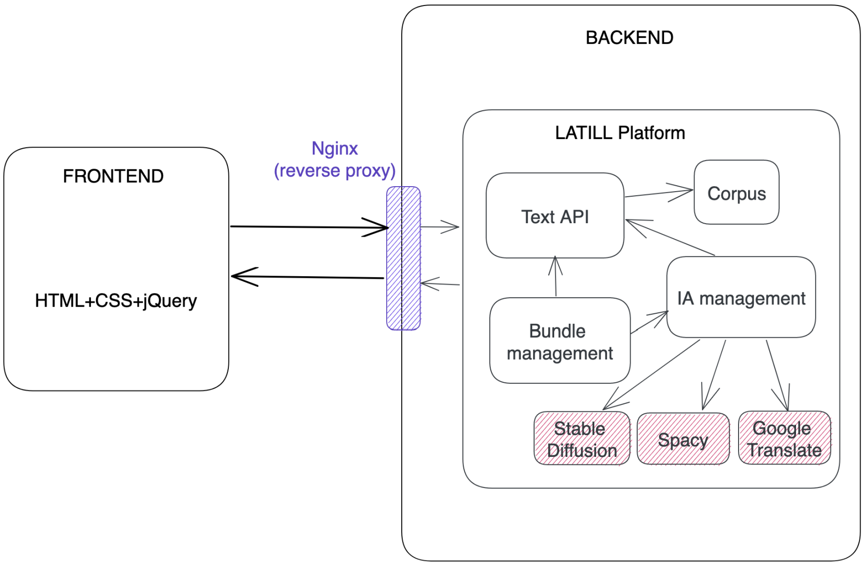


Figure 9: Architecture of the LATILL Platform

Figure 9 shows the platform's architecture and the integration of various components and technologies. The front end of the LATILL platform combines HTML, CSS, and jQuery to create an engaging and interactive user interface. These technologies work together to structure the content, control the visual presentation, and add dynamic functionality to enhance the user experience. On the other hand, the platform's backend incorporates several key components. The text API enables seamless integration with external sources to retrieve relevant texts. The corpus management module is responsible for organizing and managing the "CEFR Reference Corpus for German," which serves as the source of up-to-date texts for the platform. The bundle management feature allows users to create customized sets of texts for specific learning purposes. Additionally, the platform utilized cutting-edge technology such as the RTX4090 graphics card and CUDA for fast AI computations and graphics processing. The RTX4090's performance and CUDA's[23] parallel computing capabilities were chosen to optimize image creation and AI-related tasks, providing efficient and effective computations. The platform uses AI management, specifically the stable diffusion algorithm, Spacy, and Google Translate, to facilitate image generation, simplification, and translation.

4.3 Methodology

The methodology employed in developing the LATILL platform focuses on leveraging generative AI models and NLP algorithms to enhance the user experience. The platform incorporates several AI techniques, including translation, simplification, and image generation, to provide users with personalized and adaptive features.

1. **Translation:** By allowing users to browse content in various languages, the translation feature improves the platform's accessibility by promoting language learning and intercultural communication. Accurate and fluent translations are essential to ensure that texts are translated from one language to another without changing their original meaning. The deep-Translator translation service was used in the implementation to give users high-quality translations. Figure 10 shows the code example of this tool:

[23] https://developer.nvidia.com/cuda-toolkit

```
from deep_translator import GoogleTranslator
translated = GoogleTranslator(source='de', target='en').translate(text)
translated
```

Figure 10: Code for text Translation

2. **Simplification:** This tool makes it easier for users to understand lengthy or complex texts, saving time and improving their information retention. The text simplification feature creates concise and insightful text summaries using the Spacy library in Python. Spacy was chosen because based on Table 3 and the results of article [199], Spacy is the library that supports multilingual data, and in the LATILL project uses a German corpus. Figure 11 shows the code example of this implementation.

```
import spacy
from spacy.lang.de.stop_words import STOP_WORDS
from string import punctuation
from heapq import nlargest
def summarize(text, per):
    nlp = spacy.load('de_core_news_sm')
    doc= nlp(text)
    tokens=[token.text for token in doc]
    word_frequencies={}
    for word in doc:
        if word.text.lower() not in list(STOP_WORDS):
            if word.text.lower() not in punctuation:
                if word.text not in word_frequencies.keys():
                    word_frequencies[word.text] = 1
                else:
                    word_frequencies[word.text] += 1
    max_frequency=max(word_frequencies.values())
    for word in word_frequencies.keys():
        word_frequencies[word]=word_frequencies[word]/max_frequency
    sentence_tokens= [sent for sent in doc.sents]
    sentence_scores = {}
    for sent in sentence_tokens:
        for word in sent:
            if word.text.lower() in word_frequencies.keys():
                if sent not in sentence_scores.keys():
                    sentence_scores[sent]=word_frequencies[word.text.lower()]
                else:
                    sentence_scores[sent]+=word_frequencies[word.text.lower()]
    select_length=int(len(sentence_tokens)*per)
    summary=nlargest(select_length, sentence_scores,key=sentence_scores.get)
    final_summary=[word.text for word in summary]
    summary=''.join(final_summary)
    return summary


summary=summarize(text, 0.15)
```

Figure 11: Code for text simplification based on Spacy

3. **Image Generation:** The visualization section of the image generation feature adds new images based on chosen texts, effectively communicating the text's main concepts and ideas. The implementation's StableDiffusion technique creates text-to-images visually representing the text's content. By offering users visually appealing representations in addition to the textual content, this multi-modal learning experience improves comprehension and engagement. To implement diffusion models in Python for this hardware configuration (RTX4090 GPU and CUDA), an environment with the required programs and libraries must be set up. An overview of the steps taken for this project is provided below:
   (a) Install GPU drivers: It's critical that the system has the most recent NVIDIA GPU drivers installed. The driver version 530 has been installed in this particular case. Install the CUDA Toolkit by downloading and running the 12.1 version from the NVIDIA website. The tools and libraries required for GPU-accelerated computing are provided by the CUDA Toolkit.
   (b) Configure the Python environment with the necessary libraries and packages.
   (c) Specify any helper methods or utility functions that may be required for this implementation.
   (d) After loading the image, perform any necessary preprocessing. This could entail scaling, formatting conversion, and normalizing pixel values.
   (e) If necessary, get the mask ready. This may entail loading a mask image, scaling it to fit the input image's dimensions, and, if necessary, adjusting its brightness and contrast.
   (f) Create the desired diffusion model or sampler. Depending on the needs, this could be a custom implementation or a pre-trained model.
   (g) Configure any additional parameters or settings for the diffusion model, such as noise thresholds, sampling schemes, or noise levels.
   (h) Develop a callback procedure that will be used on the image at each stage of the diffusion procedure. The image can be subjected to operations like dynamic thresholding, static thresholding, or mask application using this function.
   (i) Use the sampler and callback function to run the diffusion process. Apply the diffusion algorithm and iterate over the desired number of steps to improve or change the image gradually.
   (j) Save the output image or display it as desired. The tensor representation may need to be changed back to a NumPy array, and any necessary post-processing operations may need to be carried out.

4.3.1 Prototype

Prototypes in platform development are mockups used to validate design concepts and gather user feedback. They visualize the user interface and functionality, allowing developers to test interactions and refine the design. Prototypes facilitate user testing and help identify usability issues, ensuring the final product meets user expectations.

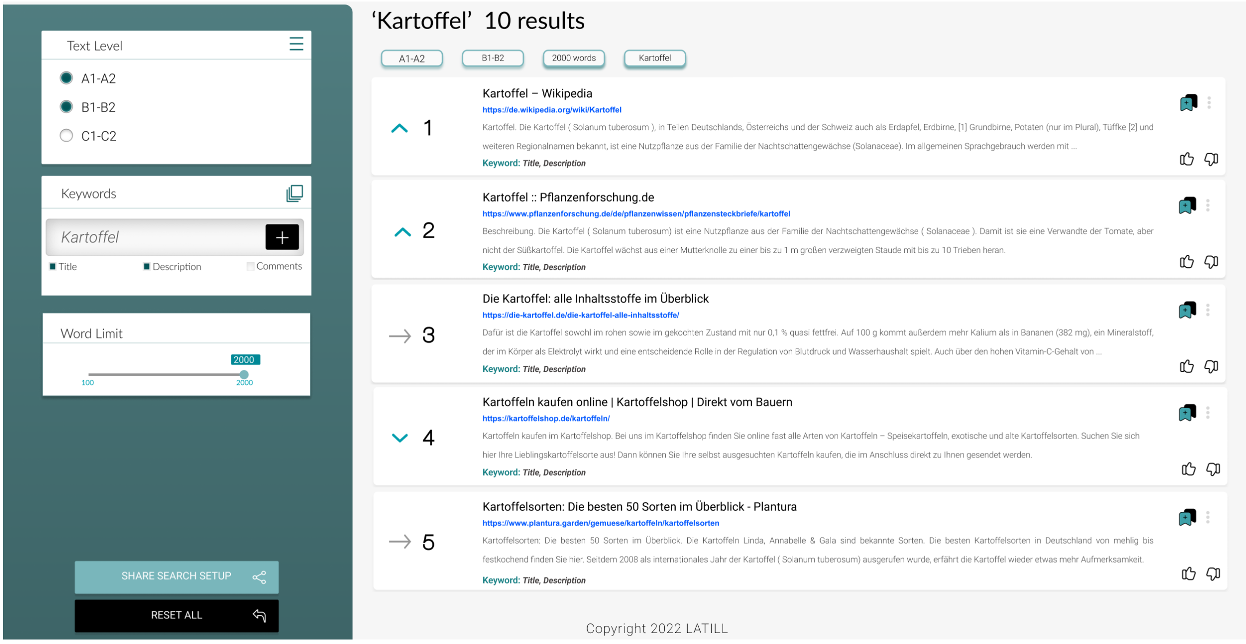
In this case study, the non-functional prototype is discussed in Section 4.3.1.1, while the functional prototype is presented in Section 4.3.1.2.

4.3.1.1 Non-functional prototype

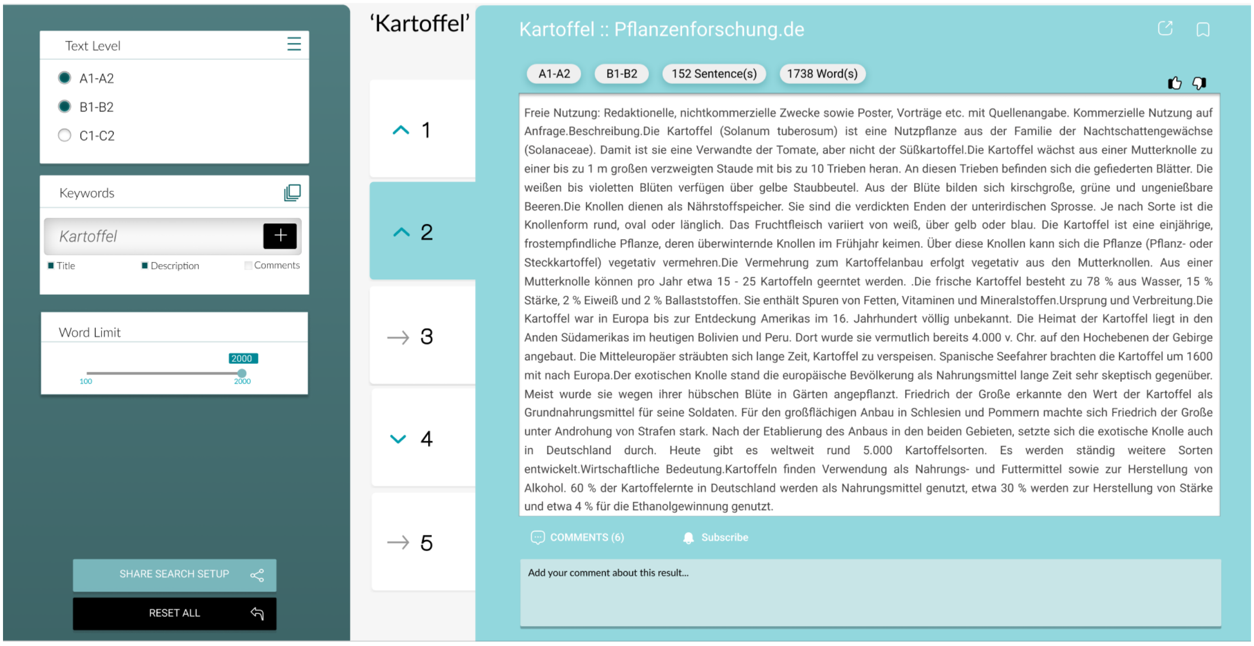
To better envision and improve the idea and vision for the final functional version, it is necessary to create a non-functional prototype. Non-functional prototypes are low-fidelity mockups of the eventual product that don't simulate its functionality but emphasize its structure, layout, and user experience. Based on the key features and the requirements, The first Non-functional prototype of the LATILL platform was designed with the Figma[24] tool, a platform for a collaborative design that can be applied to create interactive designs, prototypes, and user interfaces. Implementing the key features are an essential part of the LATILL platform, which will be defined during the early stages of prototype development. These features as shown in Figure 12 consist of:

- **Text filters:** The platform provides users with many filters for in-depth searches. Users can narrow their search results using lexical and grammatical filters and search by title or topic.
- **Text list:** Following a search, the platform shows users a curated list of relevant texts to their chosen filters.
- **Bookmarks:** Users can bookmark their preferred texts and quickly access them using shortcuts. The user interface that enables users to manage their saved texts effectively is shown in Figure 12a.
- **Comments:** Users can leave comments on the texts that have been returned, enabling them to express their opinions on how valuable they are for teaching or making suggestions. The interface where users can participate in discussions and offer insightful commentary is shown in Figure 12b.

[24] https://www.figma.com



(a) Search results



(b) Details of the bookmarks

Figure 12: Figma Non-functional prototype

4.3.1.2 Functional prototype

Having a functional platform prototype is a crucial step in the development process. In this case study, the platform development method was described in Sections 4.2 and 4.3, which allowed users to interact with the prototype and provide valuable feedback. This hands-on demonstration of the platform's key features and functionalities helps identify any issues or areas that need improvement, ensuring that the final product meets user expectations. Through user testing and evaluation, the prototype enables early validation, refinement, and optimization of the platform's design, usability, and performance.

A strong corpus is essential for the process of creating text bundles. To accommodate various educational scenarios, it is crucial to have access to a wide variety of texts with various grammatical and lexical features. For example, teachers may mandate simplified texts for less advanced students or native language translations. These transformations can be labor- and resource-intensive to prepare manually. However, the LATILL platform's integration of generative AI capabilities enables the automatic generation of bundles with various text feature variations. By doing this, the platform gains diversity and creativity while also saving time and effort when it comes to customizing educational materials to meet the needs of individual students. The platform can offer rich and customized texts for successful language learning experiences by utilizing the power of AI and a large corpus.

Figure 13 shows the main page of the platform with the filters and AI-based tools used; the first document named *"Hamburg: Unfall mit besonderem Bus"* is selected, and the results will be seen in the following parts.

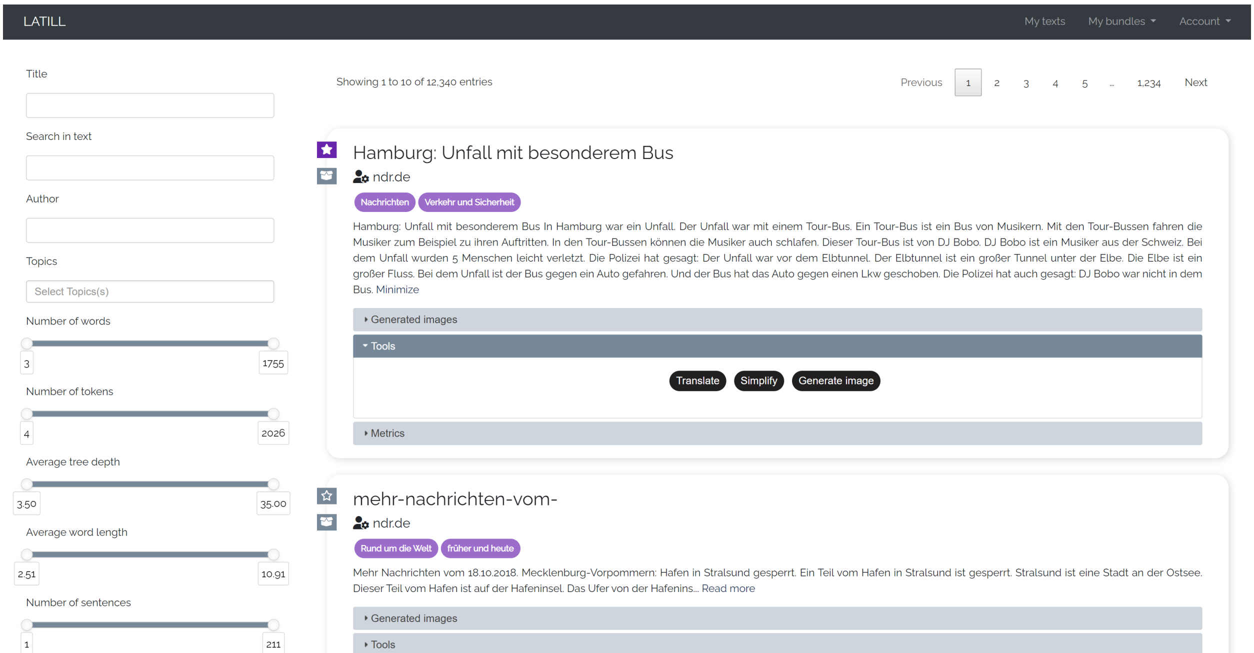


Figure 13: Main page of LATILL

Below, an explanation of different parts of the platform is listed:

- **Text Filters:** Text filters let users refine search results on the platform as shown in 13. Word count, sentence count, average sentence length, and readability score can be filters. These filters help users find texts that meet their criteria.

- **Tools:** To improve the learning experience, the platform provides various AI-powered tools. The creation of images, simplification, and translation are some of these tools, as presented in Figure 13. The translation tool promotes language learning and intercultural communication by letting users explore content in various languages. By offering more concise and insightful summaries, the simplification tool assists users in understanding complex texts. The image generation tool enhances learning by adding a visual component by creating images that visually represent the main concepts and ideas in the chosen texts. Below, the tools with the images are shown:

1. **Translation:** Figure 14 shows the Text Translation tool of the platform.

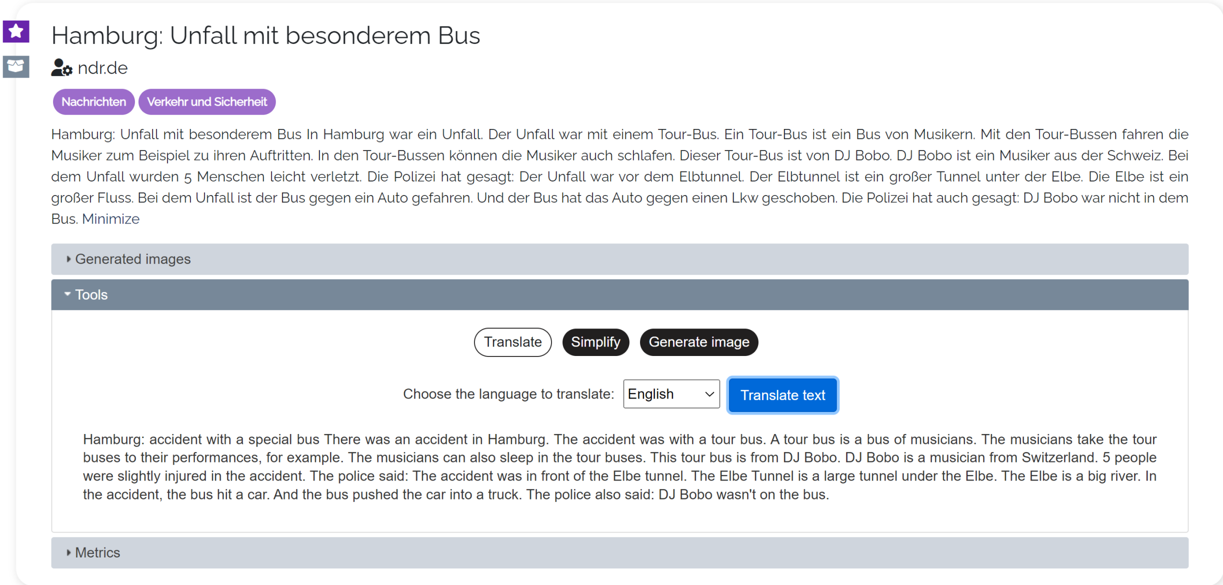


Figure 14: Text Translation

2. **Simplification:** Figure 15 shows the Text Simplification tool of the platform. This feature aims to make the text more easily understandable and accessible to a wider audience. It can be particularly useful for individuals struggling to comprehend complex or lengthy texts.

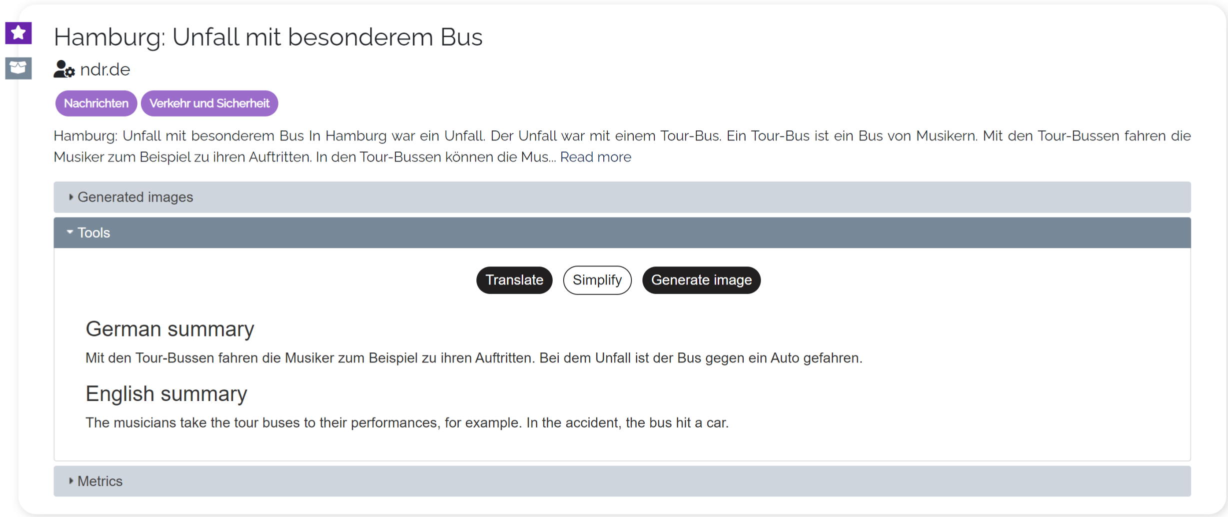


Figure 15: Text Simplification

3. **Image Generation:** Figure 16 shows the Image Generation tool, and Figure 17 shows the three samples of the images generated for three texts selected from the document.

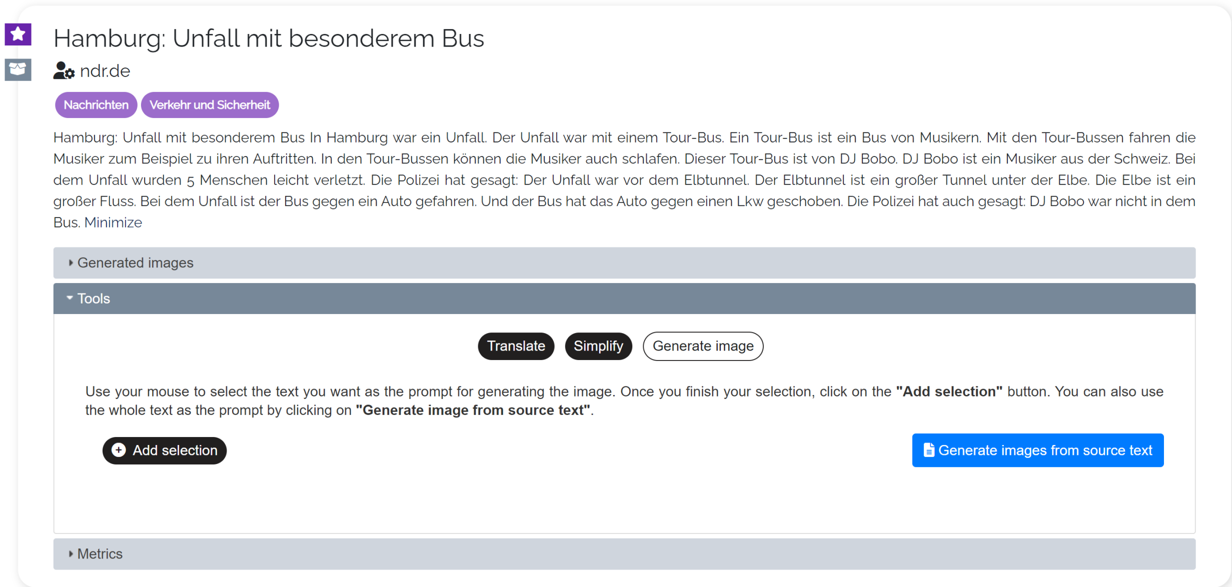


Figure 16: Image generation

Images 17a and 17b are two images created for this prompt :

Prompt 1: *"Unfall mit besonderem Bus in Humburg war ein Unfall"*

Translate: Accident with a special bus, there was an accident in hamburg.

Image 17c visualizes the sentence:

Prompt 2: *"Der Elbtunnel ist ein großer Tunnel unter der elbe"*

Translate: The Elbe Tunnel is a large tunnel under the Elbe.

(a) Prompt 1 *(b) Prompt 1* *(c) Prompt 2*

Figure 17: Three samples of generated images

- **Metrics:** As Figure 18 shows, the platform offers metrics that provide information about the text's linguistic. These metrics may include details on the text's morphology, syntax, lexicon, and genre. Users can better understand the linguistic features of the texts they are working with by looking at these metrics.

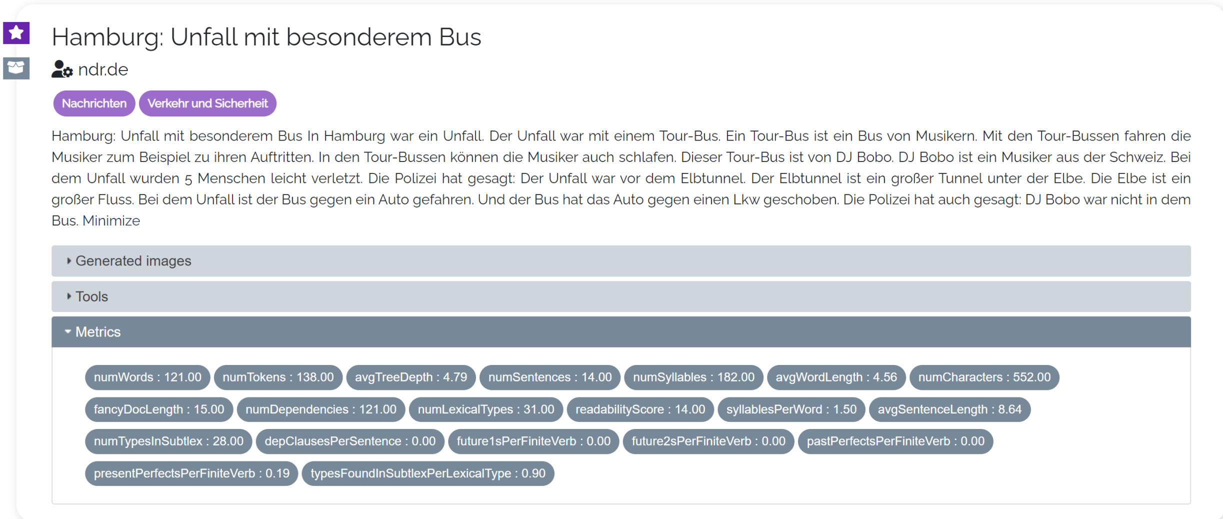


Figure 18: Metrics

- **Bundles:** Figure 19 shows platform bundle configuration options. users can assemble collections of texts and AI-generated outputs into bundles. To create unique bundles, they can combine various AI tools, choose the texts' degree of difficulty, and alter other elements. This function gives users access to various educational resources and encourages creativity and participation in the learning process.

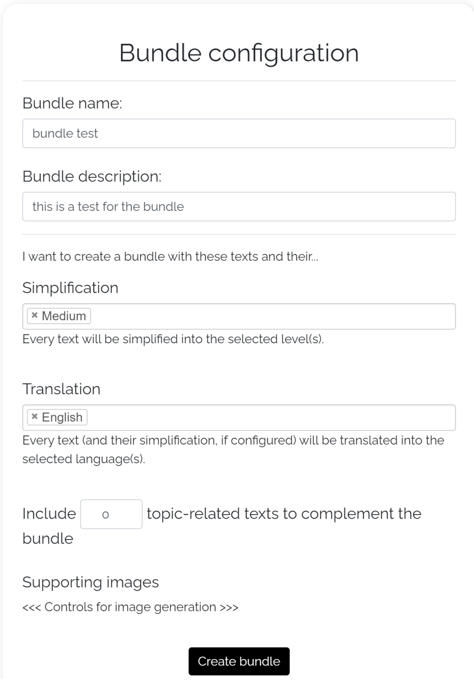


Figure 19: Bundle creation

4.3.1.3 User test

Five German teachers tested the platform. A software engineer and German as a foreign language teacher (User 1), an English and German teacher (User 2), a German teacher (User 3), a French and German teacher (User 4), and a Spanish and English teacher (User 5) were the participants. These participants were between 40 and 70 years old. they were tested on tasks like filtering texts, translating them, summarizing them, and creating images from them. Participants had trouble finding some functions, especially image generation ones. Table 15 identifies the critical issues that require attention and suggests possible solutions.

There are several areas where the LATILL platform needs to be improved. First, reviewing the filtering system to eliminate irrelevant filters and concentrate on those important for text simplification and language learning is important. The user interface will be made simpler, and platform performance will be enhanced. Second, it is important to consider the color scheme used for generated images. The images' educational value and engagement will increase by selecting the right aesthetically pleasing and educationally beneficial colors.

The user experience will be enhanced by search terms highlighted in the results, making it easier for users to find pertinent textual passages. It will be easier for users to adjust filters while comparing the original and simplified text by fixing the filters on the side of the interface and adding a reset filter button. Language learners will benefit from the comparison and comprehension of the target language made possible by including the translated text alongside the original text. Enhancing user accessibility and enabling a more personalized and efficient learning environment will result from making the tools available whenever needed.

For longer texts, making sentences shorter will help language learners understand the content by allowing for the step-by-step comprehension of complex information. Long texts can be broken up into manageable sections, and multiple images can be produced for each section to give students a well-structured educational experience. The processes for text simplification and image generation must be continually

Figure 20: Heatmap of the user interaction captured with Hotjar

improved. The text's main ideas will be preserved while being made simpler, which is possible with the improvements in the underlying algorithms.

The heatmap analysis from Hotjar[25] (Figure 20), which revealed that the participants used only a small set of filters, further supported this. Participants were pleased with the translation feature of the AI features. Overall, the image generation feature produced encouraging results, though it took participants several tries to get good results. The text-simplification feature, though, drew criticism from participants who thought the summaries were too brief and didn't capture the essence of the original text. Despite these problems, participants were satisfied with the LATILL platform's general functionality and acknowledged its potential as a useful tool for teaching German as a foreign language.

[25] https://www.hotjar.com/

Table 15: User testing of the platform

	User 1	**User 2**	**User 3**	**User 4**	**User 5**
Filters	- Number of words - Readability Some filters aren't useful	- Number of words - Average Sentence length	- Some filters aren't useful. - Some filters are similar (Len of txt, Num of sentences, len of words) Number of sentences	- Average sent length - Readability Number of sentences	- Limited search options
Interface	- Buttons of Image generation	- Trouble finding the texts and buttons.	- Side-by-side translation. - - Buttons of Image generation	- Buttons of Image generation	- Fine
Translation	- Fine	- Fine	- Fine	- Fine	- Fine
Simplification	- Fine	- Too short	- Sentences are separated from various document sections.	- Main idea is missing. - The original text was simple, and the result was short.	- Too short - The text was already simple, and replacing simplification with summarization is better.
Image Generation	- Fine	- First try were not related. - Second try was good.	- Not good and related to selected parts.	- From 4 images, only one was related.	- Not good and related to selected parts.
Observations	- Selected text was simple. - The searched term was on the main page, but it didn´t appear in the results when it was searched.	- Selected text was simple. - Difficulty finding different parts of the platform	- Selected text was long.	- Selected text was simple. - Difficulty finding different parts of the platform	- Selected text was simple and long.

4.3.2 Final Version

The platform has been significantly upgraded to improve corpus quality and filter accuracy based on evaluation and user testing. The platform can now produce high-quality documents. Improvements were found in the previous evaluation and user testing. The development team improved the platform's functionality and user experience by analyzing user feedback and observations. The current platform interface has been improved. User feedback and usability testing guided design changes, creating a more intuitive and user-friendly interface. The development team is actively improving the interface to meet user expectations and preferences. AI-based platform tools are also being developed. Translation, text simplification, and image generation tools are constantly improved to ensure accuracy, efficacy, and platform integration. The development team creates powerful AI tools for language learning and teaching. The following figures provide visual representations of various components within the platform, illustrating its different functionalities and features.

- **Text Filters:** The upgraded filters section of the platform is presented in Figure 21. The color boxes show different topics that each document has.

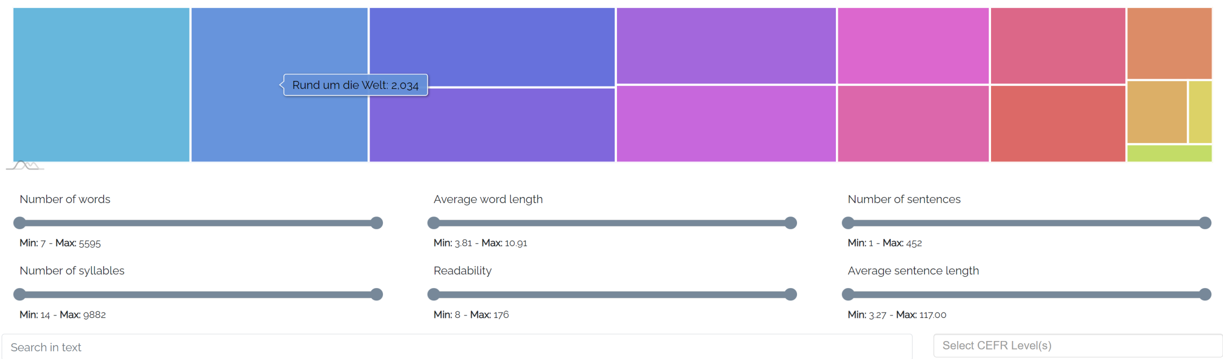


Figure 21: Filters of the search

- **Tools:** Some changes related to the tools section were done, and the new interface is shown in the following figures:
    1. **Text Translation:** The Translation section of the tools is the same because the user tests and evaluation did not recommend further changes, Figure 22.

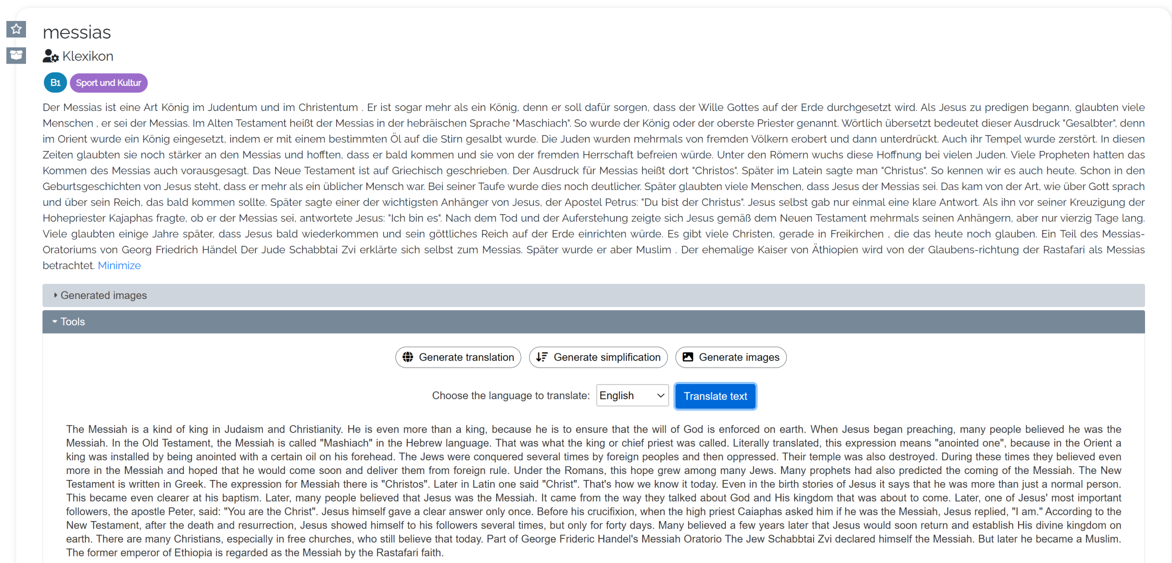


Figure 22: Text Translation tool

2. **Text Simplification:**
   By analyzing the structure and content of the text, the feature generates a summary that captures the essential information while eliminating unnecessary details. However, it is important to note that the text simplification tool is currently still under development and will be available in future versions of the platform. In Figure 23, a visual representation showcases the simplification tool, where the selected text is transformed into a more straightforward and easily understandable sentence that encapsulates the text's main idea.

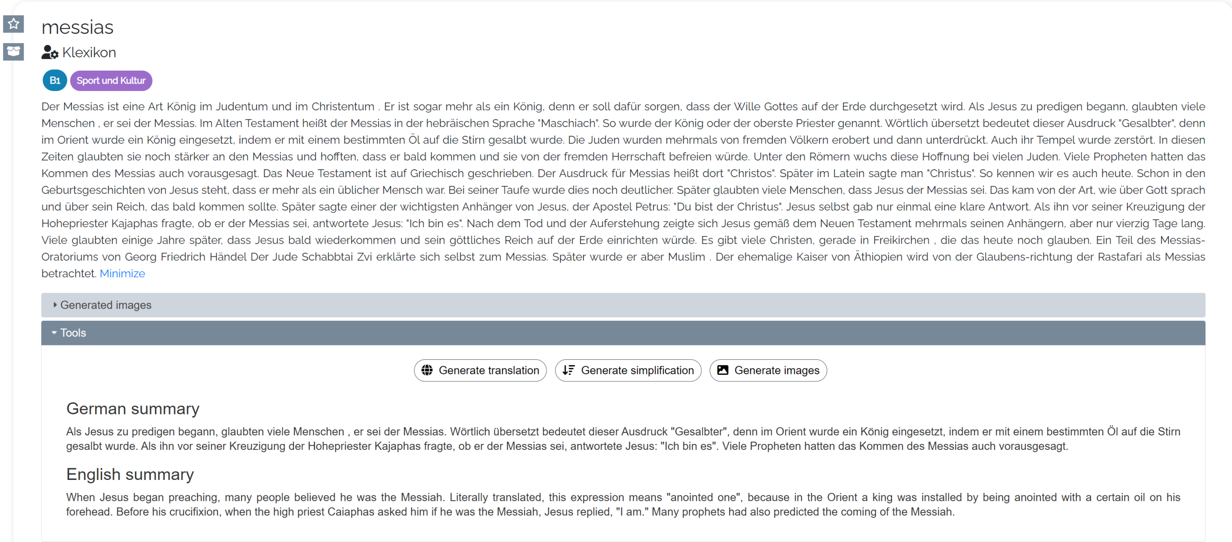


Figure 23: Text Simplification tool

3. **Image generation:** To make this tool more user-friendly, some changes were done regarding the interface shown in figure 24

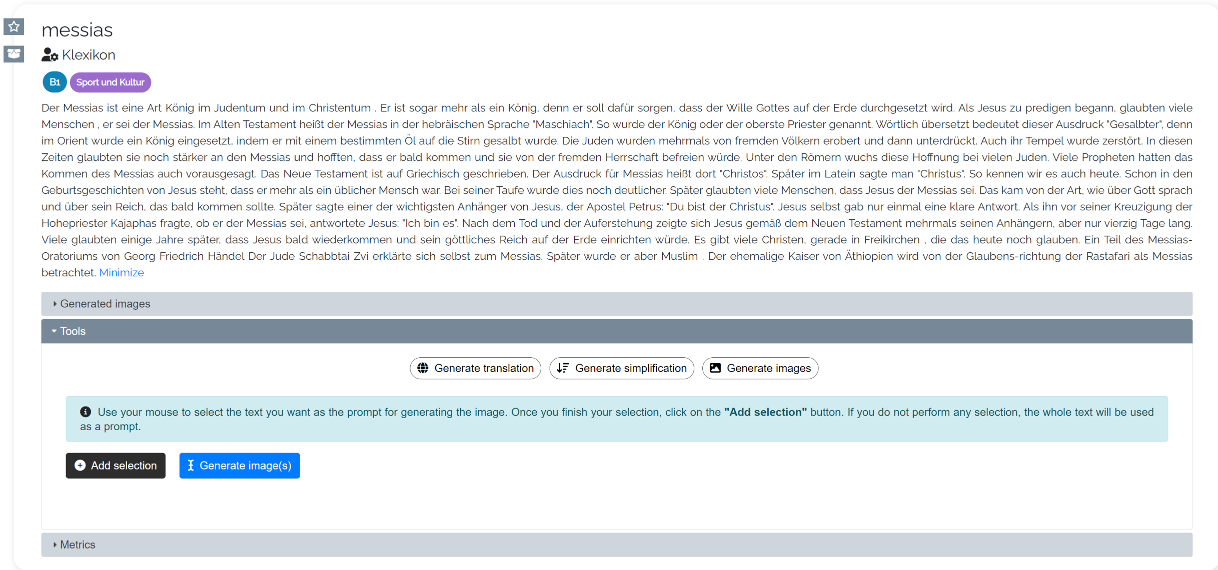


Figure 24: Image generation tool

Figures 25a, 25b, and 25c show the image generated for the selected prompts below from the document:

Prompt 1: *"Das Neue Testament ist auf Griechisch geschrieben"*

Translate: "The New Testament is written in Greek"

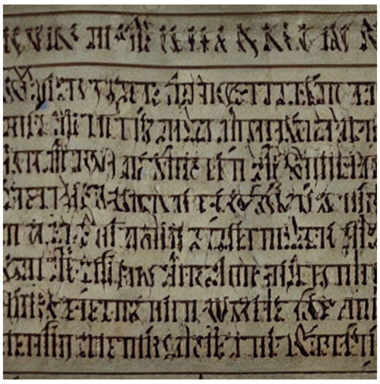
Prompt 2: *"Nach dem Tod und der Auferstehung zeigte sich Jesus gemäß dem Neuen Testament mehrmals seinen Anhängern, aber nur vierzig Tage lang. Viele glaubten einige Jahre später, dass Jesus bald wiederkommen und sein göttliches Reich auf der Erde einrichten würde. Es gibt viele Christen, gerade in Freikirchen"*

Translate: "After the death and resurrection, according to the New Testament, Jesus showed himself to his followers several times, but only for forty days. Many believed a few years later that Jesus would soon come again and establish his divine kingdom on earth. It there are many Christians, especially in free churches"

Prompt 3: *"Auch ihr Tempel wurde zerstört. In diesen Zeiten glaubten sie noch stärker an den Messias und hofften, dass er bald kommen und sie von der fremden Herrschaft befreien würde. Unter den Römern wuchs diese Hoffnung bei vielen Juden. Viele Propheten hatten das Kommen des Messias auch vorausgesagt. Das Neue Testament ist auf Griechisch geschrieben. Der Ausdruck für Messias heißt dort "Christos"."*

Translate: "Their temple was also destroyed. During these times they believed even more strongly in the Messiah and hoped that he would come soon and free them from foreign rule. Under the Romans, this hope grew among many Jews. Many prophets also foretold the coming of the Messiah. The New Testament is written in Greek. The term for Messiah there is "Christos"."

(a) Prompt 1



(b) Prompt 2

(c) Prompt 3

Figure 25: Three samples of generated images

- **Metrics:** Figure 26 shows that the platform provides text linguistic metrics. The metrics provide quantitative measurements related to the text, such as the number of words, number of tokens, average tree depth (a measure of sentence complexity), average word length, number of sentences, number of syllables, number of characters, readability score (a measure of how easy the text is to read), syllables per word, and average sentence length. These metrics can help users analyze and compare texts based on their linguistic properties and readability.

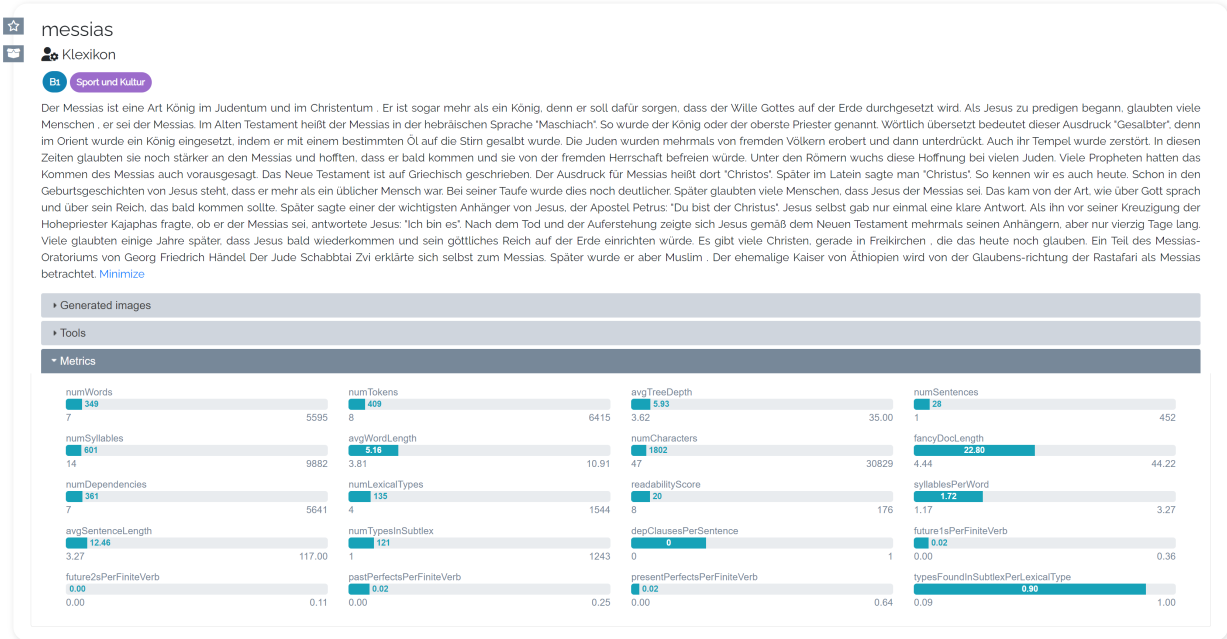


Figure 26: Metrics

- **Bundles:** The platform offers bundle configuration options, as depicted in Figure 27. After conducting tests and evaluations, as explained in Section 4.3.1.3, it was determined that important changes needed for the bundles are in the user interface. These changes aim to provide a more user-friendly interface allowing easier access to the tools within the bundles.

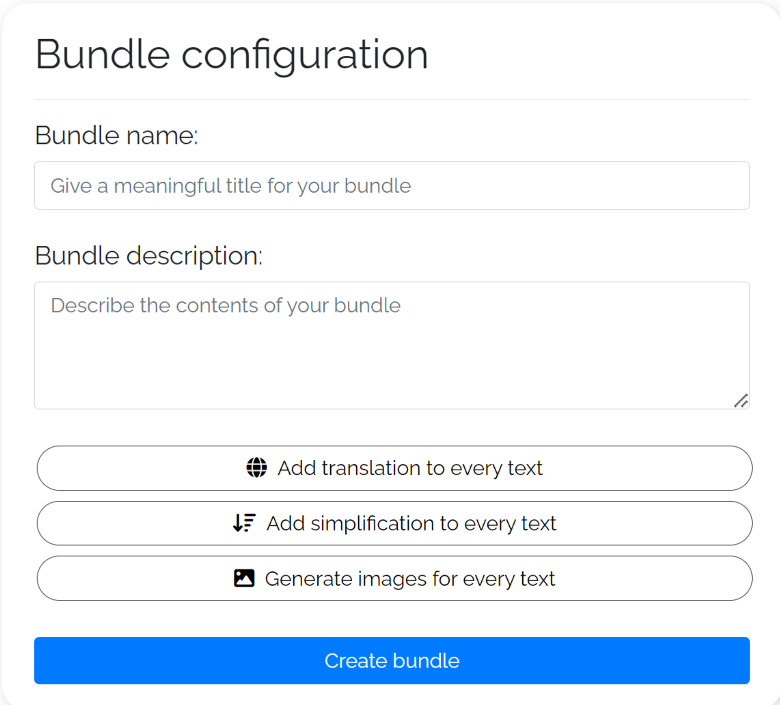


Figure 27: Bundles configuration

This platform uses AI to improve language learning, as shown in the figures in this section. Improved accessibility, comprehension, and user engagement result from using AI in text simplification, translation, and image generation. The platform is constantly improving its corpus, user interface, and AI tools to achieve excellence in learning. The most recent version shows improvements in filter performance, interface refinements, and ongoing work on AI-based tools. The team is committed to considering user feedback and meeting their changing needs to deliver a more thorough and user-centric experience.

5 Conclusions

This thesis has clarified the advantages of integrating AI into educational settings to improve user experience. Significant findings and implications have been discovered through a systematic literature review and a case study focusing on a language learning platform. The SLR found that integrating AI into education has numerous positive effects on teachers and students. AI tools offer invaluable administrative assistance, individualized learning plans, better lesson plans, improved evaluation and feedback capabilities, and increased student engagement and inspiration. AI makes learning more effective for students by enabling personalized learning experiences, improved motivation and engagement, immersive and interactive learning environments, and greater accessibility and flexibility. These effects work together to create a transformative learning environment that meets the various needs of students.

An example of how AI is used in practice to improve user experience is shown in the case study of the LATILL Project, a platform for language learning. The platform is constantly being improved due to user feedback and needs, demonstrating a dedication to developing an extensive and user-centric learning environment. An improved language learning experience results from improved corpus quality, filter improvement, interface enhancements, and ongoing AI-based tool development. Future work and research in the field of artificial intelligence in education will likely focus on many areas. These include examining how generative AI can be integrated while addressing ethical issues, performing long-term impact analyses, looking into how AI can be integrated with various pedagogical concepts, concentrating on user-centered design principles, and dealing with implementation difficulties.

The platform's future plans also emphasize ongoing efforts to improve the user experience. These plans now include Language Models for text simplification, allowing students to access texts that have been condensed to their level of language proficiency. Finding the most effective diffusion model to enhance image quality also aims to produce more aesthetically pleasing and educational learning materials. These upcoming improvements show the platform's attention to meeting the changing demands of language learners to deliver an improved and all-encompassing language learning experience by integrating Generative AI tools like LLMs and improved image diffusion models.

This research took part in three conference papers; two are already accepted, and one has been submitted.

- Nastaran Shoeibi, *Cross-lingual transfer in Generative AI-Based Educational Platforms for Equitable and Personalized Learning*, **LASI Spain 2023**, Madrid, 29-30 June 2023 (doctoral consortium)

- Andrea Vázquez-Ingelmo, Alicia García-Holgado, Roberto Theron, Nastaran Shoeibi and Francisco José García-Peñalvo, *Design and development of the LATILL platform for retrieving adequate texts to foster reading skills in German*, **Interacción 2023**, 4-6 September 2023, Lleida

- Nastaran Shoeibi, Francisco José García-Peñalvo and Roberto Therón Sánchez, *Transforming Education through Integrating AI: A Systematic Mapping Review for Enhanced User Experience*,**Technological**

ACKNOWLEDGMENTS

The project was undertaken with the support of the Erasmus+ Programme of the European Union: "KA2 - Cooperation partnership in school education." Level-Adequate Texts in Language Learning (LATILL) (Reference number 2021-1-AT01-KA220-SCH-000029604). Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA).

I also acknowledge partial financial support from project Analitica visual como apoyo a la Inteligencia Artificial explicable with reference R035.

6 References

[1] John McCarthy, Marvin L Minsky, Nathaniel Rochester, and Claude E Shannon. A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine*, 27(4):12–12, 2006.

[2] Warren S McCulloch and Walter Pitts. A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5:115–133, 1943.

[3] Computing Machinery. Computing machinery and intelligence-am turing. *Mind*, 59(236):433, 1950.

[4] Aaron Dotter, Brian Chaboyer, Darko Jevremović, Veselin Kostov, E Baron, and Jason W Ferguson. The dartmouth stellar evolution database. *The Astrophysical Journal Supplement Series*, 178(1):89, 2008.

[5] David J Chalmers. The singularity: A philosophical analysis. *Science fiction and philosophy: From time travel to superintelligence*, pages 171–224, 2016.

[6] Irving John Good. Speculations concerning the first ultraintelligent machine. In *Advances in computers*, volume 6, pages 31–88. Elsevier, 1966.

[7] Chip Walter. Kryder's law. *Scientific American*, 293(2):32–33, 2005.

[8] Carl Shulman and Nick Bostrom. How hard is artificial intelligence? evolutionary arguments and selection effects. *Journal of Consciousness studies*, 19(7-8):103–130, 2012.

[9] Ramesh C Sharma, Paul Kawachi, and Aras Bozkurt. The landscape of artificial intelligence in open, online and distance education: Promises and concerns. *Asian Journal of Distance Education*, 14(2):1–2, 2019.

[10] Silvia Pokrivcakova. Preparing teachers for the application of ai-powered technologies in foreign language education. *Journal of Language and Cultural Education*, 7(3):135–153, 2019.

[11] Steven A Wartman and C Donald Combs. Medical education must move from the information age to the age of artificial intelligence. *Academic Medicine*, 93(8):1107–1109, 2018.

[12] Ben Shneiderman. Human-centered artificial intelligence: Three fresh ideas. *AIS Transactions on Human-Computer Interaction*, 12(3):109–124, 2020.

[13] Jiehao Li, Junzheng Wang, Hui Peng, Longbin Zhang, Yingbai Hu, and Hang Su. Neural fuzzy approximation enhanced autonomous tracking control of the wheel-legged robot under uncertain physical interaction. *Neurocomputing*, 410:342–353, 2020.

[14] Chenguang Yang, Chuize Chen, Wei He, Rongxin Cui, and Zhijun Li. Robot learning system based on adaptive neural control and dynamic movement primitives. *IEEE transactions on neural networks and learning systems*, 30(3):777–787, 2018.

[15] JRahm. What is icall? `https://community.f5.com/t5/technical-articles/what-is-icall/ta-p/288206`.

[16] Trude Heift. *Intelligent Computer Assisted Language Learning*, pages 655–658. Springer International Publishing, Cham, 2021.

[17] Andrey Ignatov, Radu Timofte, William Chou, Ke Wang, Max Wu, Tim Hartley, and Luc Van Gool. Ai benchmark: Running deep neural networks on android smartphones. In *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, pages 0–0, 2018.

[18] Peng Gao, Jingyi Li, and Shuai Liu. An introduction to key technology in artificial intelligence and big data driven e-learning and e-education. *Mobile Networks and Applications*, 26(5):2123–2126, 2021.

[19] Maud Chassignol, Aleksandr Khoroshavin, Alexandra Klimova, and Anna Bilyatdinova. Artificial intelligence trends in education: a narrative overview. *Procedia Computer Science*, 136:16–24, 2018.

[20] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in neural information processing systems*, 27, 2014.

[21] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

[22] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4401–4410, 2019.

[23] Anh Nguyen, Jason Yosinski, and Jeff Clune. Multifaceted feature visualization: Uncovering the different types of features learned by each neuron in deep neural networks. *arXiv preprint arXiv:1602.03616*, 2016.

[24] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, 40(4):834–848, 2017.

[25] F. J. García-Peñalvo and A. Vázquez-Ingelmo. What do we mean by genai? a systematic mapping of the evolution, trends, and techniques involved in generative ai. *International Journal of Interactive Multimedia and Artificial Intelligence*, In Press, 2023.

[26] F. J. García-Peñalvo. The perception of artificial intelligence in educational contexts after the launch of chatgpt: Disruption or panic? *Education in the Knowledge Society*, 24:e31279, 2023.

[27] F. J. García-Peñalvo. Developing robust state-of-the-art reports: Systematic literature reviews. *Education in the Knowledge Society*, 23:e28600, 2022.

[28] Joseph CR Licklider. Man-computer symbiosis. *IRE transactions on human factors in electronics*, (1):4–11, 1960.

[29] Alan Kay and Alan Kay. *The computer revolution hasn't happened yet*. University Video Communications, 1998.

[30] Douglas C Engelbart. Augmenting human intellect: A conceptual framework. *Menlo Park, CA*, 21, 1962.

[31] Alina Gerber, Patrick Derckx, Daniel A Döppner, and Detlef Schoder. Conceptualization of the human-machine symbiosis–a literature review. 2020.

[32] Dakuo Wang, Elizabeth Churchill, Pattie Maes, Xiangmin Fan, Ben Shneiderman, Yuanchun Shi, and Qianying Wang. From human-human collaboration to human-ai collaboration: Designing ai systems that can work together with people. In *Extended abstracts of the 2020 CHI conference on human factors in computing systems*, pages 1–6, 2020.

[33] Vinton G Cerf. Augmented intelligence. *IEEE Internet Computing*, 17(5):96–96, 2013.

[34] Jonas Lowgren, John M Carroll, M Hassenzahl, T Erickson, and A Blackwell. The encyclopedia of human-computer interaction. *Interaction design foundation*, 2019.

[35] Andrea L Guzman and Seth C Lewis. Artificial intelligence and communication: A human–machine communication research agenda. *New media & society*, 22(1):70–86, 2020.

[36] Cristiana Reis and António Ferreira. The relevance of ui/ux design in human-computer interaction of educational games and therapeutic practices. In *Advances in Design and Digital Communication II: Proceedings of the 5th International Conference on Design and Digital Communication, Digicom 2021, November 4–6, 2021, Barcelos, Portugal*, pages 159–169. Springer, 2022.

[37] Wilbert O. Galitz. *The Essential Guide to User Interface Design*. John Wiley & Sons, Hoboken, 2nd edition, 2002.

[38] Hakam W Alomari, Vijayalakshmi Ramasamy, James D Kiper, and Geoff Potvin. A user interface (ui) and user experience (ux) evaluation framework for cyberlearning environments in computer science and software engineering education. *Heliyon*, 6(5), 2020.

[39] Chia-Lin Hsu and Mu-Chen Chen. How does gamification improve user experience? an empirical investigation on the antecedences and consequences of user experience and its mediating role. *Technological Forecasting and Social Change*, 132:118–129, 2018.

[40] Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence*, 2:100008, 2021.

[41] Wendy Roldan, Xin Gao, Allison Marie Hishikawa, Tiffany Ku, Ziyue Li, Echo Zhang, Jon E Froehlich, and Jason Yip. Opportunities and challenges in involving users in project-based hci education. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–15, 2020.

[42] Marianne Kinnula, Netta Iivari, Leena Kuure, and Tonja Molin-Juustila. Educational participatory design in the crossroads of histories and practices–aiming for digital transformation in language pedagogy. *Computer Supported Cooperative Work (CSCW)*, pages 1–36, 2023.

[43] Zahra Al Mahdi, Vikas Rao Naidu, and Preethy Kurian. Analyzing the role of human computer interaction principles for e-learning solution design. In *Smart Technologies and Innovation for a Sustainable Future: Proceedings of the 1st American University in the Emirates International Research Conference—Dubai, UAE 2017*, pages 41–44. Springer, 2019.

[44] Wei Xu, Marvin J Dainoff, Liezhong Ge, and Zaifeng Gao. From human-computer interaction to human-ai interaction: new challenges and opportunities for enabling human-centered ai. *arXiv preprint arXiv:2105.05424*, 5, 2021.

[45] Marisol Wong-Villacres, Adriana Alvarado Garcia, and Javier Tibau. Reflections from the classroom and beyond: Imagining a decolonized hci education. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–14, 2020.

[46] Hsu-Chan Kuo, Yuan-Chi Tseng, and Ya-Ting Carolyn Yang. Promoting college student's learning motivation and creativity through a stem interdisciplinary pbl human-computer interaction system design and development course. *Thinking Skills and Creativity*, 31:1–10, 2019.

[47] Mohammad S Hasan and Hongnian Yu. Innovative developments in hci and future trends. *International Journal of Automation and Computing*, 14:10–20, 2017.

[48] Mark Warschauer. Computer-assisted language learning: An introduction. *Multimedia language teaching*, 320, 1996.

[49] Xiaojing Weng and Thomas KF Chiu. Instructional design and learning outcomes of intelligent computer assisted language learning: Systematic review in the field. *Computers and Education: Artificial Intelligence*, page 100117, 2023.

[50] Xiaofei Lu. Natural language processing and intelligent computer-assisted language learning (icall). *The TESOL encyclopedia of English language teaching*, pages 1–6, 2018.

[51] Inn-Chull Choi. Efficacy of an icall tutoring system and process-oriented corrective feedback. *Computer Assisted Language Learning*, 29(2):334–364, 2016.

[52] Trude Heift. *Intelligent Computer-Assisted Language Learning*. 11 2012.

[53] Javier Marín-Morales, Carmen Llinares, Jaime Guixeres, and Mariano Alcañiz. Emotion recognition in immersive virtual reality: From statistics to affective computing. *Sensors*, 20(18):5163, 2020.

[54] Noureddine Elmqaddem. Augmented reality and virtual reality in education. myth or reality? *International journal of emerging technologies in learning*, 14(3), 2019.

[55] Sarah Deniz, Dakyung Lee, Grace Kurian, Lourdes Altamirano, Darren Yee, Michael Ferra, Blake Hament, Justin Zhan, Laxmi Gewali, and Paul Oh. Computer vision for attendance and emotion analysis in school settings. In *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, pages 0134–0139. IEEE, 2019.

[56] Michael R King and ChatGPT. A conversation on artificial intelligence, chatbots, and plagiarism in higher education. *Cellular and Molecular Bioengineering*, 16(1):1–2, 2023.

[57] S Manikandan, P Dhanalakshmi, S Priya, and A Mary Odilya Teena. Intelligent and deep learning collaborative method for e-learning educational platform using tensorflow. *Turkish Journal of Computer and Mathematics Education*, 12(10):2669–2676, 2021.

[58] Yuyin Jiang and Xiaomei Li. Intelligent online education system based on speech recognition with specialized analysis on quality of service. *International Journal of Speech Technology*, 23:489–497, 2020.

[59] Hui Luan and Chin-Chung Tsai. A review of using machine learning approaches for precision education. *Educational Technology & Society*, 24(1):250–266, 2021.

[60] Ann Neethu Mathew, V Rohini, and Joy Paulose. Nlp-based personal learning assistant for school education. *Int. J. Electr. Comput. Eng.(2088–8708)*, 11:4522–4530, 2021.

[61] Weng Marc Lim, Asanka Gunasekara, Jessica Leigh Pallant, Jason Ian Pallant, and Ekaterina Pechenkina. Generative ai and the future of education: Ragnarök or reformation? a paradoxical perspective from management educators. *The International Journal of Management Education*, 21(2):100790, 2023.

[62] Irene Solaiman. The gradient of generative ai release: Methods and considerations. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, pages 111–122, 2023.

[63] Roberto Gozalo-Brizuela and Eduardo C Garrido-Merchan. Chatgpt is not all you need. a state of the art review of large generative ai models. *arXiv preprint arXiv:2301.04655*, 2023.

[64] Rania Abdelghani, Yen-Hsiang Wang, Xingdi Yuan, Tong Wang, Hélène Sauzéon, and Pierre-Yves Oudeyer. Gpt-3-driven pedagogical agents for training children's curious question-asking skills. *arXiv preprint arXiv:2211.14228*, 2022.

[65] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*, 2022.

[66] Francisco José García-Peñalvo, Faraón Llorens-Largo, and Juan Vidal. The new reality of education in the face of advances in generative artificial intelligence. *RIED: revista iberoamericana de educación a distancia*, In Press, 2023.

[67] Ebrahim Gabajiwala, Priyav Mehta, Ritik Singh, and Reeta Koshy. Quiz maker: Automatic quiz generation from text using nlp. In *Futuristic Trends in Networks and Computing Technologies: Select Proceedings of Fourth International Conference on FTNCT 2021*, pages 523–533. Springer, 2022.

[68] Hyangeun Ji, Insook Han, and Yujung Ko. A systematic review of conversational ai in language education: focusing on the collaboration with human teachers. *Journal of Research on Technology in Education*, 55(1):48–63, 2023.

[69] Reham El Shazly. Effects of artificial intelligence on english speaking anxiety and speaking performance: A case study. *Expert Systems*, 38(3):e12667, 2021.

[70] Minhui Bao. Can home use of speech-enabled artificial intelligence mitigate foreign language anxiety–investigation of a concept. *Arab World English Journal (AWEJ) Special Issue on CALL*, (5), 2019.

[71] Chi-Jen Lin and Husni Mubarok. Learning analytics for investigating the mind map-guided ai chatbot approach in an efl flipped speaking classroom. *Educational Technology & Society*, 24(4):16–35, 2021.

[72] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.

[73] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

[74] Jesse Vig and Yonatan Belinkov. Analyzing the structure of attention in a transformer language model. *arXiv preprint arXiv:1906.04284*, 2019.

[75] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. *Advances in neural information processing systems*, 35:22199–22213, 2022.

[76] Farhad Pourpanah, Moloud Abdar, Yuxuan Luo, Xinlei Zhou, Ran Wang, Chee Peng Lim, Xi-Zhao Wang, and QM Jonathan Wu. A review of generalized zero-shot learning methods. *IEEE transactions on pattern analysis and machine intelligence*, 2022.

[77] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

[78] Maria Tsimpoukelli, Jacob L Menick, Serkan Cabi, SM Eslami, Oriol Vinyals, and Felix Hill. Multimodal few-shot learning with frozen language models. *Advances in Neural Information Processing Systems*, 34:200–212, 2021.

[79] W. X. Zhao et al. A survey of large language models. *arXiv*, arXiv:2303.18223v10, 2023.

[80] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022.

[81] Luciano Floridi and Massimo Chiriatti. Gpt-3: Its nature, scope, limits, and consequences. *Minds and Machines*, 30:681–694, 2020.

[82] Rachel Bawden and François Yvon. Investigating the translation performance of a large multilingual language model: the case of bloom. *arXiv preprint arXiv:2303.01911*, 2023.

[83] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022.

[84] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.

[85] Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences. *arXiv preprint arXiv:1909.08593*, 2019.

[86] Adam Roberts, Colin Raffel, and Noam Shazeer. How much knowledge can you pack into the parameters of a language model? *arXiv preprint arXiv:2002.08910*, 2020.

[87] Yiheng Liu, Tianle Han, Siyuan Ma, Jiayue Zhang, Yuanyuan Yang, Jiaming Tian, Hao He, Antong Li, Mengshen He, Zhengliang Liu, et al. Summary of chatgpt/gpt-4 research and perspective towards the future of large language models. *arXiv preprint arXiv:2304.01852*, 2023.

[88] Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*, 2022.

[89] Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. Instruction tuning with gpt-4. *arXiv preprint arXiv:2304.03277*, 2023.

[90] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*, 2022.

[91] Stable lm documentation. https://github.com/Stability-AI/StableLM.

[92] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.

[93] Standford alpaca documentation. https://github.com/tatsu-lab/stanford_alpaca.

[94] Dolly documentation. https://github.com/databrickslabs/dolly.

[95] https://plainenglish.io/blog/detailed-comparison-of-the-latest-large-language models. Detailed comparison of the latest large language models. https://plainenglish.io/blog/detailed-comparison-of-the-latest-large-language-models, 2023.

[96] Ling Yang, Zhilong Zhang, Yang Song, Shenda Hong, Runsheng Xu, Yue Zhao, Yingxia Shao, Wentao Zhang, Bin Cui, and Ming-Hsuan Yang. Diffusion models: A comprehensive survey of methods and applications. *arXiv preprint arXiv:2209.00796*, 2022.

[97] Alankrita Aggarwal, Mamta Mittal, and Gopi Battineni. Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, 1(1):100004, 2021.

[98] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.

[99] Chenshuang Zhang, Chaoning Zhang, Mengchun Zhang, and In So Kweon. Text-to-image diffusion model in generative ai: A survey. *arXiv preprint arXiv:2303.07909*, 2023.

[100] Ali Borji. Generated faces in the wild: Quantitative comparison of stable diffusion, midjourney and dall-e 2. *arXiv preprint arXiv:2210.00586*, 2022.

[101] Seongmin Lee, Benjamin Hoover, Hendrik Strobelt, Zijie J Wang, ShengYun Peng, Austin Wright, Kevin Li, Haekyu Park, Haoyang Yang, and Duen Horng Chau. Diffusion explainer: Visual explanation for text-to-image stable diffusion. *arXiv preprint arXiv:2305.03509*, 2023.

[102] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2022.

[103] Jialun Peng, Dong Liu, Songcen Xu, and Houqiang Li. Generating diverse structure for image inpainting with hierarchical vq-vae. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10775–10784, 2021.

[104] Gary Marcus, Ernest Davis, and Scott Aaronson. A very preliminary analysis of dall-e 2. *arXiv preprint arXiv:2204.13807*, 2022.

[105] Ali Razavi, Aaron Van den Oord, and Oriol Vinyals. Generating diverse high-fidelity images with vq-vae-2. *Advances in neural information processing systems*, 32, 2019.

[106] Surabhi Adhikari et al. Nlp based machine learning approaches for text summarization. In *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, pages 535–538. IEEE, 2020.

[107] Yang Liu and Mirella Lapata. Text summarization with pretrained encoders. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3730–3740, Hong Kong, China, November 2019. Association for Computational Linguistics.

[108] Ramesh Nallapati, Feifei Zhai, and Bowen Zhou. Summarunner: A recurrent neural network based sequence model for extractive summarization of documents. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017.

[109] Albert Gatt and Emiel Krahmer. Survey of the state of the art in natural language generation: Core tasks, applications and evaluation. *Journal of Artificial Intelligence Research*, 61:65–170, 2018.

[110] Lili Mou, Zhao Meng, Rui Yan, Ge Li, Yan Xu, Lu Zhang, and Zhi Jin. How transferable are neural networks in NLP applications? In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 479–489, Austin, Texas, November 2016. Association for Computational Linguistics.

[111] Yu-An Chung and James Glass. Improved speech representations with multi-target autoregressive predictive coding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2353–2358, Online, July 2020. Association for Computational Linguistics.

[112] Murugan Anandarajan, Chelsey Hill, Thomas Nolan, Murugan Anandarajan, Chelsey Hill, and Thomas Nolan. Text preprocessing. *Practical text analytics: Maximizing the value of text data*, pages 45–59, 2019.

[113] Divya Khyani, BS Siddhartha, NM Niveditha, and BM Divya. An interpretation of lemmatization and stemming in natural language processing. *Journal of University of Shanghai for Science and Technology*, 22(10):350–357, 2021.

[114] Lincoln A. Mullen, Kenneth Benoit, Os Keyes, Dmitry Selivanov, and Jeffrey Arnold. Fast, consistent tokenization of natural language text. *Journal of Open Source Software*, 3(23):655, 2018.

[115] Bhargav Srinivasa-Desikan. *Natural Language Processing and Computational Linguistics: A practical guide to text analysis with Python, Gensim, spaCy, and Keras*. Packt Publishing Ltd, 2018.

[116] Venkat N Gudivada and Kamyar Arbabifard. Open-source libraries, application frameworks, and workflow systems for nlp. In *Handbook of statistics*, volume 38, pages 31–50. Elsevier, 2018.

[117] Xinyun Cheng, Xianglong Kong, Li Liao, and Bixin Li. A combined method for usage of nlp libraries towards analyzing software documents. In *Advanced Information Systems Engineering: 32nd International Conference, CAiSE 2020, Grenoble, France, June 8–12, 2020, Proceedings 32*, pages 515–529. Springer, 2020.

[118] Alexandre Pinto, Hugo Gonçalo Oliveira, and Ana Oliveira Alves. Comparing the performance of different nlp toolkits in formal and social media text. In *5th Symposium on Languages, Applications and Technologies (SLATE'16)*. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2016.

[119] Raj Dabre, Chenhui Chu, and Anoop Kunchukuttan. A survey of multilingual neural machine translation. *ACM Computing Surveys (CSUR)*, 53(5):1–38, 2020.

[120] Felix Stahlberg. Neural machine translation: A review. *Journal of Artificial Intelligence Research*, 69:343–418, 2020.

[121] Translators package. https://github.com/uliontse/translators.

[122] Translators documentation. https://github.com/uliontse/translators.

[123] Deep-translator package. https://github.com/nidhaloff/deep-translator.

[124] Deep-translator documentation. https://deep-translator.readthedocs.io/.

[125] Google translate package. https://github.com/ssut/py-googletrans.

[126] Google translate dopcumentation. https://py-googletrans.readthedocs.io/en/latest/.

[127] Deepl translator package. https://github.com/DeepLcom/deepl-python.

[128] Deepl translator documentation. https://www.deepl.com/docs-api?utm_source=github&utm_medium=github-python-readme.

[129] Matthew J Page, Joanne E McKenzie, Patrick M Bossuyt, Isabelle Boutron, Tammy C Hoffmann, Cynthia D Mulrow, Larissa Shamseer, Jennifer M Tetzlaff, Elie A Akl, Sue E Brennan, et al. The prisma 2020 statement: an updated guideline for reporting systematic reviews. *International journal of surgery*, 88:105906, 2021.

[130] Barbara A Kitchenham, David Budgen, and O Pearl Brereton. Using mapping studies as the basis for further research–a participant-observer case study. *Information and Software Technology*, 53(6):638–651, 2011.

[131] Barbara Kitchenham, O. Pearl Brereton, David Budgen, Mark Turner, John Bailey, and Stephen Linkman. Systematic literature reviews in software engineering – a systematic literature review. *Information and Software Technology*, 51(1):7–15, 2009. Special Section - Most Cited Articles in 2002 and Regular Research Papers.

[132] Mark Petticrew and Helen Roberts. *Systematic Reviews in the Social Sciences: A Practical Guide*, volume 11. 01 2006.

[133] Jingshu He. An exploratory study on the application of artificial intelligence technology in the teaching of japanese language in university. In *2021 2nd International Conference on Information Science and Education (ICISE-IE)*, pages 1454–1457. IEEE, 2021.

[134] Jake Renzella, Andrew Cain, and Jean-Guy Schneider. An intelligent tool for combatting contract cheating behaviour by facilitating scalable student-tutor discussions. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering: Companion Proceedings*, pages 298–299, 2020.

[135] Zhigeng Pan, Yawen Sun, Zheng Wei Yao, and Ming Li. Application of virtual reality in english teaching. In *2021 3rd World Symposium on Artificial Intelligence (WSAI)*, pages 64–71. IEEE, 2021.

[136] Salah Bouktif and Ayisha Manzoor. Artificial intelligence as a gear to preserve effectiveness of learning and educational systems in pandemic time. In *2021 IEEE Global Engineering Education Conference (EDUCON)*, pages 1703–1711. IEEE, 2021.

[137] Yi Yang, Jiasong Sun, and Lu Huang. Artificial intelligence teaching methods in higher education. In *Intelligent Systems and Applications: Proceedings of the 2019 Intelligent Systems Conference (IntelliSys) Volume 1*, pages 1044–1053. Springer, 2020.

[138] Yanxiao Jiang. Artificial intelligence technology for python test simulation of oral english teaching evaluation. In *2022 Sixth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, pages 654–657. IEEE, 2022.

[139] Hiroaki Sakon and Tomohito Yamamoto. Body movements for communication in group work classified by deep learning. In *Human-Computer Interaction. Recognition and Interaction Technologies: Thematic Area, HCI 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part II 21*, pages 388–396. Springer, 2019.

[140] Naka Gotoda, Yusuke Kometani, Rihito Yaegashi, and Toshihiro Hayashi. Educational environment of video system using superimposing symbols to support for skill training. In *Human Interface and the Management of Information. Interacting with Information: Thematic Area, HIMI 2020, Held as Part of the 22nd International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part II 22*, pages 164–174. Springer, 2020.

[141] Marko Bjorn, Werner Ravyse, Diego Sanz Villafruella, Mika Luimula, and Sanne Leivo. Higher education learner experience with fuzzy feedback in a digital learning environment. In *2018 9th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, pages 000253–000260. IEEE, 2018.

[142] Scottie Murrell, Fang Wang, Eric Aldrich, and Xinhao Xu. Meteorologyar: A mobile ar app to increase student engagement and promote active learning in a large lecture class. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pages 848–849. IEEE, 2020.

[143] Matthew Pears, James Henderson, Iraklis Tsoupouroglou, Panagiotis D Bamidis, Eirini Schiza, Constantinos S Pattichis, Natalia Stathakarou, Klas Karlgren, and Stathis Th Konstantinidis. Prototype for crowd-based co-creation of artificial intelligence natural language conversational agents. In *2022 IEEE Global Engineering Education Conference (EDUCON)*, pages 2013–2021. IEEE, 2022.

[144] Chengjie Lai, Qiang Gao, Zefeng Zheng, Disha Yuan, Bailing Zhou, and Ruifeng Hong. Research on head-up and down behavior computer detection by deep learning and artificial intelligence. In *2021 IEEE 3rd International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*, pages 597–600. IEEE, 2021.

[145] Luca Benedetto and Paolo Cremonesi. Rexy, a configurable application for building virtual teaching assistants. In *Human-Computer Interaction–INTERACT 2019: 17th IFIP TC 13 International Conference, Paphos, Cyprus, September 2–6, 2019, Proceedings, Part II 17*, pages 233–241. Springer, 2019.

[146] Ting Liu, Takaya Yuizono, Yifen Lu, and Zhisheng Wang. Application of human-machine dialogue in foreign language teaching at universities. In *IOP Conference Series: Materials Science and Engineering*, volume 573, page 012047. IOP Publishing, 2019.

[147] Soohyun Shin, Jaekyung Cho, and Seong-Woo Kim. Jumple: Interactive contents for the virtual physical education classroom in the pandemic era. In *Augmented Humans Conference 2021*, pages 268–270, 2021.

[148] Chaoyang Wang and Xiang Liu. Affective computing oriented to intelligent education—reflection and prospect. In *2019 International Joint Conference on Information, Media and Engineering (IJCIME)*, pages 241–245. IEEE, 2019.

[149] DanDan Yu, MuRong Ding, WenJing Li, Limin Wang, and Bin Liang. Designing an artificial intelligence platform to assist undergraduate in art and design to develop a personal learning plans. In *Design, User Experience, and Usability. Application Domains: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part III 21*, pages 528–538. Springer, 2019.

[150] Rahul R Divekar*, Jaimie Drozdal*, Samuel Chabot*, Yalun Zhou, Hui Su, Yue Chen, Houming Zhu, James A Hendler, and Jonas Braasch. Foreign language acquisition via artificial intelligence and extended reality: design and evaluation. *Computer Assisted Language Learning*, pages 1–29, 2021.

[151] Lianjing Ni and Liping Wang. Model study of vr technology in the professional teaching of preschool education. In *2021 2nd International Conference on Information Science and Education (ICISE-IE)*, pages 1490–1493. IEEE, 2021.

[152] Yuying Gu, Jingxyan Hu, Yihui Zhou, and Laifeng Lu. Online teaching gestures recognition model based on deep learning. In *2020 International Conference on Networking and Network Applications (NaNA)*, pages 410–416. IEEE, 2020.

[153] Doaa Hamam. The new teacher assistant: A review of chatbots' use in higher education. In *HCI International 2021-Posters: 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings, Part III 23*, pages 59–63. Springer, 2021.

[154] Mohammad Nehal Hasnine, Brendan Flanagan, Gokhan Akcapinar, Hiroaki Ogata, Kousuke Mouri, and Noriko Uosaki. Vocabulary learning support system based on automatic image captioning technology. In *Distributed, Ambient and Pervasive Interactions: 7th International Conference, DAPI 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings 21*, pages 346–358. Springer, 2019.

[155] Maria Perez-Ortiz, Claire Dormann, Yvonne Rogers, Sahan Bulathwela, Stefan Kreitmayer, Emine Yilmaz, Richard Noss, and John Shawe-Taylor. X5learn: A personalised learning companion at the intersection of ai and hci. In *26th International Conference on Intelligent User Interfaces-Companion*, pages 70–74, 2021.

[156] Albertus Retnanto, Mohamed Fadlelmula, Nayef Alyafei, and Ali Sheharyar. Active student engagement in learning-using virtual reality technology to develop professional skills for petroleum engineering education. In *SPE Annual Technical Conference and Exhibition*. OnePetro, 2019.

[157] Tim Schlippe and Jörg Sawatzki. Ai-based multilingual interactive exam preparation. In *Innovations in Learning and Technology for the Workplace and Higher Education: Proceedings of 'The Learning Ideas Conference'2021*, pages 396–408. Springer, 2022.

[158] Hanwen Zheng and Dandan Dai. Construction and optimization of artificial intelligence-assisted interactive college music performance teaching system. *Scientific Programming*, 2022, 2022.

[159] A Almufarreh. Performance evaluation and measurement of learning management system through usability, user interface, and user experience. *INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND NETWORK SECURITY*, 2022.

[160] Lijuan Guo and Jiping Wang. A framework for the design of plant science education system for china's botanical gardens with artificial intelligence. In *HCI International 2020–Late Breaking Posters: 22nd International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part II 22*, pages 267–271. Springer, 2020.

[161] Xuesheng Wang, Qiuhong Han, and Feng Gao. Design of sports training simulation system for children based on improved deep neural network. *Computational Intelligence and Neuroscience*, 2022, 2022.

[162] Ting-Sheng Weng, Chien-Kuo Li, and Meng-Hui Hsu. Development of robotic quiz games for self-regulated learning of primary school children. In *2020 3rd Artificial Intelligence and Cloud Computing Conference*, pages 58–62, 2020.

[163] Sifeng Jing, Ying Tang, Xiwei Liu, Xiaoyan Gong, Wei Cui, and Joleen Liang. A parallel education based intelligent tutoring systems framework. In *2020 IEEE International Conference on Networking, Sensing and Control (ICNSC)*, pages 1–6. IEEE, 2020.

[164] Yunqing Xu, Yi Ji, Peng Tan, Qiaoling Zhong, and Ming Ma. Intelligent painting education mode based on individualized learning under the internet vision. In *Intelligent Human Systems Integration 2021: Proceedings of the 4th International Conference on Intelligent Human Systems Integration (IHSI 2021): Integrating People and Intelligent Systems, February 22-24, 2021, Palermo, Italy*, pages 253–259. Springer, 2021.

[165] Narmeen Al-Hiyari and Shaidah Jusoh. The current trends of virtual reality applications in medical education. In *2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, pages 1–6. IEEE, 2020.

[166] Shuiqiao Yang, Kun Yu, Thorsten Lammers, and Fang Chen. Artificial intelligence in pilot training and education–towards a machine learning aided instructor assistant for flight simulators. In *HCI International 2021-Posters: 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings, Part II 23*, pages 581–587. Springer, 2021.

[167] Sun Tao. Big data system for dragon boat rowing action training based on multidimensional stereo vision. *Mathematical Problems in Engineering*, 2022, 2022.

[168] Ping Xia. Design of personalized intelligent learning assistant system under artificial intelligence background. In *The 2020 International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy: SPIoT-2020, Volume 1*, pages 194–200. Springer, 2021.

[169] Yunpeng Sang and Xingquan Chen. Human-computer interactive physical education teaching method based on speech recognition engine technology. *Frontiers in Public Health*, 10, 2022.

[170] Mark J Nelson and Amy K Hoover. Notes on using google colaboratory in ai education. In *Proceedings of the 2020 ACM conference on innovation and Technology in Computer Science Education*, pages 533–534, 2020.

[171] Olaf Resch and Aglika Yankova. Open knowledge interface: A digital assistant to support students in writing academic assignments. In *Proceedings of the 1st ACM SIGSOFT International Workshop on Education through Advanced Software Engineering and Artificial Intelligence*, pages 13–16, 2019.

[172] Shan Gu, Xingyou Song, and Lei Wu. Optimization of english language and literature teaching management system based on artificial intelligence and computer-aided design. 2022.

[173] Tarik Ahajjam, Mohammed Moutaib, Haidar Aissa, Mourad Azrour, Yousef Farhaoui, and Mohammed Fattah. Predicting students' final performance using artificial neural networks. *Big Data Mining and Analytics*, 5(4):294–301, 2022.

[174] Rui Zhen, Wenchao Song, and Juan Cao. Research on the application of virtual human synthesis technology in human-computer interaction. In *2022 IEEE/ACIS 22nd International Conference on Computer and Information Science (ICIS)*, pages 199–204. IEEE, 2022.

[175] ANTONIO NOVELLINO, LUCA BONOFIGLIO, VINCENZO CIMMINO, and LEONARDO NAPOLETANI. Step-smart education platform.

[176] Xingjiang Tian, Shujing Cui, et al. The application of scientific games by artificial intelligence in preschool education under the smart city. *Security and Communication Networks*, 2022, 2022.

[177] Chia-Chen Chen, Mu-Yen Chen, Sajjad Waheed, Wei-Che Chien, and Wenhai Xu. The teaching pattern of law majors using artificial intelligence and deep neural network under educational psychology. *Deep Learning in Adaptive Learning: Educational Behavior and Strategy*, 2022.

[178] Kissinger Sunday, Solomon Sunday Oyelere, Friday Joseph Agbo, Muhammad Bello Aliyu, Oluwafemi Samson Balogun, and Nacir Bouali. Usability evaluation of imikode virtual reality game to facilitate learning of object-oriented programming. *Technology, Knowledge and Learning*, pages 1–32, 2022.

[179] IS Al-mandhari, L Guan, and EA Edirisinghe. Advances in information and communication networks, 2019.

[180] Astrid Weiss, Rafael Vrecar, Joanna Zamiechowska, and Peter Purgathofer. Using the design of adversarial chatbots as a means to expose computer science students to the importance of ethics and responsible design of ai technologies. In *Human-Computer Interaction–INTERACT 2021: 18th IFIP TC 13 International Conference, Bari, Italy, August 30–September 3, 2021, Proceedings, Part III 18*, pages 331–339. Springer, 2021.

[181] Joshua A Fisher and Janíce Tisha Samuels. A proposed curriculum for an introductory course on interactive digital narratives in virtual reality. In *International Conference on Interactive Digital Storytelling*, pages 462–477. Springer, 2021.

[182] Asim Mohammed Eltahir, Hussam Abdulla, Jan Platos, and Vaclav Snasel. An overview of chatbot structure and source algorithms. In *2022 26th International Conference on Circuits, Systems, Communications and Computers (CSCC)*, pages 91–98. IEEE, 2022.

[183] Kristine Mackare and Anita Jansone. Artificial intelligence aspects in developed e-material formatting application. In *Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing*, pages 1–6, 2019.

[184] Yuji Sasaki, Masanori Fukui, Jo Hagikura, Jun Moriyama, and Tsukasa Hirashima. Development of an interactive educational tool to experience machine learning with image classification. In *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*, pages 78–80. IEEE, 2020.

[185] Jo-Yu Kuo, Xue Ting Song, Chun-Hsien Chen, and Chandrakant D Patel. Fostering design thinking in transdisciplinary engineering education. *Transdisciplinary Engineering for Resilience: Responding to System Disruptions; IOS Press: Amsterdam, The Netherlands*, pages 63–70, 2021.

[186] Elsy Meis, Samuel Pugh, Rachel Dickler, Mike Tissenbaum, and Leanne Hirshfield. Hci strategies for informing the design of a teacher dashboard: How might real-time situational data determine the potential for technological support in the classroom? In *International Conference on Human-Computer Interaction*, pages 161–168. Springer, 2022.

[187] Juliano Sales, Katerina Tzafilkou, Adamantios Koumpis, Thomas Gees, Heinrich Zimmermann, Nicolaos Protogeros, and Siegfried Handschuh. Let the end user in peace: Ux and usability aspects related to the design of tutoring systems. In *Intelligent Tutoring Systems: 16th International Conference, ITS 2020, Athens, Greece, June 8–12, 2020, Proceedings 16*, pages 23–26. Springer, 2020.

[188] Liangfu Jiang. Virtual reality action interactive teaching artificial intelligence education system. *Complexity*, 2021:1–11, 2021.

[189] Maria Korozi, Eleni Stefanidi, Georgia Samaritaki, Antonis Prinianakis, Antonis Katzourakis, Asterios Leonidis, and Margherita Antona. Shaping the intelligent classroom of the future. In *HCI International 2019–Late Breaking Posters: 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings 21*, pages 200–212. Springer, 2019.

[190] Monica Ionita Ciolacu and Paul Svasta. Education 4.0: Ai empowers smart blended learning process with biofeedback. In *2021 IEEE Global Engineering Education Conference (EDUCON)*, pages 1443–1448. IEEE, 2021.

[191] Wei Feng. Design for teaching surroundings based on human-computer interaction techniques. In *Design, User Experience, and Usability. Application Domains: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part III 21*, pages 503–513. Springer, 2019.

[192] Ting Wang and Jinkyung Park. Design and implementation of intelligent sports training system for college students' mental health education. *Frontiers in psychology*, 12:634978, 2021.

[193] Liu Shuguang and Ba Lin. Construction and implementation of embodied mixed-reality learning environments. In *2021 International Conference on Big Data Engineering and Education (BDEE)*, pages 126–131. IEEE, 2021.

[194] Joshua Schiefelbein, Irene-Angelica Chounta, and Emanuele Bardone. To gamify or not to gamify: Towards developing design guidelines for mobile language learning applications to support user experience. In *Transforming Learning with Meaningful Technologies: 14th European Conference on Technology Enhanced Learning, EC-TEL 2019, Delft, The Netherlands, September 16–19, 2019, Proceedings 14*, pages 626–630. Springer, 2019.

[195] Sherry Ruan, Liwei Jiang, Justin Xu, Bryce Joe-Kun Tham, Zhengneng Qiu, Yeshuang Zhu, Elizabeth L Murnane, Emma Brunskill, and James A Landay. Quizbot: A dialogue-based adaptive learning system for factual knowledge. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13, 2019.

[196] Zsuzsanna Soproni. Common european framework of reference for languages: Learning, teaching, assessment, companion volume with new descriptors. *Modern Nyelvoktatás*, 26(1-2):168–170, 2020.

[197] Martina Kienberger, Alicia García-Holgado, Karen Schramm, Anne Raveling, Detmar Meurers, Bohdana Labinska, Tetiana Koropatnitska, and Roberto Therón. *Enhancing Adaptive Teaching of Reading Skills Using Digital Technologies: The LATILL Project*, pages 1092–1098. 05 2023.

[198] Linda Rising and Norman S Janoff. The scrum software development process for small teams. *IEEE software*, 17(4):26–32, 2000.

[199] Swaranjali Jugran, Ashish Kumar, Bhupendr Singh Tyagi, and Vivek Anand. Extractive automatic text summarization using spacy in python & nlp. *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, pages 582–585, 2021.