Exploring the Potential of Generative AI in Initial Teacher Training: A Motivational Analysis

Mohammed Lamrabet, Hamza Fakhar*, Noureddine Echantoufi, Khalid El Khattabi, and Lotfi Ajana

Center for Doctoral Studies: Sciences, Technologies, and Medical Sciences, Laboratory for Scientific Innovation in Sustainability, Environment, Education, and Health in the Age of Artificial Intelligence (LISDEESEIA), Ecole Normale Superieure (ENS), Sidi Mohamed Ben Abdellah University, B.P 5206 Bensouda Fez, Morocco

Email: mohammed.lamrabet@usmba.ac.ma (M.L); hamza.fakhar@usmba.ac.ma (H.F); noureddine.echantoufi@usmba.ac.ma (N.E); khalid.elkhattabi@usmba.ac.ma (K.E.K); lotaja@yahoo.fr (L.A)

*Corresponding author

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***Abstract*—Artificial Intelligence is reshaping teacher training by enhancing pedagogical practices through automation, personalized support, and intelligent content generation. As AI technologies integration is advancing globally, its adoption into in Moroccan teacher training remains constrained due to institutional resistance, insufficient training and lack of awareness. These challenges hinder future teachers' engagement with GenAI technologies. This study examines the motivational dimensions influencing GenAI adoption among Moroccan future teachers, specifically ChatGPT, DeepSeek, and Grok, as intelligent supports for pedagogical task preparation during their initial training, using Keller's Attention, Relevance, Confidence, and Satisfaction (ARCS) model and the Academic Motivation Scale (AMS). A quasi-experimental, quantitative approach was employed. Data were collected through a structured questionnaire based on the Attention, Relevance, Confidence, and Satisfaction-Instructional Materials Motivation Survey (ARCS-IMMS) and AMS components, administered to 146 future teachers enrolled in three distinct training specializations within ENS teacher training institution. Purposive and convenience sampling ensured disciplinary representation. Statistical analysis revealed that gender did not significantly affect motivation levels, as evidenced by an independent samples t-test ($p = 0.403$), with males reporting a mean score of 3.35 and females 3.41. The effect size, Cohen's $d = -0.156$, indicated a small and practically negligible difference. Whereas, training specialization significantly influenced motivation (Fisher's exact test, $p = 0.046$), with future teachers in literary disciplines reporting higher motivation ($M = 3.49$, SD = 0.385), likely due to the alignment between GenAI's capabilities and language-related pedagogical tasks. Multiple regression analysis confirmed that components of both ARCS and AMS significantly predicted motivation levels ($p < 0.001$ for all variables). The model demonstrated high explanatory power, with a multiple correlation coefficient $R = 0.987$, indicating a very strong positive relationship between the motivational components and the overall motivation score. These findings highlighting the value of designing motivationally rich, cognitively engaging, and professionally relevant teacher training programs to support the effective pedagogical integration of GenAI tools. This study contributes to the growing body of literature on AI in education by addressing a gap in Moroccan teacher training. Further investigations are required to systematically evaluate its long-term impact across diverse educational settings.**

***Keywords*—Generative Artificial Intelligence (GenAI), ChatGPT, DeepSeek, grok, motivation, initial teacher training, Attention, Relevance, Confidence, and Satisfaction (ARCS) model, Instructional Materials Motivation Survey (IMMS), Academic Motivation Scale (AMS) model**

I. Introduction

Generative Artificial Intelligence (GenAI) has evolved into a transformative force in education, particularly in the initial training of future teachers, reshaping pedagogical preparation and training dynamics by fostering divergent thinking, mitigates expertise bias, supports idea evaluation and refinement, and enhances collaboration among trainees [1]. Among these tools, ChatGPT demonstrates significant transformative potential by streamlining access to information, supporting diverse content generation and promoting pedagogical innovation, thereby empowering both learners and educators [2]. It further enhances personalized learning, fosters critical thinking through interactive and self-directed learning, and aids future teachers in lesson planning, curriculum design, and assessment development [3].

Beyond ChatGPT, newer models such as DeepSeek and Grok further exemplify GenAI's growing capabilities. DeepSeek, known for its advanced linguistic processing and data modeling functions, supports academic writing and data-driven decision-making [4–6]. Grok, developed by xAI, integrates multimodal reasoning and real-time data analysis, setting itself apart through its responsiveness, sentiment analysis, and educational utility, although it remains under empirical evaluation [7, 8].

GenAI's integration into educational settings is reshaping traditional teaching, training, and learning practices. Its flexibility promotes individual engagement, improves instructional effectiveness, and enhances self-directed learning through intelligent tutoring systems [1, 9, 10]. However, the increasing presence of GenAI in education underscores the need for responsible implementation guided by legal, ethical, and regulatory standards to ensure equity, inclusivity, and sustainable improvements in academic outcomes [11].

The successful implementation of GenAI in the initial training of future teachers depends significantly on their motivation and engagement to adopt and utilize such technologies in pedagogical context. Collie and Martin highlight the influence of contextual factors, occupational variables, and personal background on how GenAI is valued [12]. Similarly, Alvarez *et al.* identify subjective norms, self-efficacy, enjoyment, and perceived usefulness as key predictors of GenAI acceptance among future teachers [13]. Motivation remains central to engagement, persistence, and cognitive development, as emphasized by

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Mohamed *et al*. [14]. Additionally, Monib *et al*. and UNESCO underscore the importance of cultural and linguistic inclusivity in GenAI content to ensure equity and learner connection [15]. UNESCO further stresses that intrinsic motivation, supported by ethically responsible integration and robust teacher training, is essential for the effective and equitable implementation of GenAI in educational settings [16].

While international research on GenAI's potential and its motivational implications is increasingly well established and expanding. Studies focusing on its integration within the Moroccan educational context remain scarce. This gap is partly due to the relatively recent introduction of GenAI tools in Morocco's educational system, where limited access to AI technologies and institutional resources constrains both implementation and scholarly inquiry. Moreover, current teacher-training curricula have yet to incorporate AI-related content, resulting in limited exposure and awareness among future educators. To date, no studies in Morocco have specifically examined the motivational factors influencing prospective teachers' adoption of GenAI tools during initial training.

The research problem addressed in this study is the lack of empirical understanding of the motivational factors—guided by Keller's ARCS model and the Academic Motivation Scale (AMS)—that influence future Moroccan teachers' adoption of GenAI tools such as ChatGPT, DeepSeek, and Grok as intelligent support tools for pedagogical tasks during their initial training.

Self-Determination Theory (SDT) provides a comprehensive framework for understanding motivation to adopt GenAI in future teacher training, conceptualizing motivation along a continuum from intrinsic and extrinsic forms to amotivation [17, 18].

Complementing this, Keller's ARCS model emphasizes four components, Attention, Relevance, Confidence, and Satisfaction, as key to enhancing learner motivation, which can encourage future teachers to adopt innovative technologies such as GenAI into their pedagogical practices [19]. The ARCS model has been extensively employed to examine the motivational dimensions associated with the adoption of innovative technologies in educational contexts. Its adaptability and relevance have been demonstrated across a wide range of technology-enhanced environments, including online and blended learning, gamification, mobile and ubiquitous learning, augmented and virtual reality, and STEM education [19–23].

Building on this foundation, recent studies have applied the ARCS framework to explore motivation in the context of AI integration. One such study investigated teachers' motivation to utilize AI-based tools, specifically ChatGPT-4, for self-directed professional development in lesson planning. Conducted with a cohort of physics teachers in the Fez-Meknes region of Morocco, the study implemented a training program involving both traditional and AI-assisted instructional methods. Motivation was assessed using the Instructional Materials Motivation Survey based on the ARCS model indicating a generally positive disposition toward the use of ChatGPT. The four motivational components were strongly correlated, suggesting that increased attention, perceived relevance, confidence, and satisfaction significantly contribute to teachers' motivation to adopt AI tools for developing pedagogical competencies and enhancing teaching effectiveness [24]. In a parallel line of inquiry, another ARCS-based study examined the motivational strategies influencing learners' engagement with AI and found that fostering intrinsic motivation, sustaining attention, emphasizing the relevance of AI, and building learner confidence collectively enhanced their career-oriented motivation to engage with AI tools [25].

Additionally, the AMS further refines this understanding by distinguishing between subtypes of intrinsic motivation (to know, toward accomplishment, to experience stimulation), extrinsic motivation (identified, introjected, external regulation), and amotivation, offering nuanced insights into future teachers' motivational orientations [26]. The AMS has been widely applied in educational research and has demonstrated strong validity and reliability across various contexts, including initial teacher education [27, 28].

In recent studies related to AI tools integration, researchers have either adopted the AMS model or developed new tools rooted in its theoretical foundation. For example, Jiajing Li *et al*. developed and validated the AI Motivation Scale (AIMS) to measure university students' motivation to learn with AI, based on SDT and the AMS framework. Their findings revealed that supportive learning environments foster increased engagement with AI tools through enhanced motivation, emphasizing the central role of motivation in AI-based learning [29]. These studies explicitly connect their analyses to SDT—on which the AMS is built—and demonstrate how its motivational subtypes can be extended to investigate the use of GenAI in education [30]. This methodological alignment reinforces the relevance of ARCS and AMS frameworks in exploring future teachers' motivational orientations toward AI tools and contributes to establishing a valid analytical framework for the present study.

II. Literature Review

A. *Artificial Intelligence Technologies*

1) *Generative AI*

GenAI refers to a class of AI models designed to create new content across various modalities, including text, images, sound, video, and code. These models leverage advanced machine learning architectures, primarily Large Language Models (LLMs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs). LLMs, such as GPT-3 (Generative Pretrained Transformer), GPT-4, DeepSeek, and PaLM (Pathways Language Model), excel in text generation, while bidirectional models like BERT (Bidirectional Encoder Representations from Transformers) enhance text comprehension. GANs employ competing neural networks to produce realistic samples, and VAEs encode and decode data to preserve essential features for generative modeling.

Cutting-edge tools like ChatGPT, DeepSeek, Stable Diffusion, and DALL-E exemplify GenAI's ability to process complex prompts, generate high-quality responses, and create realistic multimedia content. This transformative capability is driving research and innovation across diverse sectors, including healthcare, education, media, and tourism [31–33].

The potential of GenAI to enhance societal well-being and foster innovation is immense; however, its rapid deployment necessitates robust regulatory frameworks to address ethical concerns, mitigate biases, and prevent unintended consequences at societal, institutional, and individual levels [34]. Particularly in the educational sector, GenAI is redefining traditional paradigms of learning, teaching, and assessment, initiating a transformative shift in instructional methodologies and evaluative practices [35–37].

2) Intelligent tutoring systems

Intelligent Tutoring Systems (ITSs) are AI-driven, computer-based learning platforms designed to simulate personalized, one-on-one tutoring. Originating in the 1970s, ITSs adapt instruction to each student's psychological states, prior knowledge, skills, and preferences, offering tailored feedback and learning tasks [38]. They integrate fields such as cognitive science, AI, computational linguistics, and mathematics, delivering individualized support across subjects like language, physics, and law without human intervention [39]. As transformative educational tools, ITSs have significantly shaped modern teaching and learning by enabling adaptive, interactive, and feedback-driven instruction [40]. These systems monitor learner progress, analyze performance, and adjust content to target specific strengths and weaknesses, fostering a personalized learning experience [41].

3) Natural language processing

Natural Language Processing (NLP) has evolved from early rule-based methods in the 1950s, influenced by linguistics and Chomsky's grammar theories, to data-driven, statistical approaches in the 1990s that harness annotated corpora and machine learning techniques [42]. Today, NLP stands as a transformative AI technology, enabling machines to understand and generate human language, impacting fields such as sentiment analysis, translation, and medical text processing, thus reshaping communication and information retrieval. As a multidisciplinary field, NLP combines linguistics, AI, and cognitive psychology, bridging human-machine interaction and unlocking diverse applications through processing unstructured text [43]. In education, NLP enhances e-learning, generates materials, and promotes teacher-student participation. It aids in accessing reliable resources, filtering unreliable content, and supports information retrieval and quality assessment, contributing to more efficient educational systems [44].

4) Machine learning

Machine Learning (ML), a pivotal subset of AI, focuses on designing algorithms that enable systems to autonomously learn from data, adapt, over time, and make informed predictions without explicit programming for every task [45]. In 1997, Tom Mitchell provided a canonical definition of ML, describing it as the capacity of a system "*to learn from experiences concerning some class of tasks and performance measures*." He emphasized three core elements: the task being learned, the performance metric and well-defined experiences from which the system learns [46]. ML employs sophisticated algorithms to process and analyze extensive datasets, enabling robust pattern recognition and predictive modeling. Core ML methods include supervised learning, which utilizes labeled data for accurate prediction and classification, and unsupervised learning, which uncovers hidden structures within unlabeled data to aid in exploratory analysis. Reinforcement learning optimizes decision-making through trial-and-error feedback, while semi-supervised learning combines labeled and unlabeled data to enhance learning efficiency when labeled data is limited. Together, these approaches support data-driven insights and informed decision-making [47].

ML applications span diverse areas, from data mining, where extensive datasets reveal historical patterns, to model-based forecasting, which supports predictions for future outcomes based on learned experiences. Advanced techniques such as neural networks, support vector machines, and decision trees, are extensively used in supervised learning, while clustering techniques, like k-means, are essential in unsupervised learning. Together, these approaches empower ML systems to independently model, adapt, and respond to new data, enhancing their ability to optimize processes, generate insights, and anticipate trends in complex, dynamic environments [46].

5) Adaptive learning platforms

Adaptive learning systems are AI-driven platforms that personalize instruction by adapting content, task sequencing, feedback timing, and difficulty based on individual learner needs and learning styles. Leveraging ML, NLP, and data analytics, these systems enable trainee autonomy by using automated feedback loops for self-paced progression without constant instructor involvement [48]. Built upon AI, learning analytics, and educational data mining, adaptive systems improve learner motivation, engagement, and outcomes. Research in AI in Education combines computer science, cognitive science, and educational theory to create adaptive solutions for diverse learning needs and objectives [49].

6) Cognitive computing

Cognitive computing represents an advanced form of data analysis that enables systems to continuously learn, reason, and adapt based on evolving data, ultimately aiming to emulate certain aspects of human cognitive processes. Unlike AI that often seeks autonomous decision-making, cognitive computing is designed as a supportive tool for humans, enhancing the ability to process and make sense of complex, large-scale data [50]. The approach hinges on key components like NLP, ML, neural networks, and emotional analysis, enabling these systems to tackle intricate problems similarly to how humans would, yet without the intent of replacing human thought [51]. Fundamentally, cognitive computing systems are built upon four core capabilities: assisting users, understanding advanced data and language, facilitating decision-making, and driving cognition and discovery [50]. These systems operate within an interactive and iterative framework, adapting to both historical and real-time data inputs, which allows them to respond with increasingly relevant insights over time [51].

In education, cognitive systems provide personalized learning through cognitive tutors, which adapt lessons to student progress, simulating a human tutor's guidance. Additionally, NLP-driven tools assist in course selection by aligning offerings to students' profiles and learning patterns, supported by fields like Educational Data Mining and

Learning Analytics [52].

B. Overview of Artificial Intelligence in Education

AI has advanced into a sophisticated field aimed at replicating human cognitive processes, including reasoning, learning, and decision-making [53]. AI broadly refers to the science of developing systems capable of performing tasks traditionally requiring human intelligence, such as problem-solving, language understanding, and perception [54]. Today, AI's transformative influence spans numerous sectors, from healthcare and finance to education, driven by innovations in ML, NLP, robotics and computer vision, alongside diverse applications [55].

The integration of AI in educational settings is reshaping traditional teaching, training and learning practices. Through diverse applications, AI enables more personalized, independent, and interactive learning experiences by analyzing learner profiles to tailor content to individual needs. This adaptability enhances individual engagement and supports more effective educational outcomes [1, 10].

AI supports teachers by automating routine tasks, freeing their time to focus on personalized instruction [56]. Research indicates that AI-enhanced personalized learning environments enable learners to outperform those in traditional settings, with AI playing a key role in fostering self-directed learning through ITS [9].

AI supports individualized tutoring and customizes content to meet each learner's unique needs and progress through tailored instruction, real-time feedback, and automated assessments. Classroom applications, such as AI-powered monitoring tools, allow educators to assess engagement and refine teaching strategies, while predictive analytics identify at-risk students to enable timely intervention and reduce dropout rates. Additionally, chatbots and intelligent tutors provide continuous support, fostering autonomous learning and alleviating educators' administrative load [57].

Beyond instruction, AI tools also enhance accessibility and create immersive learning experiences through VR/AR, making education more inclusive and engaging. Real-time dashboards, AI-based proctoring, and predictive insights further streamline grading, uphold academic integrity, and support strategic decision-making at institutional levels [1, 58]. The transformative potential of AI in education underscores the need for responsible integration, guided by legal, regulatory, and ethical standards, to ensure equity, legitimacy, and the sustained improvement of academic outcomes [11].

AI's progression in education, from basic systems to advanced, web-based platforms, has introduced targeted improvements across three areas. Learner-facing AI tailors learning paths to help individuals achieve content mastery, while teacher-facing AI automates tasks like assessment and plagiarism checks, providing essential insights into individual progress. System-facing AI supports institutional management by offering data-driven insights, aiding in strategic decision-making and policy development. This triad of applications advances personalized learning, enhancing the overall educational experience [59].

The integration of AI into education raises questions about the evolving role of teachers in the classroom. While AI offers innovative tools and transformative capabilities, it does not replace the unique, human aspects of teaching. Human teachers contribute irreplaceable qualities such as moral guidance, emotional intelligence, creativity, empathy, interpersonal skills and the ability to foster existential reflection, norms, and values. Consequently, state-of-the-art AI lacks the bodily presence and human connection that are central to effective teaching [60].

Research suggests that teaching remains a relatively stable profession amid automation, as AI serves to enhance rather than replace educators' roles. This enhancement through AI allows teachers to focus more on personalized, impactful teaching while streamlining tasks and broadening instructional methods. Teachers recognize their continued importance and often pursue professional development to integrate AI tools effectively into their practice, utilizing AI as a supportive asset rather than a replacement. Thus, AI's role in education is to empower teachers, making the profession more attractive while retaining the foundational aspects that have historically enriched it [1, 61].

AI's transformative effects in education extend across multiple dimensions. It facilitates communication and interaction, advances personalized learning, promotes creative problem solving, and enhances time management and collaborative communication. Additionally, AI strengthens cognitive abilities, accelerates decision-making, and increases the effectiveness of strategic planning and instructional processes. Notably, AI-based tools improve individual performance predictions, helping identify learner at risk and enabling timely intervention [62].

C. Generative AI in Education: Opportunities and Challenges

1) ChatGPT

Since its launch in November 2022, ChatGPT has become a transformative tool in education, excelling in various pedagogical tasks. Built on the GPT architecture and trained with Reinforcement Learning from Human Feedback (RLHF), it delivers contextually relevant and high-quality responses [63]. In early 2025, OpenAI launched the o3-mini model, enhancing reasoning and providing faster, more accurate responses. Available in ChatGPT and API services, it offers higher usage limits for paid users. The o3-mini-high variant, designed for demanding tasks like coding, offers even greater performance. These advancements support diverse applications, including answering questions, composing emails, and generating code, meeting the needs of educators and learners [64].

ChatGPT, an advanced AI language model, presents a transformative potential for education, particularly in initial training of future teachers. By streamlining information access and generating diverse content, it empowers learners, future and practice educators [2].

Learners can benefit from personalized learning experiences, accessing tailored explanations and engaging with interactive learning environments. This fosters deeper understanding and encourages critical thinking skills through structured debates and self-directed learning. For future and practice educators, ChatGPT offers valuable support in pedagogical tasks, lesson planning, curriculum development, and assessment design. Automating routine tasks allows for increased focus on individualized learners support and innovative pedagogical approaches. Furthermore, ChatGPT can serve as a valuable tool for teacher training, enabling future educators to develop pedagogical strategies, simulate classroom scenarios, and refine pedagogical task preparation techniques through AI-driven insights [3, 24, 65].

However, the integration of ChatGPT also presents significant challenges. Concerns regarding data privacy, algorithmic bias, and the potential for misuse, such as plagiarism and over-reliance on AI, necessitate careful consideration. Ensuring the ethical and responsible use of AI in education requires a nuanced approach that prioritizes human interaction, critical thinking, and the development of AI literacy skills among both learners and educators [65, 66]. By thoughtfully integrating GenAI, such as ChatGPT into initial teacher training programs, future educators can acquire valuable skills in AI literacy, develop innovative pedagogical approaches, effectively navigate and utilize AI tools, and ultimately enhance their future teaching practice while ensuring ethical and responsible use of this powerful technology [67].

2) DeepSeek

DeepSeek has established itself as a leading innovator in the development of cost-efficient, large-scale language models (LLMs). The Hangzhou-based company introduced DeepSeek v3 in December 2024, which quickly gained prominence and reinforced the company's commitment to open-access AI solutions. This suite of models, including DeepSeekMath, DeepSeek-V2, DeepSeekMoE, DeepSeek-V3, and DeepSeek-R1, represents a series of significant advancements in AI, specifically in the area of language processing. DeepSeek, a next-generation AI model, is trained on vast datasets that enable it to process complex linguistic structures and generate high-quality text. This capability has generated significant discussions about its potential impact on academic writing and content creation, offering both researchers and educators, whether future or experienced teachers, an advanced tool for scholarly production. Moreover, its scalability and accessibility have solidified DeepSeek's position as a key driver in the evolution of AI-driven research and innovation [4].

Beyond academic applications, DeepSeek is also revolutionizing data-driven decision-making. Through the use of advanced machine learning algorithms and deep neural networks, it extracts insights with high precision, uncovers hidden patterns, and generates synthetic data for predictive modeling. The platform's scalable architecture ensures its adaptability across various applications, setting new standards for intelligent automation and innovation [5].

The release of DeepSeek-R1 on January 10, 2025, further solidified the company's position in the AI field. This model matches the performance of leading AI models while maintaining lower computational costs. As an open-source platform, DeepSeek-R1 has experienced rapid adoption, marking a significant milestone in AI [6]. However, it is important to acknowledge that research on the integration of DeepSeek in educational contexts, particularly in initial teacher training, remains limited.

3) Grok

Grok, developed by xAI under the leadership of Elon Musk, represents a rapidly evolving GenAI model designed to address limitations in existing chatbot technologies. Since its initial prototype, Grok 0, with 33 billion parameters, the model has undergone significant advancements, culminating in Grok 3, which, as of March 2025, is speculated to exceed 1 trillion parameters. With each iteration, Grok has integrated enhanced reasoning capabilities, multimodal processing, and real-time data analysis, positioning itself as a competitive AI system. Notably, its unique approach to user engagement, leveraging humor, sentiment analysis, and responsiveness to complex queries, distinguishes it from traditional LLMs. While its full potential is yet to be empirically validated, Grok's emerging capabilities in real-time social media insights and interactive user experiences suggest promising applications in education, content generation, and digital communication [7, 8].

D. Motivational Factors Influencing the Adoption of Generative AI in Initial Teacher Training

Motivation is a multifaceted construct that plays a pivotal role in human behavior, including the educational context. It can be conceptualized as the internal drive that energizes, directs, and sustains an individual's efforts towards achieving specific goals. While intangible, motivation is influenced by a complex interplay of beliefs, interests, values, and external factors [25, 68].

Drawing on theories of human behavior, scholars have offered various perspectives on motivation [69]. Spolsky emphasizes the temporal aspect, focusing on the time and effort invested in tasks. Ortega-Martín highlights the interplay between internal dispositions and external circumstances, while Bhatia emphasizes its role in overcoming initial reluctance. Cole views motivation as the internal state that directs and sustains behavior towards specific goals. Kleinginna and Kleinginna conceptualize motivation as the internal condition that activates and energizes behavior, while Reeve emphasizes its role in sustaining learner engagement. Robbins, Judge, and Campbell further define motivation through its three key components: intensity, direction, and persistence [68].

Within the context of initial teacher training, motivation emerges as a critical factor in ensuring the success and engagement of future educators. It drives individuals to actively seek knowledge, develop essential skills, and fully engage in both the learning process and the preparation of pedagogical tasks. Given the critical role of motivation in initial teacher training, it is essential to explore how emerging technologies, particularly GenAI, are reshaping pedagogical practices and influencing future teachers' motivation. AI tools are transforming initial teacher training by redefining pedagogical practices and influencing the motivations of future teachers. By leveraging AI, initial teacher training programs can offer innovative approaches to teaching and learning, such as personalized learning pathways, AI-powered tutoring and mentoring, and access to a wealth of educational resources [19]. Thereby equipping aspiring teachers with the skills and competencies required to navigate and thrive in an increasingly digitalized educational environment [70].

However, understanding the factors that motivate future teachers is crucial for predicting their professional behaviors and ensuring effective educational outcomes. According to the Theory of Planned Behavior, intentions serve as strong predictors of actions, providing valuable insights into educators' decisions and behaviors within the teaching context [71]. Additionally, SDT offers a valuable framework for understanding future teacher motivation, conceptualizing it as a continuum ranging from intrinsic motivation to amotivation [18].

Intrinsic motivation, driven by internal satisfaction and fulfillment, is considered the most desirable form of motivation, fostering greater autonomy, engagement, and professional growth [14, 18, 69].

Intrinsic motivation, as conceptualized by Deci and Ryan, stems from internal satisfaction and enjoyment, fostering autonomy, engagement, and professional growth [17]. Brophy emphasizes that intrinsic motivation not only encourages voluntary engagement but also facilitates the development of expertise through sustained interest and effort [72]. Asor further elucidates that intrinsic motivation, fueled by curiosity and enjoyment, yields numerous benefits, including positive emotional experiences, identity formation, deep learning, social connectedness, and effective coping mechanisms for challenges [69].

These motivational dimensions are drawn from the AMS, a validated instrument grounded in SDT. The AMS conceptualizes motivation along a continuum that includes intrinsic motivation (with its three subtypes), extrinsic motivation (composed of three subtypes), and amotivation. This framework allows for a nuanced understanding of the psychological mechanisms influencing future teachers' motivation with pedagogical tasks and emerging technologies.

According to Vallerand *et al*., the taxonomy of intrinsic motivation is composed of three subtypes, each representing a distinct internal drive for engaging in academic activities [26]:

- Intrinsic Motivation To Know (IMTK): refers to engaging in an activity for the inherent pleasure and satisfaction derived from learning, exploring, and understanding new concepts. It is often driven by curiosity and a desire for intellectual growth.
- Intrinsic Motivation Toward Accomplishment (IMTA): reflects motivation based on the satisfaction experienced when attempting to accomplish or create something, often associated with a sense of competence and personal achievement.
- Intrinsic Motivation To Experience Stimulation (IMES): involves engaging in activities to experience stimulating sensations, such as excitement, aesthetic enjoyment, or sensory pleasure.

Although intrinsic motivation is key to fostering autonomy, extrinsic motivation remains influential, particularly when intrinsic motivation is insufficient.

Extrinsic motivation, driven by external factors such as rewards, recognition, or the anticipation of specific outcomes, can also influence future teacher behavior, albeit to a lesser degree. It refers to the engagement in activities driven by external factors [68].

According to Deci and Ryan, extrinsic motivation exists along a self-determination spectrum, ranging from fully externally controlled behaviors to those that are progressively more aligned with personal values [69].

Within this framework, extrinsic motivation is conceptualized as a multidimensional construct that reflects varying degrees of internalization and autonomy in the regulation of behavior. This continuum is typically composed of three subtypes:

- Extrinsic Motivation-External Regulation (EMER), behavior is driven by external contingencies such as demands, rewards, punishments, or imposed constraints.
- Extrinsic Motivation -Introjected Regulation (EMIjR) refers to motivation controlled by internal pressures, including guilt, self-criticism, or the desire to avoid shame, even though the behavior is not fully self-endorsed.
- Extrinsic Motivation -Identified Regulation (EMIR), the individual engages in an activity because it is consciously valued and seen as personally important, thus aligning with one's goals and values.
- Amotivation (AMT) refers to a complete lack of intention to act. It reflects a psychological state in which learners perceive no contingency between their actions and expected outcomes, resulting in feelings of incompetence, expectations of uncontrollability, disinterest, and low engagement with academic tasks [26].

The AMS has been extensively employed in educational research and has consistently shown sound psychometric qualities, including validity and reliability, particularly within the context of initial teacher education [27, 28]. In more recent investigations into AI integration in educational settings, researchers have either utilized the AMS framework or developed new instruments grounded in its theoretical principles. For instance, the study titled "The AI Motivation Scale (AIMS): A Self-Determination Theory Perspective" introduced and validated the AI Motivation Scale (AIMS) to assess university students' motivation to engage with AI-based learning, drawing on both SDT and the AMS model. Their results highlighted that motivational enhancement within supportive academic environments significantly increases learners' engagement with AI tools, underscoring motivation as a key factor in AI-mediated education [29]. These studies affirm the methodological relevance of SDT and its motivational subtypes—central to the AMS—in exploring the role of GenAI in teaching and learning processes [30].

In addition, personal relevance significantly influences learner engagement by connecting educational content to real-world experiences. Research by Stuckey *et al.* emphasizes the importance of aligning learning with learners' lived experiences. Kapon further highlights the crucial role of personal relevance in bridging the gap between formal education and learners' everyday lives. Schmidt found that when instructors emphasize the real-world applications of learning, trainees perceive greater value and exhibit higher engagement. Building upon the foundation of personal relevance, self-efficacy emerges as a critical determinant of learning and training success. Ghasem identifies self-efficacy as a pivotal motivational factor, influencing learners' persistence, pedagogical task completion, and effective knowledge application. Drawing from socio-cognitive theory, Mete emphasizes the profound impact of self-efficacy on various aspects of human behavior, including goal-setting, decision-making, and resilience. Furthermore, Sanli reveals that higher levels of self-efficacy significantly reduce test anxiety, underscoring the interconnectedness of self-efficacy, task value, and emotional well-being in learning outcomes [73].

While this discussion addresses key elements affecting motivation, it is important to acknowledge the existence of additional factors beyond the scope of this analysis.

E. The ARCS Model Approach

The ARCS model, developed by John Keller, provides a robust framework for designing and implementing instructional strategies that significantly enhance learner motivation across diverse educational contexts, notably in the initial training of future educators [74]. Grounded in expectancy-value theory, the model highlights the importance of maintaining learners' attention, aligning content with their goals, and fostering confidence in achieving them. As learners deepen their understanding, their confidence and perceived relevance of the content grow, resulting in more satisfying learning experiences [75]. The ARCS model has been widely applied in technology-enhanced environments including online and blended learning; gamification; mobile and ubiquitous learning; augmented and virtual reality and STEM education as well as various other technological contexts, demonstrating its versatility and contemporary relevance [19–23].

A recent study explored teachers' motivation to adopt GenAI tools—specifically ChatGPT-4—as a means of self-professional development in pedagogical tasks. Conducted with a group of physics teachers, the study implemented a training program that incorporated both conventional and AI-supported instructional strategies. Motivation levels were assessed using the Instructional Materials Motivation Survey (IMMS), grounded in the ARCS model. Findings revealed an overall positive attitude toward the use of ChatGPT-4, with strong intercorrelations among the four motivational dimensions—Attention, Relevance, Confidence, and Satisfaction—highlighting their collective influence on teachers' motivation to integrate AI tools for enhancing pedagogical skills and instructional effectiveness [24]. Complementarily, another ARCS-driven investigation focused on learners' engagement with AI technologies, emphasizing that strategies, which promote intrinsic motivation, maintain attention, demonstrate relevance, and build confidence significantly contribute to strengthening learners' career-oriented motivation to engage with AI tools [25].

A systematic review by Li and Keller further underscores its extensive application across various educational contexts, instructional methodologies, and motivational outcomes. The model serves as a valuable framework for guiding instructional design, analyzing motivational constructs, and functioning as a measurement tool through the IMMS [76].

The ARCS model emphasizes four key components, Attention, Relevance, Confidence, and Satisfaction, which collectively foster engagement and motivation in learners. In the context of initial teacher training, this framework is particularly valuable for understanding and enhancing future teachers' motivation to adopt innovative technologies in their instructional practices.

- Attention (A): involves capturing and sustaining learners' curiosity and interest through novel and varied instructional techniques, fostering active participation and engagement.
- Relevance (R): ensures that instructional materials align with learners' goals, needs, and prior experiences. By demonstrating clear utility for future application, it enhances the personal significance and value of learning.
- Confidence (C): cultivates learners' belief in their ability to succeed by setting clear objectives, scaffolding learning experiences, providing constructive feedback, and ensuring a structured progression of tasks. This fosters a positive expectation of success, encouraging effort and persistence.
- Satisfaction (S): determines the extent to which learners experience reward and achievement. It includes intrinsic and extrinsic reinforcement, such as skill application, recognition of achievements, and fair evaluation, to ensure learners feel valued and motivated to persist [22, 74].

The ARCS model offers a strong theoretical foundation for investigating GenAI as an intelligent support tool. By aligning the motivational aspects involved in the preparation of pedagogical tasks during initial teacher training with emerging AI technologies, researchers can better assess how these tools influence the motivation and engagement of future teachers. Integrating the ARCS framework with the analysis of GenAI applications, such as ChatGPT-4, DeepSeek V3 and Grok3 offers a novel perspective on the interplay between technology and future teacher motivation. This approach enables systematic evaluation of how AI-driven instructional strategies capture attention, establish relevance, build confidence, and provide satisfaction, thereby enhancing overall learning outcomes. Ultimately, employing the ARCS model in this context not only deepens our understanding of motivational dynamics in teacher training but also supports the development of more effective, technology-enhanced educational practices [23, 74, 76].

F. Insights from Recent Studies

Recent research highlights key factors influencing teachers' motivation and engagement in integrating GenAI into educational practices. Collie and Martin emphasizes that contextual (autonomy-supportive and autonomy-thwarting leadership), occupational (professional growth striving, change-related stress), and background factors (gender, age, teaching experience, school level, specialization), could significantly enhance the adoption of AI-powered generative tools in teaching [12].

In a complementary perspective, Alvarez *et al.* underscores that subjective norm, self-efficacy, enjoyment, and perceived usefulness are strong predictors of GenAI technologies adoption among future teachers, though gender disparities emerge, with males showing greater responsiveness to social norms [13].

Møgelvang *et al.* further support these findings by demonstrating that male engage more frequently with GenAI tools and utilize them across a broader range of tasks, reflecting higher perceived utility and stronger alignment with future career relevance. In contrast, female primarily employ GenAI for text-related tasks and express greater concerns regarding critical thinking, autonomous judgment, and the need for clearer guidance on when and how to appropriately trust such technologies. Despite these differences, both genders exhibit motivation to engage with GenAI technologies, albeit shaped by different needs and expectations [77].

Similarly, Nyaaba *et al*. report a significant gender disparity in the frequency of GenAI tools use among pre-service teachers, with male exhibiting a higher usage rates. Nonetheless, both male and female groups expressed positive attitude towards the use of GenAI in academic research, noting among other benefits that these tools provided them with confidence and independence in their research writing [78].

In line with these observations, recent research conducted in the Moroccan context by Fakhar *et al*. found that both male and female teachers reported motivation to use GenAI tools, with no significant differences in the level of motivation based on gender [24]. This suggests that the universal appeal of GenAI motivation in educational settings may be more strongly associated with individual perceptions of its utility and effectiveness rather than demographic differences [79, 80].

Supporting this conclusion, Al Darayseh found no statistically significant differences between male and female science teachers in their behavioral intentions to use GenAI in teaching, indicating that gender may not always play a decisive role in the adoption motivation of Gen AI [81].

However, Otis *et al*. present a broader concern by documenting a near-universal gender gap in GenAI usage across global regions, sectors, and occupations. Their findings reveal that women are underrepresented among GenAI users—even when access is equal—suggesting that deeper issues such as motivation, confidence, and social norms may hinder adoption. If unaddressed, this gap could lead to biased AI systems trained predominantly on male-generated data, further entrenching inequality and neglecting women's perspectives in technological development [82].

These findings underscore the critical importance of understanding and mitigating gender-based barriers to GenAI adoption, particularly in education and professional development contexts. Addressing these disparities is essential to ensure equitable access to emerging technologies and to foster inclusive AI practices in teacher training programs.

The integration of GenAI in initial teacher education has become a critical area of exploration, particularly within the context of language education. Despite the increasing presence of GenAI in educational settings, its implications for Initial Language Teacher Education (ILTE) remain relatively underexplored [13]. Moorhouse and Kohnke highlights this gap, emphasizing that the perceptions of language teacher educators regarding GenAI's influence on ILTE have not been sufficiently examined. His findings indicate that educators foresee significant impacts of GenAI on the curriculum, instructional practices, and assessment frameworks within ILTE programs [83].

Complementary to this, several empirical studies have examined the use of AI tools in language learning. For instance, Jeon conducted an intervention study involving language learners and observed that participants who perceived a customized English-learning chatbot as an authentic conversational partner demonstrated a greater willingness to engage with it [84]. Similarly, Chiu *et al*. reported that the integration of AI chatbots significantly enhanced learners' interest and motivation in language learning activities [85].

Ali *et al*., who conducted a quantitative survey shortly after the release of ChatGPT, provide further evidence. Their study revealed that both language instructors and trainees perceived ChatGPT-based instruction as positively influencing learners' autonomous, intrinsic, and extrinsic motivation. The authors suggest that this effect may partly result from the novelty of the tool, which initially captures learners' interest and engagement [86].

Moreover, prospective language teachers appear to recognize the pedagogical value of GenAI, particularly in its ability to provide immediate, individualized feedback and generate diverse linguistic examples to support instruction [87]. These affordances contribute to a growing appreciation of GenAI as a valuable complement to traditional language teaching methodologies.

Beyond the domain of language education, similar trends are observed in science education. Al Dayareh reports a high level of acceptance of GenAI tools among science teachers, with positive correlations identified between GenAI adoption and variables such as self-efficacy, perceived ease of use, anticipated benefits, attitudes, and behavioral intentions [81].

Collectively, these findings underscore the dynamic and transformative potential of GenAI in education training. As Alvarez *et al*. emphasize, the rapidly evolving educational landscape necessitates informed and strategic adoption of GenAI within teacher training institutions [13].

Furthermore, motivation proves central to learning and training outcomes, as Mohamed *et al*. asserts it shapes engagement, perseverance, and cognitive processes [15]. Monib *et al*. and UNESCO highlight the importance of cultural and linguistic representation in GenAI content, fostering learner connection and equitable learning experiences [16]. UNESCO further stresses that intrinsic motivation, paired with responsible AI integration and teacher training, is crucial for effective implementation [17].

In terms of practical applications, recent studies explore ChatGPT's potential to enhance personalized learning, facilitate interactive tutoring, streamline lesson planning, and foster collaborative learning environments [88, 89]. Sangwoo Ha illustrates its utility in physics lesson simulations, noting its ability to generate diverse content and real-time responses. However, concerns arise regarding content reliability and the risk of uncritical acceptance of AI-generated information, emphasizing the need for targeted teacher training [90].

While research indicates that prospective teachers recognize the potential benefits of ChatGPT, studies reveal a lack of confidence and competence in effectively utilizing these tools. This highlights the critical need for comprehensive teacher training programs that equip educators with the necessary knowledge, skills, and confidence to integrate GenAI effectively and responsibly into their teaching practices [3, 83]. In the Moroccan context, recent findings reveal a significant positive correlation between educators' knowledge of AI-based tools and their perceived importance, observed among both prospective and experienced teachers. Moreover, interest in and proficiency with emerging technologies were identified as critical determinants of favorable perceptions. Despite contextual challenges, there was strong consensus on the necessity of incorporating AI tools into teacher training programs, irrespective of years of professional experience. These findings not only reflect both the opportunities and challenges associated with AI integration in the Moroccan educational landscape but also emphasize the imperative to embed AI-related competencies within initial teacher education curricula to align with the evolving demands of 21st-century teaching [91].

Although international research exploring the motivation and potential of GenAI is well established, and insights from recent studies confirm the increasing interest in exploring the role of motivation in AI-enhanced learning environments, significant gaps persist in the existing research literature. In particular, research has rarely focusing on future teachers' motivation to adopt GenAI tools during initial training in pedagogical task within the Moroccan educational context particularly using robust theoretical models such as AMS and ARCS model.

Several factors contribute to this discrepancy. First, the integration of these technologies tools as a pedagogical support tools in educational systems is relatively new in Morocco, and many educational institutions face challenges such as limited access to AI technologies and resources. These barriers hinder both the practical implementation and the study of AI tools in education. Second, empirical studies that compare traditional and AI-supported task performance remain limited. Third, the influence of contextual variables such as gender and specialization teacher training on motivational dynamics is still underexplored. Additionally, the current teacher-training curriculum in Morocco has not yet fully incorporated AI-related content or AI-based tools, leading to a lack of exposure and awareness among future teachers.

To date, no know studies in Morocco have examined the motivational factors influencing future teachers' adoption of GenAI tools like ChatGPT, DeepSeek and Grok for preparing pedagogical tasks during their initial training.

These gaps underscore the need for targeted investigations that address these limitations—an objective this study seeks to fulfill. In response to these challenges, the present research aims to examine the motivational factors that influence future teachers' engagement with GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent pedagogical support during their initial training. This inquiry is designed to provide empirical evidence and contextual insights that can guide the integration of AI-based tools in teacher education programs in Morocco.

III. Materials and Methods

A. Purpose of the Present Study

To further understand the motivational dynamics, this study draws upon Keller's ARCS model, which suggests that motivation can be enhanced by capturing learners' attention, aligning tasks with personal goals (relevance), building confidence, and ensuring satisfaction. These components can foster future teachers' motivation to integrate innovative technologies like GenAI into their instructional practices [74].

In parallel, the study incorporates the AMS model, which distinguishes between intrinsic motivation (to know, toward accomplishment, to experience stimulation), extrinsic motivation (identified, introjected, and external regulation), and amotivation. These subscales offer deeper insights into the underlying motivational orientations of future teachers [26]. Therefore, this study proposes a conceptual model to explore how the dimensions and subscales of the ARCS, along with the AMS motivational components, influence future teachers' motivation to adopt GenAI as intelligent support tools during their initial teacher training, particularly for pedagogical tasks.

The study's conceptual model.

The hypotheses tested in the model include the following:

H1: Gender significantly influences future teachers' motivation to adopt GenAI in pedagogical tasks.

H2: Specialization significantly influences future teachers' motivation to adopt GenAI in pedagogical tasks.

H3: ARCS-based motivational components positively influence future teachers' motivation to adopt GenAI in pedagogical tasks.

H4: AMS-based motivation dimensions positively influence future teachers' motivation to adopt GenAI in pedagogical tasks.

B. Methodological Framework

This study employed a quasi-experimental design, conducted during the spring semester of the 2024-2025 academic year. Participants were 146 future teachers from three distinct specialty groups (primary, science and future literary education teachers) within a Moroccan initial teacher-training program. A quantitative approach was adopted to investigate the motivational factors influencing future teachers' motivation to adopt GenAI (ChatGPT, DeepSeek and Grok) as intelligent support tools during initial teacher training, specifically for pedagogical tasks.

A structured questionnaire was employed for data collection. The instrument underwent to reliability and validity testing to ensure its robustness. reliability was assessed using Cronbach's alpha and McDonald's Omega coefficient, while content validity was evaluated to confirm the appropriateness and relevance of the items.

Quantitative analyses involved inter-dimensional correlations as a preliminary check to assess the relationships between different dimensions and ensure construct cohesion. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted to validate the factor structure of the questionnaire.

To examine potential disparities in motivation to adopt GenAI tools, gender and specialization were included as independent variables. An Independent Samples T-Test was conducted to assess whether motivation scores differed significantly by gender, in light of prior research suggesting gender-based variations in the adoption of digital technologies. In parallel, a One-Way ANOVA was performed to compare motivation levels across the three training specializations (primary, scientific, and literary education), given the distinct pedagogical approaches and subject matter focus within each program. These disciplinary differences may influence how future teachers engage with GenAI tools. The inclusion of these variables enabled the investigation of whether significant motivational differences exist across groups and informed the potential need for differentiated training strategies tailored to specific learner profiles in AI-integrated teacher education. Additionally, Multiple Linear Regression (MLR) Analysis was utilized to examine the effect of each subscale of the ARCS components and the AMS dimensions on the motivation to adopt GenAI. The dependent variable, measured as a continuous variable (based on the mean from a 5-point Likert scale), represented future teachers' motivation to adopt GenAI tools (such as ChatGPT, DeepSeek, and Grok) as intelligent support tools during their initial teacher training, particularly for pedagogical tasks.

To visually synthesize the research design and procedural steps, a flowchart of the methodology (Fig. 1) is presented to enhance clarity and facilitate understanding of the overall research process.

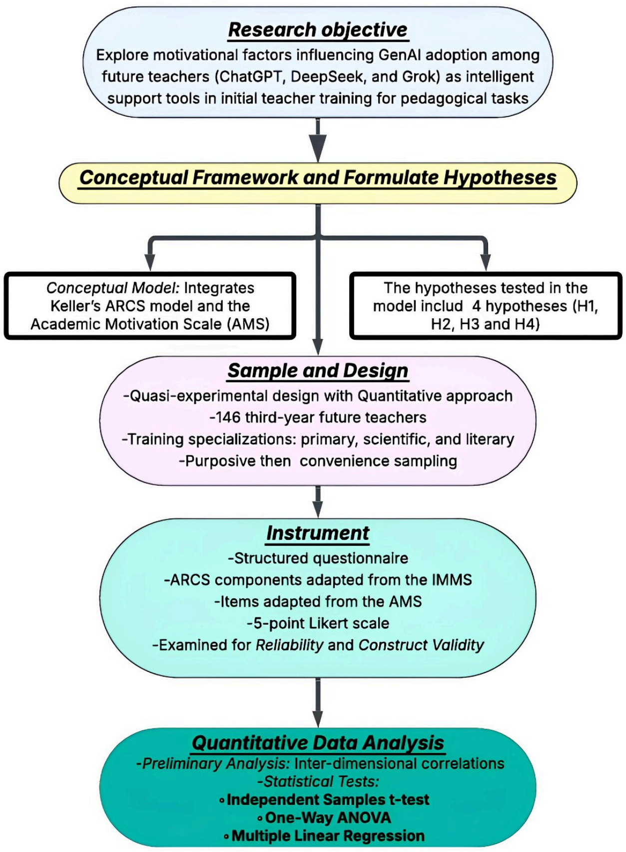

Fig. 1. Flowchart of the methodology.

C. Sample

The sample for this quasi-experimental study was purposefully selected based on predefined criteria to ensure its relevance to the study's objectives. Participants consisted of 3rd year future teachers enrolled in the initial teacher-training program at the ENS of Fes, Morocco. This cohort was specifically chosen as third-year future teachers are in their final year of training, possessing advanced academic experience and a deeper conceptual understanding of pedagogical practices. Their positioning within the digital and technological era equips them with the necessary skills to effectively utilize GenAI tools, such as ChatGPT, DeepSeek and Grok for pedagogical tasks during their initial training.

The sample included future teachers from three distinct specializations, primary, scientific, and literary education, to ensure comprehensive representation across all academic tracks offered within the ENS. A mixed sampling strategy was employed: purposive sampling (criterion-based) was used to select participants based on their specialization, while convenience sampling within each group facilitated practical access and voluntary participation.

Ethical approval was obtained prior to data collection, adhering to ethical research standards. Informed consent was gathered from all participants, ensuring they were fully aware of the study's purpose and procedures. Participation was voluntary, and all data was collected anonymously to protect participants' privacy.

Potential participants were invited to complete the survey, and from a pool of 200 candidates, 146 complete responses were obtained and analyzed, yielding a response rate of 73 %. As indicated in Table 1, in terms of gender distribution, 27.4% of participants (n = 40) identified as male, while 72.6% (n = 106) identified as female. Regarding specialization, 30.1% (n = 44) of participants were enrolled in primary education, 34.9% (n = 51) in scientific education, and 34.9% (n = 51) in literary education.

The age of participants ranged from 20 to 23 years, with an average age of 20.64 years. The majority of future teachers held a DEUG (68.5%), while less than 9.6% possessed a Licence and 21.9% held only a Bac. While this sample provides valuable insights, it may not fully represent the broader population of future teachers at ENS Fes. Therefore, further research involving a larger and more diverse sample is recommended to enhance the generalizability of the findings.

Table 1. Demographic characteristics of sample

Variable	Demographic	Frequency	(%)	Cumulative (%)
Gender	Male	40	27.4	27.4
	Female	106	72,6	100.0
Specialty	Primary	44	30.1	30.1
	Scientific	51	34.9	65.1
	Literary	51	34.9	100.0
Age	20 years	73	50	50
	21 years	56	38.4	88.4
	22 years	13	8.9	97.3
	23 years	4	2.7	100.0
Diploma	Bac	32	21.9	21.9
	DEUG	100	68.5	90.4
	Licence	14	9.6	100.0

D. Instrument

An instrument was meticulously adapted to investigate the influence of ARCS motivational components, and the AMS motivational elements on future teachers' motivation to adopt GenAI as intelligent support tools. The questionnaire utilized a 5-point Likert scale to capture participants' responses, ranging from strong disagreement to strong agreement. In addition to measuring motivational constructs, the survey collected demographic information from participants, including gender, specialization, age, and academic qualifications.

The instrument's items were adapted from established and validated sources to ensure content relevance and construct validity. Specifically:

- The ARCS motivational components were sourced from the IMMS.
- Intrinsic motivation, extrinsic motivation, and amotivation items were adapted from the AMS.

To ensure content validity, six expert educators specializing in scientific research, who provided critical feedback to refine the instrument, reviewed the finalized questionnaire.

The psychometric properties of the instrument were rigorously tested. Reliability analysis was conducted using both Cronbach's alpha and McDonald's Omega to assess internal consistency. Furthermore, the construct validity was evaluated through EFA to explore underlying structures, followed by CFA to validate the factor structure and confirm the model's fit.

E. Design Strategies

1) Study design

This quasi-experimental study investigates the motivational factors influencing future teachers' to adopt GenAI, specifically ChatGPT, DeepSeek, and Grok, as intelligent support tools during their initial training for pedagogical tasks. A comparative approach was employed across three initial training specialties. Each specialty was assigned to complete pedagogical tasks using two distinct methods:

- **Traditional Method:** Participants prepare a pedagogical topic aligned with their initial training program. Tasks are completed in PDF, Word, or handwritten format using conventional resources (e.g., books, search engines, and websites).
- **GenAI-Based Method:** Participants prepare a different pedagogical topic than the one used in the traditional method. Tasks are completed in PDF, PowerPoint, or Word format using GenAI tools (ChatGPT, DeepSeek, and Grok). Additional AI-based tools (e.g., automatic PowerPoint design, image, sound, simulation, and video generation tools) may also be utilized.

This structured experimental design allows for a systematic comparison between traditional lesson preparation methods and AI-assisted approaches, providing insights into future teachers' motivation to integrate GenAI applications in educational practices.

2) Training phase

In the era of AI and digital transformation, Generation Z, who constitute our sampling "future teacher" have been immersed in AI-driven technologies from an early age. This generation frequently integrates AI tools into both their personal and professional activities, including education, training, and task automation.

To ensure the seamless integration of GenAI tools, such as ChatGPT, DeepSeek, and Grok, into pedagogical practices, this training phase is designed to equip future teachers with essential AI competencies. The focus is on understanding GenAI functionalities, crafting effective prompts, and optimizing AI-generated content for pedagogical tasks.

3) Controlling biases for experimental rigor

To maintain the validity and reliability of the study, several methodological controls were implemented to mitigate potential biases that could distort the results.

1) Social Desirability and Hawthorne Effects

To minimize social desirability bias, where participants alter their behavior to align with perceived expectations, the study's objective was deliberately withheld until after data collection. Additionally, tasks were integrated into a familiar, non-evaluative setting, encouraging natural and spontaneous engagement.

To reduce the Hawthorne effect, where participants modify their effort due to awareness of being observed, all tasks were directly linked to the initial training curriculum. This ensured that participants perceived them as part of their regular training rather than as an experimental condition, thereby fostering authentic engagement.

2) Learning and Transfer Effects

A key methodological consideration was preventing the learning effect, where performance improves due to task familiarity rather than the tool used. To mitigate this, different pedagogical topics were assigned for the traditional and GenAI-based tasks.

Additionally, the transfer effect, where prior knowledge from one condition influences performance in the next, was controlled by maintaining a one-week interval between phases (**Traditional task → GenAI training → GenAI-based task**). This separation helped ensure that observed improvements were attributable to the methodology rather than prior exposure.

3) Order and Fatigue Effects

A fixed task sequence was applied to all participants:

- Traditional method task completion
- GenAI tool training
- GenAI-based task completion

While this standardization ensured uniformity, it could introduce an order effect, where experience from the first task influences performance in the second. To counteract this, a one-week interval was maintained between each phase.

To mitigate fatigue effects, which could reduce engagement due to cognitive overload, the study employed a structured timeline with one-week intervals between phases. This approach ensured that participants remained consistently engaged throughout the study.

4) Motivation and Complacency Effects

Revealing the study's objective prematurely could have led to biased motivation, where participants intentionally optimize their performance in one condition over the other. Keeping the objective undisclosed ensured that participants approached both tasks with genuine effort.

Furthermore, the pedagogical tasks were presented as routine educational activities rather than as assessments, preventing the complacency effect, where participants might either approach the tasks too casually or artificially exaggerate their efforts. This methodological choice maintained consistent engagement levels across both conditions.

A design strategy flowchart is presented to visually illustrate the study's framework (Fig. 2), offering an overview of the sequential phases that guided this quasi-experimental research process.

F. Data Collection

This study employed a structured questionnaire for data collection. To ensure the instrument's reliability and validity, a rigorous evaluation process was conducted prior to data collection. This process comprised two key preliminary phases:

1) **Initial Testing Phase:** This phase assessed the clarity, comprehensibility, and feasibility of the questionnaire to ensure its appropriateness for the target population.
2) **Pilot Study:** A pilot test was conducted with 45 future teachers specializing in primary, scientific, and literary education to gather feedback on the instrument's design, item formulation, and overall usability. Insights from this phase informed necessary refinements to enhance the questionnaire's effectiveness.

Given the characteristics of the participant group, all of whom were physically present during the data collection period, the questionnaire was administered in a paper-based format. This approach was chosen to maximize participant engagement, ensure higher response rates, and facilitate accurate data collection.

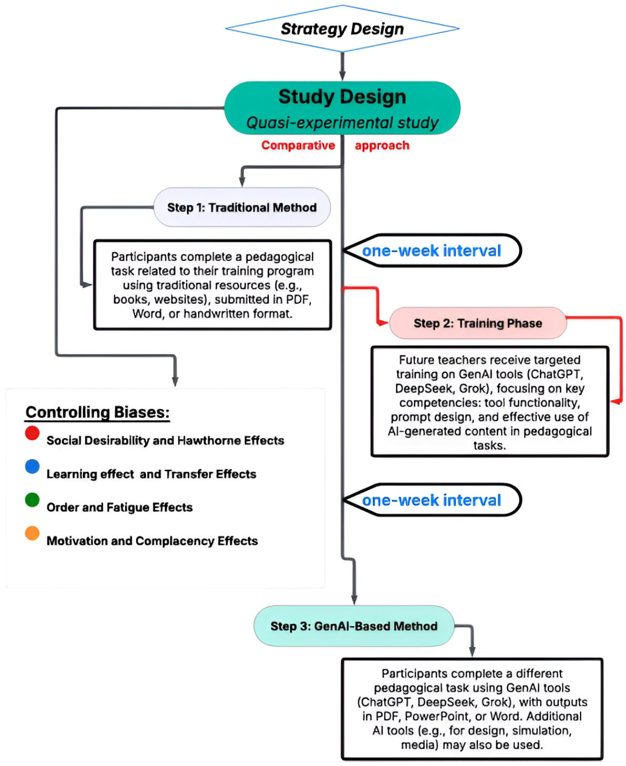

Fig. 2. Flowchart of the strategy design.

G. Data Analysis

Data analysis was conducted using JAMOVI 2.6.26, an open-source statistical software package. A quantitative approach was employed, incorporating inter-dimensional correlation analysis, EFA, CFA, Independent Samples T-Test One-Way ANOVA, and MLR Analysis to systematically examine the data.

Given the study's conceptual model, specialization and gender was treated as independent variables to analyze their effects on future teachers' motivation to adopt GenAI in pedagogical tasks.

All independent variables were computed by calculating **the mean scores** of the respective items within each subscale (based on the means of 5-point Likert scales). Similarly, the dependent variable (**Motivation**) was calculated as a composite mean score derived from all items across the relevant subscales.

Table 2 outlines a detailed overview of the variables included in the study, along with the statistical methods employed to analyze the relationships and effects related to future teachers' motivation to adopt GenAI as intelligent support tools during initial teacher training.

Table 2. Table summarizing the variables and statistical methods used in the analysis

Category	Variable	Type	Measurement
Independent Variables	Gender	Dichotomous	Male, Female
	Specialization	Categorical	Primary, Scientific, Literary
	ARCS Components	(5-point Likert scale)	1 = Not at all true to 5 = Completely true
	AMS Dimensions	(5-point Likert scale)	
Dependent Variable	Motivation	Composite mean score	Motivation to adopt GenAI in pedagogical tasks
Statistical methods applied	Correlation Analysis	Factor Analysis	Check that items are correlated enough to justify the factor structure.
	EFA		Identifying underlying structures of a set of observed variables
	CFA		Validating the factor structure of motivation constructs
	Independent Samples T-Test	Inferential	Testing whether motivation scores differ significantly between gender
	One-Way ANOVA		Comparing motivation levels across different specializations
	Multiple Linear Regression		Modeling effects ARCS components and AMS dimensions, on motivation to adopt GenAI

IV. Result and Discussion

A. Result

1) Instrument reliability

Table 3 presents the internal consistency coefficients (Cronbach's alpha and McDonald's omega) and descriptive statistics for each subscale employed in the present study (ARCS and AMS dimensions) and the Overall Global Scale.

Table 3. Scale reliability statistics

Dimensions	Item (n)	Mean	SD	α	ω
Confidence	8	2.85	0.529	0.702	0.704
Attention	5	2.73	0.895	0.784	0.789
Satisfaction	4	3.99	0.796	0.778	0.780
Relevance	7	3.86	0.665	0.753	0.755
IMTK	4	4.12	0.737	0.742	0.752
IMTA	4	3.88	0.812	0.767	0.769
IMES	4	3.93	0.762	0.743	0.745
EMIR	4	3.94	0.796	0.753	0.767
EMIjR	4	3.05	1.08	0.828	0.829
EMER	4	2.97	1.02	0.759	0.778
AMT	4	1.84	0.970	0.847	0.853
Overall Global Scale	52	3.61	0.442	**0.898**	**0.910**

To evaluate the internal consistency of the measurement instruments, both Cronbach's alpha (α) and McDonald's omega (ω) coefficients were computed. Prior to this, item-rest correlations were examined for each item within its respective subscale. In accordance with standard psychometric guidelines, items exhibiting item-rest correlation values below 0.30 are considered to contribute minimally to the internal consistency of the construct and may reflect conceptually divergent or ambiguous content.

Following this criterion, 12 items were removed (Table 4) from the final analysis to enhance the reliability and construct validity of the instrument.

Table 4. Items removed based on low item-rest correlation

Dimension	Item Code	Item-Rest Correlation (r)
Confidence	C05	0.0461
Attention	A01	0.175
	A02	0.157
	A03	0.170
	A06	0.191
	A07	0.0960
	A09	0.242
	A10	0.159
Satisfaction	S01	0.0846
	S04	0.345
Relevance	R06	0.307
	R07	−0.0935

All retained subscales demonstrated acceptable to excellent levels of reliability, with α and ω values exceeding the recommended threshold of 0.70. The Overall Global Scale, which comprises 52 items, exhibited excellent internal consistency ($\alpha = 0.898$, $\omega = 0.910$). The number of items per subscale ranged from 4 to 8.

These findings affirm the psychometric robustness of the scales and support their reliability for assessing motivational constructs in this context.

Descriptive statistics indicate that participants reported the highest levels of agreement on the Intrinsic Motivation – To Know subscale ($M = 4.12$, SD = 0.737), while the lowest mean score was observed for the Amotivation subscale ($M = 1.84$, SD = 0.970). These findings indicate a predominantly high level of intrinsic engagement and a relatively low degree of amotivation regarding the use of GenAI as intelligent support tools during their initial training for pedagogical tasks.

2) Inter-dimensional correlation analysis

In one set of analyses, Spearman's rank-order correlations (Table 5) were performed among the four dimensions of ARCS components. Statistically significant and positive correlations were observed between Confidence and the other three dimensions: Confidence–Attention ($r_s = 0.273$, $p < 0.001$), Confidence–Satisfaction ($r_s = 0.240$, $p = 0.003$) and Confidence–Relevance ($r_s = 0.274$, $p < 0.001$).

Table 5. Spearman's correlation matrix of ARCS components

		C	A	S	R
C	Spearman's rho	—			
	p-value	—			
A	Spearman's rho	0.273***	—		
	p-value	<0.001	—		
S	Spearman's rho	0.240**	0.050	—	
	p-value	0.003	0.545	—	
R	Spearman's rho	0.274***	0.036	0.698***	—
	p-value	<0.001	0.664	<0.001	—

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Furthermore, a strong positive correlation was found between Satisfaction and Relevance ($r_s = 0.698$, $p < 0.001$), supporting their conceptual association within the motivational model. In contrast, Attention was not significantly correlated with either Satisfaction ($r_s = 0.050$, $p = 0.545$) or Relevance ($r_s = 0.036$, $p = 0.664$). Nevertheless, the overall pattern of correlations supports the interrelated yet distinct nature of the dimensions, which aligns with the theoretical expectations of the ARCS model.

These findings provide preliminary empirical support for the construct cohesion of the ARCS components and justify proceeding with EFA.

In a second set of analyses, Spearman's correlations (Table 6) were conducted among the seven motivational dimensions of AMS constructs. Strong and significant correlations were observed among IMTK, IMTA, IMES, and EMIR (all $r_s > 0.56$, $p < 0.001$), indicating robust interrelationships among the intrinsic motivation and identified regulation constructs. This supports their theoretical proximity within the self-determination continuum.

Table 6. Spearman's correlation matrix of AMS dimensions

		IMTK	IMTA	IMES	EMIR	EMIjR	EMER	AMT
IMTK	Spearman's rho	—						
	p-value	—						
IMTA	Spearman's rho	0.578***	—					
	p-value	<0.001	—					
IMES	Spearman's rho	0.598***	0.611***	—				
	p-value	<0.001	<0.001	—				
EMIR	Spearman's rho	0.563***	0.617***	0.611***	—			
	p-value	<0.001	<0.001	<0.001	—			
EMIjR	Spearman's rho	0.101	0.200*	0.095	0.263**	—		
	p-value	0.225	0.016	0.253	0.001	—		
EMER	Spearman's rho	0.259**	0.281***	0.292***	0.280***	0.290***	—	
	p-value	0.002	<0.001	<0.001	<0.001	<0.001	—	
AMT	Spearman's rho	0.411***	0.390***	0.372***	0.468***	0.015	−0.058	—
	p-value	<0.001	<0.001	<0.001	<0.001	0.858	0.489	—

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additionally, EMER and EMIjR demonstrated weaker, yet still statistically significant, correlations with intrinsic and identified motivations (e.g., IMES–EMER: $r_s = 0.292$, $p < 0.001$), reflecting their distinct but related positioning as external forms of regulation.

As expected, Amotivation exhibited moderate negative or low positive correlations with most types of motivation. Notably, AMT was not significantly correlated with EMIjR ($r_s = 0.015$, $p = 0.858$) and EMER ($r_s = –0.058$, $p = 0.489$), which aligns with its theoretical distinction from externally regulated behaviors.

Overall, the correlation patterns are consistent with the theoretical expectations of SDT, thereby offering strong empirical justification for proceeding with EFA.

3) Construct validity

a) Exploratory factor analysis

EFA was employed to identify the underlying structure of a set of observed variables without imposing a predefined model. In this study, EFA was conducted to examine whether the questionnaire items reliably cluster into the hypothesized 11 subscales. Specifically, the analysis aimed to empirically validate the factorial structure of the instrument, assess the internal coherence of items within each subscale, eliminate weak or cross-loading items (i.e., factor loadings <0.30), and evaluate the overall psychometric quality of the scale. This process also serves to reduce dimensional complexity while preserving the core constructs of motivational engagement.

Prior to conducting EFA, the assumption of normality was examined. The Shapiro–Wilk test revealed significant deviations from normality for all dimensions, including Attention (p = 0.019), Relevance (p = 0.004), EMIjR (p = 0.003) and EMER (p = 0.006), confirming non-normality in the data. Bartlett's Test of Sphericity yielded statistically significant results across all dimensions (p < 0.001), indicating sufficient correlations among the variables to justify the application of factor analysis. Furthermore, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy demonstrated an overall value of 0.780, with individual subscale KMO values ranging from 0.667 to 0.811. These results suggest that the data exhibit an acceptable level of factorability, thereby supporting the suitability of proceeding with EFA.

Principal Axis Factoring with Promax rotation was employed to extract and rotate the underlying factors. Each subscale yielded eigenvalues exceeding the threshold of 1.0, explaining a total variance ranging from 24.7% to 54.9% (Table 7).

Table 7. Factor summary of total variance explained

Subscale	SS Loadings	% of Variance
C	1.97	24.7
A	2.17	43.4
S	1.89	47.1
R	2.15	30.7
IMTK	1.74	43.5
IMTA	1.82	45.5
IMES	1.69	42.3
EMIR	1.84	46.0
EMIjR	2.20	54.9
EMER	1.93	48.2
AMT	2.38	59.5

Items with factor loadings ≥ 0.400 were retained as significant contributors. Internal consistency was evaluated using both Cronbach's alpha and McDonald's Omega coefficients, based on the retained items, and demonstrated acceptable reliability levels across subscales.

To further validate the factorial structure derived from the EFA and to assess the overall model fit, CFA will be conducted in a subsequent phase.

b) Confirmatory factor analysis

CFA was conducted to confirm the alignment of the observed data with the hypothesized measurement model. This step ensured that the constructs measured in the study were valid and reliable. The ARCS model subscale are significantly associated with their respective sets of observed variables. The model exhibits a good overall fit to the observed data, as reflected by multiple standard fit indices (Table 8). The CFI (0.924) and the TLI (0.912), both exceeding the commonly accepted threshold of 0.90, indicating a satisfactory model-data fit.

Table 8. CFA fit measures (ARCS)

				RMSEA 90% CI			
CFI	TLI	SRMR	RMSEA	Lower	Upper	AIC	BIC
0.924	0.912	0.0411	0.0541	0.0451	0.0631	7210	7432

Test for Exact Fit		
χ^2	df	p
305	164	<0.001

Regarding absolute fit, the RMSEA (0.0541), with a 90% confidence interval of [0.0451, 0.0631], suggesting a close approximation of the model to the population covariance structure. The SRMR (0.0411), well below the 0.08 threshold, signifying low residual variance and acceptable standardized discrepancies between the observed and predicted covariance.

The model's information criteria, AIC (7210) and BIC (7432), further provide a reference for model parsimony and complexity. Finally, the chi-square goodness-of-fit test yields a statistically significant result (χ^2 = 305, df = 164, p < 0.001)

Collectively, these indices indicate that the ARCS model demonstrates acceptable to good fit, with all key indices aligning with conventional benchmarks, thereby supporting the model's structural validity and theoretical coherence.

Following the validation of the ARCS model, a CFA was similarly conducted to assess the structural validity of the AMS model subscale. The results indicate that the model also demonstrates a satisfactory fit to the observed data, supported by multiple conventional fit indices (Table 9). Specifically, the CFI (0.950) and the TLI (0.944), which falls within the acceptable range, suggesting that the hypothesized model adequately captures the underlying structure of academic motivation.

In terms of absolute fit, the RMSEA (0.0520), with a 90% confidence interval ranging from 0.0410 to 0.0670, falls within the acceptable limits (< 0.06), indicating a reasonable approximation of the population model. Moreover, the SRMR (0.0590) remains well below the conventional cut-off of 0.08, reflecting low residual discrepancies between the observed and predicted values.

Table 9. CFA fit measures (AMS)

				RMSEA 90% CI			
CFI	TLI	SRMR	RMSEA	Lower	Upper	AIC	BIC
0.950	0.944	0.0590	0.0520	0.0410	0.0670	10885	11175

Test for Exact Fit		
χ^2	df	p
581	329	<0.001

The model's parsimony and complexity are further reflected in the AIC (10885) and BIC (11175). Finally, although the chi-square test (χ^2 = 581, df = 329, p < 0.001) is statistically significant.

In sum, these findings confirm that the AMS model exhibits good psychometric properties and structural validity, rendering it a reliable instrument for measuring academic motivation within the present study context.

4) Independent samples t-test (student's t)

To investigate the relationship between Motivation and Gender as a demographic variable, an Independent Samples t-test was conducted. This analysis aimed to evaluate whether gender significantly influences future teachers' motivation to adopt GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support systems during their initial teacher training for pedagogical tasks.

Prior to performing the t-test, key assumptions were assessed to ensure the validity of the statistical procedure. The Shapiro–Wilk test was used to examine the assumption of normality. The resulting p-value ($p = 0.676$) exceeded the conventional threshold of 0.05 (Table 10), indicating that the distribution of the motivation scores does not significantly deviate from normality and may be considered approximately normal. Additionally, Levene's test for homogeneity of variances (Table 11) yielded a non-significant result ($p = 0.312$), suggesting that the assumption of equal variances across gender groups is also met.

Given that both assumptions of normality and homogeneity of variance are satisfied, the application of the Independent Samples t-test is justified. This test will compare the mean scores of motivation, computed as the overall average of responses across the ARCS and AMS subscales, between male and female participants. This methodological approach ensures the robustness and reliability of the statistical inferences drawn, providing valuable insight into how gender may shape the motivation to adopt GenAI tools in pedagogical practice.

Table 10. Normality test (Shapiro-Wilk)

Dependent variable	W	p
Motivation	0.993	0.676

Table 11. Homogeneity of variance test (Levene test)

Dependent variable	F	df	df2	P
Motivation	1.03	1	144	0.312

The results indicated no significant difference between the group means ($p = 0.403$, Table 12). The mean motivation score for Male was 3.35, while for Female it was 3.41, yielding a small mean difference of −0.0652 (Table 13).

Table 12. Independent samples t-test results examining the effect of gender on future teachers' motivation to adopt generative AI tools

Dependent variable	Test	Statistic	df	P	MD	SE difference
Motivation	Student's t	−0.839	144	0.403	−0.0652	0.0777
Effect Size Measure	**Value**					
Cohen's d	−0.156					
Hypothesis	H1					
Results	No significant difference between the group means					

The effect size, represented by Cohen's $d = -0.156$ (Table 12), further suggests that the magnitude of the difference is small and practically negligible difference in motivation between gender, reinforcing the conclusion that gender does not substantially influence motivation in this context.

The inclusion of effect size (Cohen's d) is commendable, as it provides insight into the practical significance of the findings beyond statistical significance.

Table 13. Descriptive statistics by gender for the independent samples t-test examining the effect of gender on future teachers' motivation to adopt generative AI tools

Dependent variable	Group	N	Mean	Median	SD	SE
Motivation	**Male**	40	3.35	3.35	0.391	0.0619
	Female	106	3.41	3.45	0.429	0.0416

5) One-way ANOVA

To investigate the relationship between Motivation and Specialization as a demographic variable, a One-Way ANOVA was conducted. This analysis aimed to evaluate whether specialization significantly influences future teachers' motivation to adopt GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support systems during their initial teacher training for pedagogical tasks.

Prior to performing the analysis, the key assumptions underlying ANOVA were systematically assessed to ensure the validity of the statistical procedure. The Shapiro–Wilk test revealed a p-value of 0.535 (Table 14), indicating that the distribution of motivation scores does not significantly deviate from normality. Furthermore, Levene's test yielded a p-value of 0.202 (Table 15), suggesting no significant difference in variances between the specialization groups and variances are equal across groups. The assumption of independence of observations was also satisfied, as each future teacher belonged exclusively to one specialization group (Primary, Scientific, or Literary).

Table 14. Normality test (Shapiro-Wilk)

Dependent variable	W	P
Motivation	0.992	0.535

Table 15. Homogeneity of variance test (Levene test)

Dependent variable	F	df1	df2	P
Motivation	1.62	2	143	0.202

Given that the assumptions of normality, homogeneity of variance and independence were all confirmed, the application of Fisher's One-Way ANOVA was deemed appropriate.

The ANOVA test was thus employed to determine whether statistically significant differences exist in motivation scores among the three specialization groups by comparing between-group and within-group variance. This methodological rigor ensures the robustness and reliability of the statistical inferences drawn, providing valuable insights into how specialization may influence the motivation to adopt GenAI tools into pedagogical practices.

Fisher's One-Way ANOVA revealed a statistically significant effect of specialization on future teachers' motivation ($p = 0.046$, Table 16). Descriptive statistics (Table 17) showed that participants in the Literary specialization reported the highest motivation levels ($M = 3.49$, SD = 0.385), followed by those in the scientific ($M = 3.41$, SD = 0.353) and Primary specializations ($M = 3.28$, SD = 0.498).

Table 16. Fisher's one-way ANOVA results examining the influence of specialization on future teachers' motivation to adopt generative AI tools

Dependent variable	Test	F	df1	df2	p	Hypothesis
Motivation	Fisher's	3.14	2	143	0.046	H2
Hypothesis	H2					
Results	A statistically significant difference in motivation					

Table 17. Descriptive statistics by specialization for motivation to adopt generative AI tools

Dependent variable	Specialty	N	Mean	SD	SE
Motivation	Primary	44	3.28	0.498	0.0751
	Scientific	51	3.41	0.353	0.0495
	Literary	51	3.49	0.385	0.0538

Post-hoc analysis using the Tukey HSD test (Table 18) revealed a statistically significant difference between the literary and primary groups ($p = 0.036$), indicating that future teachers in the literary specialization demonstrated significantly higher motivation to adopt GenAI tools. However, no significant differences were observed between the primary and scientific groups ($p = 0.281$) or between the scientific and literary groups ($p = 0.575$).

Table 18. Tukey post-hoc test results for pairwise comparisons of motivation scores across specialization groups

Group		Primary	Scientific	Literary
Primary	Mean difference	—	−0.130	−0.2117*
	t-value	—	−1.53	−2.50
	df	—	143	143
	p-value	—	0.281	0.036
Scientific	Mean difference		—	−0.0821
	t-value		—	−1.01
	df		—	143
	p-value		—	0.575
Literary	Mean difference			—
	t-value			—
	df			—
	p-value			—

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These findings suggest that specialization may play a role in shaping the motivation of future teachers to adopt GenAI tools into their instructional practices during initial teacher training.

6) Multiple linear regression analysis

a) Model specification

Given the continuous nature of the dependent variable, MLR analysis was conducted to investigate the predictive influence of the ARCS-based motivational components and the AMS-based motivation dimensions on future teachers' motivation to adopt GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support tools during their initial teacher training for pedagogical tasks. This analysis facilitated the assessment of the explanatory power of the independent variables, providing valuable insights into the key factors shaping participants' motivational orientations. The modeling process entailed a series of analytical steps aimed at examining the relationships between variables and evaluating the overall fit and significance of the regression model.

b) Main hypothesis

The MLR model was guided by the primary hypotheses **H3** and **H4**, which articulate the anticipated directional relationships between the independent variables (the ARCS and the AMS components) and the dependent variable, defined as future teachers' motivation to adopt GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support tools during their initial teacher training for pedagogical tasks:

To examine these theoretical propositions more comprehensively, a series of sub-hypotheses were formulated and tested:

(H3)a: Confidence positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H3)b: Attention positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H3)c: Satisfaction positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H3)d: Relevance positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H4)a: Intrinsic Motivation-To Know positively influences future teachers' motivation to adopt genAI tools in pedagogical tasks.

(**H4)b**: Intrinsic Motivation-Toward Accomplishment positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H4)c: Intrinsic Motivation-To Experience Stimulation positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H4)d: Extrinsic Motivation-Identified Regulation positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H4)e: Extrinsic Motivation-Introjected Regulation positively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

(H4)g: Amotivation negatively influences future teachers' motivation to adopt GenAI tools in pedagogical tasks.

c) Data collection

Data were collected through a structured questionnaire using a 5-point Likert scale to measure participants' responses. Ethical approval was obtained, and participants provided informed consent. The collected data were deemed reliable, valid, and representative of the target population, with no missing or contradictory values.

d) Verification of the conditions

- Linearity of the relationship

To evaluate the assumption of linearity required for MLR analysis, scatterplots were generated to examine the relationship between each independent variable and the dependent variable. The visual inspection of these scatterplots revealed a generally linear trend. The fitted regression lines adequately captured the directionality of the data, indicating a consistent linear pattern across the predictors.

These observations suggest that the assumption of linearity is reasonably satisfied, thereby supporting the appropriateness of applying MLR to model the data in this study.

- Independence of residuals

Table 19 presents the results of the global Durbin–Watson (DW) test for the MLR model, which includes all independent variables representing the ARCS and AMS dimensions. The DW statistic was 1.95, a value very close to

2, indicating the absence of first-order autocorrelation in the model's residuals. The autocorrelation coefficient was 0.0253, which is notably low and suggests minimal serial correlation. Furthermore, the p-value was 0.624, exceeding the conventional threshold of 0.05, thereby leading to a failure to reject the null hypothesis of no first-order autocorrelation.

Table 19. Durbin–Watson test for autocorrelation

Autocorrelation	DW Statistic	p
0.0253	1.95	0.624

In summary, the residuals do not exhibit significant autocorrelation, satisfying the assumption of independent errors, one of the key conditions for the proper application of MLR. This finding supports the robustness and validity of the regression model results.

- Constant Variance of Errors (homoscedasticity)

To assess the assumption of homoscedasticity in the MLR model, a scatterplot of residuals versus fitted values was employed. The plot (Fig. 3) revealed a random dispersion of residuals around the horizontal reference line at zero, with no discernible pattern or funnel-shaped distribution. The residuals appeared to be evenly spread, and the variance remained relatively stable across the range of fitted values.

In summary, the visual inspection of the scatterplot indicates that the residuals exhibit approximately constant variance, suggesting that the assumption of homoscedasticity is reasonably satisfied. This supports the suitability of the MLR model for the data.

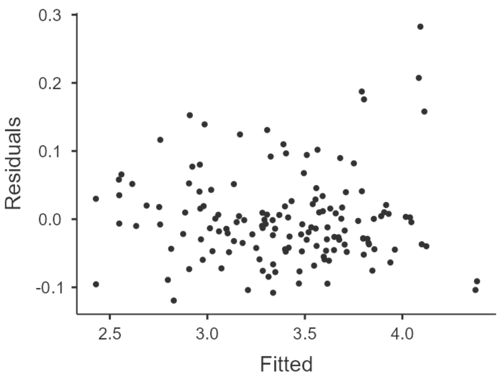

Fig. 3. The scatterplot of residuals against fitted values.

- Normality of residuals

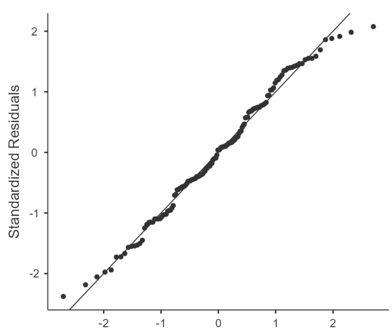

Fig. 4. The Q-Q plot of residuals.

The Q–Q plot (quantile–quantile) (Fig. 4) was employed to assess the normality of residuals, a key assumption of MLR analysis. The visual inspection of the standardized residuals indicates that most points align closely with the reference line, particularly in the central portion of the distribution. This suggests that the residuals are approximately normally distributed in the middle range of values, thereby supporting the assumption of normality to a reasonable extent.

- Multicollinearity

To assess the presence of multicollinearity among the independent variables (the ARCS and AMS dimensions), the Variance Inflation Factor (VIF) and Tolerance values were examined. The VIF values ranged from 1.18 to 2.83, while the corresponding Tolerance values varied between 0.354 and 0.849 (Table 20).

Based on established thresholds, none of the predictors' exhibit VIF values approaching or exceeding the commonly accepted cutoff of 5, and all Tolerance values are well above the critical threshold of 0.2. These results indicate that multicollinearity is not a concern in the present model. The predictors demonstrate acceptable levels of independence, thereby satisfying a key assumption of MLR. This reinforces the reliability of the model estimates and supports the validity of the inferences drawn from the regression analysis.

Table 20. Collinearity statistics

Independent variables	VIF	Tolerance
Confidence	1.28	0.781
Attention	1.18	0.849
Satisfaction	2.83	0.354
Relevance	2.37	0.421
IMTK	2.33	0.429
IMTA	2.31	0.433
IMES	2.47	0.406
EMIR	2.08	0.482
EMIjR	1.26	0.797
EMER	1.27	0.788
AMT	1.34	0.748

- Outliers or influential observations

To evaluate the presence of influential observations that could disproportionately affect the regression results, Cook's Distance was examined for all cases. The values ranged from 1.51e-5 to 0.0666, with a mean of 0.00739 and a median of 0.00337 (Table 21).

Conventionally, a Cook's Distance greater than 1.0 is considered indicative of highly influential points. In this case, all values fall well below this threshold, suggesting that no individual data point exerts an undue influence on the regression model. These results confirm the absence of problematic outliers or influential observations, thereby supporting the stability and reliability of the regression estimates.

Table 21. Cook's distance

Mean	Median	SD	Min	Max
0.00739	0.00337	0.0107	1.51e-5	0.0666

e) Data analysis

To examine the primary hypotheses (H3 and H4) regarding the factors influencing motivation to adopt GenAI, a MLR analysis was performed following a rigorous verification of the underlying statistical assumptions. The analysis produced the following results:

- Omnibus ANOVA test

To evaluate the overall significance of the regression model, an Omnibus ANOVA test was conducted. This test assesses whether each predictor variable (independent variable) explains a statistically significant portion of the variance in the dependent variable, beyond what would be expected by chance.

As presented in Table 22, all predictors demonstrate statistically significant contributions to the model. The p-values for all predictors are less than 0.001, indicating that each variable contributes meaningfully to the explanation of the dependent variable. The F-statistics, ranging from 25.0 to 298.0, reflect the strength and consistency of these effects across variables. Additionally, the residual sum of squares is relatively small (SS = 0.633, df = 135), suggesting a good overall fit of the model.

Table 22. Omnibus ANOVA test

Independent variables	Sum of Squares	df	Mean Square	F	P
Confidence	0.320	1	0.31970	68.2	<0.001
Attention	1.324	1	1.32450	282.7	<0.001
Satisfaction	0.216	1	0.21555	46.0	<0.001
Relevance	0.400	1	0.39978	85.3	<0.001
IMTK	0.125	1	0.12453	26.6	<0.001
IMTA	0.296	1	0.29558	63.1	<0.001
IMES	0.274	1	0.27376	58.4	<0.001
EMIR	0.117	1	0.11714	25.0	<0.001
EMIjR	1.100	1	1.10002	234.8	<0.001
EMER	1.396	1	1.39634	298.0	<0.001
AMT	1.297	1	1.29694	239.2	<0.001
Residuals	0.633	135	0.00469		

In summary, these findings confirm that each independent variable significantly enhances the model's explanatory power. The Omnibus ANOVA test thus supports the inclusion of all predictors and validates the overall statistical significance and robustness of the regression model.

- Model fit

To assess the overall adequacy of the MLR model, several model fit indices were examined (Table 23). The results indicate that the model demonstrates a very high explanatory power, as reflected by the following statistics:

The multiple correlation coefficient (R = 0.987) indicates a very strong positive linear relationship between the set of independent variables and the dependent variable. This suggests that the predictors collectively provide a highly accurate estimation of the outcome variable within the regression model.

The coefficient of determination (R^2 = 0.975) indicates that approximately 97.5% of the variance in the dependent variable is explained by the set of independent variables. This exceptionally high value suggests a near-perfect model fit, highlighting the strong explanatory power of the predictors.

The Adjusted R^2 = 0.973 confirms the robustness of the model.

The Root Mean Square Error (RMSE= 0.0658) is relatively low, indicating that the average prediction error is small and the model predictions are precise.

The Akaike Information Criterion (AIC = −356) and Bayesian Information Criterion (BIC = −320) are both substantially negative, which is typically interpreted as evidence of strong model parsimony and quality. Negative AIC and BIC values suggest that the model achieves a good balance between fit and complexity.

The Overall F-test is highly significant (528, p < 0.001), indicating that the set of predictors, taken together, significantly improve the model compared to a model with no predictors.

Taken together, these model fit statistics demonstrate that the MLR model is both statistically significant and substantively strong. The high R^2 and low RMSE support the accuracy and precision of the model's predictions. Moreover, the significant F-test confirms that the predictors, as a whole, contribute meaningfully to explaining variance in the outcome variable. These findings justify further interpretation of individual regression coefficients and support the use of the model for inferential purposes.

Table 23. Model fit measures of multiple linear regression

Overall Model Test									
R	R²	Adjusted R²	AIC	BIC	RMSE	F	df1	df2	p
0.987	0.975	0.973	−356	−320	0.0658	528	10	135	<0.001

- Regression coefficients

Table 24 presents the results of the multiple linear regression analysis for a statistically robust and theoretically grounded model that integrates the ARCS motivational components (Attention, Relevance, Confidence, and Satisfaction) alongside the dimensions of the AMS model, which include intrinsic motivation, extrinsic motivation with its sub-dimensions, and amotivation.

All predictors are statistically significant at p < 0.001, indicating that each independent variable contributes meaningfully to the prediction of the dependent variable when controlling for the others. The associated t-values and consistently low p-values across all predictors suggest that these effects are highly unlikely to have occurred by chance.

On the one hand, regarding the ARCS model, the standardized coefficients (β) demonstrate substantial positive contributions from Attention (β = 0.2479), Relevance (β = 0.1933), and Satisfaction (β = 0.1550). These findings underscore the importance of motivational design elements in fostering higher levels of engagement, perceived value, and motivation among future teachers. Confidence (β = 0.1270) also shows a moderate yet statistically significant positive influence, suggesting that a strong belief in one's own capabilities, reflected in positive self-concept and favorable self-efficacy perceptions, contributes to improved performance and sustained motivational involvement.

On the other hand, with respect to the AMS dimensions, Intrinsic Motivation to Know (β = 0.1069), to Accomplish (β = 0.1639), and to Experience Stimulation (β = 0.1631) all show positive and significant effects on the dependent variable. These results are consistent with motivational theory, which posits that intrinsic motivations are strongly associated with sustained effort and engagement.

Furthermore, Extrinsic Motivation-Introjected Regulation (β = 0.2332) and External Regulation (β = 0.2643) emerge as strong positive predictors. This indicates that even externally driven motivations, particularly when internalized or perceived as purposeful, can significantly enhance task-related outcomes. Identified Regulation (β = 0.0979) also contributes positively, albeit to a lesser extent.

Finally, Amotivation (β = −0.261) is the only negative predictor, as theoretically anticipated. Its strong inverse relationship with the dependent variable highlights the detrimental impact of disengagement, lack of purpose, or motivational absence on performance and task-related outcomes.

Table 24. Model coefficients—motivation

Predictor	Estimate	SE	t	p	Β
Intercept	0.3348	0.04651	7.20	<0.001	
Confidence	0.0762	0.00923	8.26	<0.001	0.1270
Attention	0.1158	0.00689	16.81	<0.001	0.2479
Satisfaction	0.0815	0.01202	6.78	<0.001	0.1550
Relevance	0.1216	0.01317	9.24	<0.001	0.1933
IMTK	0.0607	0.01177	5.16	<0.001	0.1069
IMTA	0.0845	0.01064	7.94	<0.001	0.1639
IMES	0.0895	0.01171	7.64	<0.001	0.1631
EMIR	0.0515	0.01030	5.00	<0.001	0.0979
EMIjR	0.0907	0.00592	15.32	<0.001	0.2332
EMER	0.1087	0.00630	17.26	<0.001	0.2643
AMT	−0.1127	0.00729	−15.47	<0.001	−0.261

- Conclusion

The results of the MLR analyses (Tables 22, 23, and 24) highlight the significant influence of both ARCS motivational components and AMS motivational dimensions on future teachers' motivation to adopt GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent supports for pedagogical tasks during initial teacher training.

These findings underscore the pivotal role of Confidence, Attention, Satisfaction, and Relevance, alongside Intrinsic and Extrinsic motivational dimensions, in shaping positive attitudes toward GenAI adoption. Additionally, the negative coefficient associated with Amotivation aligns with theoretical expectations, confirming its inverse relationship with productive engagement.

Overall, these outcomes provide strong empirical support for the primary hypotheses (**H3** and **H4**) and their sub-hypotheses, reinforcing the validity of the conclusions drawn. The robustness of the results is further substantiated by the rigorous verification of all necessary statistical assumptions underpinning the multiple linear regression model.

An overall summary table of the statistical results (Table 25) synthesizes the key findings. While gender differences did not significantly influence participants' motivation to use GenAI tools (p = 0.403, Cohen's d = −0.156), training specialty showed a significant effect (p = 0.046), with participants from literary programs reporting higher motivation than those in scientific and primary education. Most notably, motivation-related dimensions, as measured by the ARCS and AMS models, significantly predicted participants' perceptions (R^2 = 0.975), confirming the critical influence of these variables in shaping future teachers' motivation to adopt GenAI tools during their initial training.

Table 25. Overall summary table of the statistical results

Variable / Comparison	Test Used	p-value	Mean(s) / SD(s)	Effect Size / R / R²	Significant?	Hypothesis
Gender differences	Independent Samples t-test	0.403	Male: M = 3.35, SD = 0.391 Female: M = 3.41, SD = 0.429	Cohen's d = −0.156	No	H1 not supported
Training specialty differences	One-Way ANOVA (Fisher's test)	0.046	Literary: M = 3.49, SD = 0.385 Scientific: M = 3.41, SD = 0.353 Primary: M = 3.28, SD = 0.498	—	Yes	H2 supported
Motivation prediction (ARCS & AMS)	Multiple Linear Regression	< 0.001	—	R = 0.987, R^2 = 0.975	Yes	H3 & H4 supported

B. Discussion

The present study aimed to investigate the motivational factors influencing future teachers' motivation to adopt Generative Artificial Intelligence tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support tools during their initial teacher training, particularly for pedagogical tasks. To achieve this objective, a structured questionnaire was administered, drawing upon the motivational framework components (ARCS and the AMS) to capture relevant motivational constructs. Quantitative data were collected and analyzed using a range of robust statistical methods to ensure the validity and reliability of the findings.

- Inter-dimensional correlation analysis "ARCS and AMS elements"

An inter-dimensional correlation analysis using Spearman's rank-order correlations was performed among the motivational framework elements IMMS-ARCS and the AMS to assess the relationships between different dimensions (Table 5, Table 6).

On the one hand, the findings underscore the pivotal role of Confidence in reinforcing other key motivational components to adopt GenAI tools, within the ARCS framework. This, in turn, positively influences Attention, Relevance, and Satisfaction.

This positive relationship suggests that when future teachers feel more confident in their ability to successfully carry out instructional tasks using GenAI as intelligent support tools, their overall satisfaction with these emerging applications increases. Confidence is fostered through the establishment of clear training objectives, the scaffolding of instructional experiences, the provision of constructive feedback, and a structured progression of pedagogical tasks. This sense of accomplishment and perceived value contributes to greater satisfaction, thereby promoting sustained engagement and motivation throughout the initial teacher training process.

Furthermore, the perceived relevance of these tools is enhanced when future teachers recognize a clear alignment between GenAI applications and their personal goals, prior experiences, and anticipated professional needs. This alignment increases the perceived utility and meaningfulness of the initial training.

In addition, attention is heightened as GenAI effectively capture and sustain trainees' curiosity and interest, stimulating active cognitive engagement and encouraging deeper involvement in the training process.

These findings align well with Keller's ARCS motivational model and are consistent with previous research in the field, which emphasizes the importance of sustaining individuals' attention, aligning content with their personal goals, and fostering confidence in their ability to succeed. As trainees deepen their understanding, both their self-efficacy and their perception of relevance increase, ultimately leading to more meaningful and satisfying technology-enhanced educational experiences and practices [3, 22, 75].

On the other hand, both intrinsic motivation and well-internalized forms of extrinsic motivation, especially identified regulation, are closely interconnected and collectively exert a positive influence on future teachers' motivation to adopt GenAI tools. These favorable motivational orientations play a central role in fostering meaningful engagement with intelligent support tools, particularly within the framework of the AMS model.

This positive relationship suggests that when future teachers exhibit higher levels of intrinsic motivation, they are more inclined to engage in learning and training activities for the inherent satisfaction and pleasure it provides. This motivation manifests in several interrelated dimensions.

Firstly, a higher intrinsic motivation to know reflects a profound desire to explore, understand and utilize emergent technologies. This motivation, driven by curiosity and a commitment to cognitive development, encourages future teachers to engage with GenAI tools as an integral part of their pedagogical development during initial training.

Furthermore, a heightened intrinsic motivation toward accomplishment is evident when future teachers derive satisfaction from attempting and completing pedagogical tasks using GenAI. This form of motivation is directly associated with enhanced feelings of competence and personal achievement.

Moreover, an elevated intrinsic motivation to experience stimulation is evident when future teachers engage in the pursuit of engaging and stimulating experiences, such as the excitement, aesthetic pleasure, or novelty offered by interacting with GenAI tools during initial training.

This result is consistent with the positive findings reported in previous studies, which emphasize the significant impact of internal motivational factors on various dimensions of human behavior, including the adoption of GenAI tools as intelligent support tools for pedagogical task preparation during initial teacher training. Notably, Mohamed *et al*, Nitza Davidovitch and Ruth Dorot similar conclusions [14, 69].

In parallel, extrinsic motivation in the form of identified regulation plays a significant and complementary role. When future teachers perceive the use of GenAI tools as personally meaningful and aligned with their values, professional goals, and aspirations, this motivation becomes internalized, consistent with the theoretical propositions of Deci and Ryan's SDT [17]. As a result, even though it originates externally, it functions similarly to intrinsic motivation in promoting sustained engagement and tool adoption.

In contrast to these forms of motivation, amotivation, as a distinct motivational construct, holds particular significance in understanding future teachers' engagement with GenAI tools. The findings, characterized by low negative or low positive correlations with other forms of motivation, and the absence of statistically significant associations, highlight the inverse role of amotivation in motivational dynamics. This pattern is consistent with the foundational principles of SDT, which posits that amotivation reflects a state of lacking intentionality or perceived value in an activity [17]. These results are further reinforced by the work of Vallerand *et al.* [26] particularly through the development and validation of AMS model, which conceptualizes amotivation as a motivational dimension that is both theoretically and empirically distinct from intrinsic and extrinsic motivation in educational contexts.

The interplay between intrinsic motivation (in all its dimensions) and identified extrinsic motivation indicates that future teachers who are driven by curiosity, a desire for mastery, and stimulating training experiences are more likely to embrace GenAI tools. Moreover, when extrinsic motivations become internalized, meaning they are consciously valued and self-endorsed, they become powerful in promoting the motivation of adoption.

In sum, the synergy between intrinsic and internalized extrinsic motivational drivers highlights the necessity of designing initial teacher training programs that foster personal interest, cognitive challenge, and alignment with future professional goals. Such motivationally informed frameworks can significantly enhance the adoption and pedagogical integration of GenAI tools in initial teacher training contexts.

- Impact of Demographic and Motivational Factors on Future Teachers' Motivation to Adopt Generative AI Tools

The adoption of GenAI tools as intelligent support systems in initial teacher training has become an increasingly prominent subject of interest and discussion within the educational research community. This section examines the influence of selected independent variables, namely gender, training specialization, ARCS-based motivational components, and AMS-based motivational dimensions, on future teachers' motivation to adopt such tools.

Demographic Factors (gender and training specialty):

To test the related hypotheses (**H1**) and (**H2**), a series of statistical analyses were conducted, including Independent Samples t-tests (Student's t) and one-way Analysis of Variance (ANOVA) as proposed by Fisher. The findings presented in Tables 10 through 18 form the empirical basis for this evaluative discussion.

Regarding the relationship between gender and future teachers' motivation, the results reveal no statistically significant differences between male and female participants. Both groups exhibit comparable levels of motivation, suggesting that gender is not a significant predictor of motivational orientations toward adoption GenAI tools adoption in pedagogical practices (Tables 12–13). Accordingly, Hypothesis (**H1**) is rejected.

This finding is consistent with recent studies, which similarly report negligible gender-based disparities in AI emergent technology adoption and motivational orientation in educational contexts [24]. For instance, Møgelvang *et al.* found no significant gender differences in the integration of GenAI chatbots training or integration in their courses in higher education, indicating that both male and female demonstrate a positive motivational orientation toward the use of GenAI, albeit informed by distinct priorities and expectations. Their study indicates that male tend to engage with GenAI tools more frequently and across a broader spectrum of academic tasks, often perceiving these tools as highly relevant to their future professional relevance. Conversely, female predominantly utilize GenAI for text-based assignments and express heightened concerns about issues such as critical thinking, autonomous decision-making, and the need for clearer pedagogical guidance on the appropriate use and trustworthiness of such technologies [77].

Similarly, Nyaaba *et al*. in their study titled "Generative AI in Academic Research: A Descriptive Study on Awareness, Gender Usage, and Views among Pre-Service Teachers", identified a significant gender disparity in the use of GenAI tools, with male future teachers exhibiting a higher frequency of use compared to their female counterparts. Despite this difference, both genders expressed a positive attitude towards GenAI tools in academic research, noting among other benefits that these tools provided them with confidence and independence in their research writing [78]. Together, these findings suggest that while motivational orientation toward GenAI tools is broadly positive across genders, the frequency of use and underlying motivations may diverge, pointing to the importance of gender-sensitive pedagogical strategies in future teacher training. Consistent with these findings, recent research conducted in the Moroccan educational context by Fakhar *et al*. revealed that both male and female teachers exhibited comparable levels of motivation toward the use of GenAI tools, with no statistically significant gender-based differences. This indicates that the motivational drive to adopt GenAI in educational environments may be more closely linked to individual perceptions of its practical utility and pedagogical effectiveness than to demographic variables [24]. Supporting this perspective, Al Darayseh similarly reported an absence of significant differences in behavioral intentions between male and female science teachers regarding the integration of GenAI in instructional practices. These results further suggest that gender may not constitute a determining factor in influencing educators' motivational orientation toward GenAI adoption [81]. However, it is important to note that other studies have reported gender disparities in the adoption and use of GenAI tools; Otis *et al*. highlight a pervasive and systemic gender gap in the use of GenAI across diverse global contexts, including various regions, sectors, and professional domains. Their research indicates that female remain significantly underrepresented among GenAI users, even in environments where technological access is equitable. This disparity points to underlying barriers—such as reduced motivation, lower confidence levels, and prevailing sociocultural norms—that may disproportionately inhibit female's engagement with these emerging technologies. If left unaddressed, this imbalance risks reinforcing gender biases in AI systems, as the data used to train these tools may predominantly reflect male-generated input, thereby marginalizing female perspectives and exacerbating existing inequities in digital innovation and development [82].

These contrasting findings underscore the complexity of gender dynamics in GenAI adoption and highlight the need for further research to understand the underlying factors contributing to these differences, particularly within the domain of teacher-training education.

While gender does not appears to significantly predict motivational orientations toward the adoption GenAI tools in pedagogical practices, training specialization may constitute a significant factor, as discussed subsequently.

Concerning the relationship between training specialization and future teachers' motivation, the results revealed a statistically significant effect. Descriptive statistics demonstrated that participants in the literary specialization reported the highest motivation levels, followed by those in the scientific and primary specializations (Table 16, 17 and 18). Consequently, Hypothesis (**H2**) is partially supported.

These findings suggest that training specialization may serve as a determining factor influencing the motivation of future teachers to adopt these tools in their instructional practices during initial teacher training. Notably, among the various specializations examined, literary education appears to be associated with the highest levels of motivation for the GenAI tool adoption.

This heightened motivation may be attributed to a stronger alignment between the functional affordances of GenAI applications and the pedagogical demands of literary disciplines. Specifically, GenAI technologies, such as ChatGPT, DeepSeek, and Grok, are well-suited to support tasks commonly encountered in literary training, including writing assistance, text generation, and linguistic analysis. This perceived pedagogical relevance and utility may enhance the willingness of future teachers in literary fields to engage with such tools.

This finding is consistent with recent empirical evidence reporting that future language teachers recognize the pedagogical potential of GenAI in enhancing language instruction, particularly through its ability to provide immediate feedback and generate diverse linguistic examples [87]. Indeed, the interest in AI tools within the field of language education is well established; language educators and researchers have long explored the adoption of AI-driven applications, especially chatbots and digital writing assistants, owing to their perceived effectiveness in supporting language learning and fostering self-directed learning practices [83]. In support of this perspective, a growing body of empirical research has investigated the integration of AI-based tools in the context of language learning. Jeon, for example, conducted an intervention study with language learners and found that those who perceived an AI-powered English-learning chatbot as a genuine conversational partner exhibited a higher degree of motivation to engage in interactive tasks [84]. In a similar vein, Chiu *et al*. reported that the incorporation of AI chatbots into language learning environments significantly boosted learners' interest and motivation to participate in educational activities [85]. Further evidence is provided by Ali *et al*., whose quantitative survey—conducted shortly after the launch of ChatGPT—demonstrated that both language instructors and pre-service teachers perceived ChatGPT-supported instruction as positively influencing learners' autonomous, intrinsic, and extrinsic motivational orientations. The authors attributed this motivational enhancement in part to the novelty effect of the tool, which initially stimulates learners' attention and engagement [86].

Thus, this potential synergy between GenAI capabilities and the nature of pedagogic tasks may contribute to a more favorable motivational orientation among different specialization trainees, encouraging them to adopt these emerging technologies into their future teaching practices [13].

Motivational Factors (ARCS and AMS dimensions):

To further examine and evaluate the potential causal impact of motivational factors, specifically the ARCS-based components and AMS-based motivational dimensions, on future teachers' motivation, a multiple linear regression analysis was conducted. This analytical approach allowed for the identification of the most significant predictors influencing the perceived motivation to adopt GenAI. The results provide a robust empirical foundation for understanding motivational orientations and developing targeted recommendations. These recommendations aim to assist educational stakeholders in recognizing the strategic importance of integrating GenAI tools into the training curricula of prospective teachers, thereby fostering more informed and effective implementation strategies within initial teacher education programs [13, 24, 78].

The MLR analysis revealed that the independent variables, namely Confidence, Attention, Relevance, and Satisfaction as components of the ARCS model, along with Intrinsic Motivation, Extrinsic Motivation, and Amotivation as dimensions of the AMS scale, exert a statistically significant influence on future teachers' perceived motivation. These findings are consistent with the formulated hypotheses (H3) and (H4), thereby supporting and validating all associated sub-hypotheses.

Building on the ARCS motivational framework and grounded in expectancy-value theory, the MLR analysis underscores the pivotal role of Attention, Relevance, and Satisfaction in shaping future teachers' motivation to adopt GenAI. The strong positive contributions of these components highlight the effectiveness of motivational design in capturing trainees' interest, aligning intelligent technological applications with their instructional goals, and providing meaningful, rewarding training experiences. These findings are consistent with prior research emphasizing that sustained engagement and perceived utility are critical for fostering motivational orientation and driving behavioral intentions in educational contexts. Moreover, the moderate yet statistically significant influence of Confidence further reinforces the importance of developing a strong sense of self-efficacy among trainees. As emphasized in the ARCS model, cultivating belief in one's ability to successfully engage with and adopt GenAI tools, through clear objectives, structured learning progression, and supportive feedback mechanisms, can foster persistence and a willingness to experiment with innovative pedagogical approaches [22, 74, 75, 91].

Consistent with these findings, a recent study examined teachers' motivation to adopt GenAI tools as a means of self-directed professional development in pedagogical contexts. The study, conducted with a cohort of physics teachers, implemented a training program integrating both traditional and AI-supported instructional strategies. Motivation was measured using the Keller's ARCS model. The results indicated a generally positive disposition toward the use of GenAI, with strong intercorrelations among the four motivational dimensions—Attention, Relevance, Confidence, and Satisfaction—underscoring their combined impact on teachers' motivation to utilize AI tools for enhancing pedagogical competencies and instructional effectiveness [24]. Complementing this, another investigation rooted in the ARCS framework explored learners' engagement with AI technologies. It emphasized that motivational strategies fostering intrinsic interest, sustaining attention, reinforcing perceived relevance, and building confidence significantly enhance learners' career-oriented motivation to interact with AI tools [25].

The AMS dimensions including Intrinsic Motivation to Know, to Accomplish, and to Experience Stimulation exhibited positive and statistically significant effects on future teachers' motivation. These findings are align with SDT as articulated by Deci and Ryan and extended by Vallerand *et al*, which posits that intrinsic motivations, rooted in internal satisfaction, enjoyment and a sense of fulfillment, is strongly linked to autonomy, sustained effort, engagement and professional development [17, 26, 35, 69]. Complementing these results, a recent study explored university students' motivation to engage with AI-based learning environments through the lens of both SDT and the AMS model. The study revealed that motivational enhancement within academically supportive contexts significantly increased learners' engagement with AI tools, reinforcing the central role of motivation in AI-mediated education [29]. These findings underscore the methodological relevance of SDT and its associated motivational subtypes—fundamental to the AMS model—in understanding the pedagogical implications and learner dynamics introduced by the integration of GenAI in teaching and learning processes [30].

When educational practices are aligned with future teachers' interests and providing opportunities for self-directed learning and meaningful engagement, they foster an environment conducive to intrinsic motivation. Such conditions not only enhance the effectiveness of initial teacher training but also support the broader goals of lifelong learning and holistic professional growth [73, 91].

Furthermore, extrinsic motivation, conceptualized as a multidimensional construct that reflects varying degrees of internalization and autonomy in behavioral regulation, from externally controlled actions to those progressively aligned with personal values, also emerged as a significant positive predictor of motivation. Specifically, Introjected Regulation and External Regulation demonstrated strong positive effects, indicating that even when motivations originate from external sources, they can meaningfully drive engagement when prospective teachers perceive them as relevant or compelling. These findings support the view that extrinsic motivations, particularly those perceived as purposeful or partially internalized, can facilitate productive and goal-oriented behavior within training educational contexts. Conversely, amotivation was the only negative predictor in the model, as theoretically anticipated by SDT. Its strong inverse relationship with future teachers' motivation underscores the detrimental effects of disengagement, lack of perceived value, and absence of intentionality on performance and pedagogical outcomes [17, 26]. These results emphasize the importance of fostering both intrinsic and well-internalized extrinsic motivational states to support the effective adoption of intelligent technologies within initial teacher training programs.

In sum, this research affirms the critical importance of adopting GenAI tools as intelligent support systems within initial training curricula. By prioritizing the development of AI-driven technological competencies, teacher education programs can more effectively prepare future educators to navigate the evolving instructional landscape. Embedding GenAI proficiency into future teacher programs ensures that pre-service teachers not only acquire the skills to utilize tools such as ChatGPT, DeepSeek, and Grok effectively for pedagogical tasks, but also develop the capacity to critically evaluate their pedagogical implications. This proactive strategy supports both teachers' readiness and broader educational innovation, aligning teacher training with the demands of contemporary, AI-enhanced learning environments [35, 37].

V. Conclusion

As GenAI technologies, continue to evolve rapidly, ongoing research is crucial to understand the long-term impact of these tools on teaching, training and learning processes. Longitudinal studies are particularly valuable for tracking changes in teacher attitudes, identifying emerging challenges, and continuously refining teacher education programs to meet the evolving needs of the 21st-century education.

This study revealed that future educators in initial training are increasingly recognizing the value and potential of GenAI tools as an intelligent supports for pedagogical tasks. The findings also emphasize the influential role of motivational dimensions, specifically those captured by the ARCS model and the AMS dimensions, in shaping participants' perceptions motivation regarding the adoption of these tools from the early stages of their professional development.

These important findings underscore the necessity for decision-makers in initial teacher training programs, particularly within the institution ENS, to prioritize the engaging with GenAI tools into their curricula. This adoption should go beyond mere introduction but also systematically support the meaningful implementation of AI-based technologies [67]. By fostering digital competence and reflective practice, future teachers can be better equipped to navigate and shape the evolving landscape of teaching and learning in the era of AI.

The study's promising outcomes also suggest several avenues for further research. Future investigations, particularly those employing qualitative approaches, could deepen our understanding of the cognitive and emotional responses of future teachers when engaging with GenAI tools, shedding light on the underlying factors that shape motivation, resistance, or ethical concerns. These avenues would contribute to a more comprehensive framework for integrating GenAI into teacher education in a sustainable and pedagogically sound manner.

VI. Limitations

This study provides valuable insights into the motivational factors influencing Moroccan future teachers' adoption of GenAI tools, specifically ChatGPT, DeepSeek, and Grok, as intelligent support systems during their initial teacher training, particularly for pedagogical tasks. However, several limitations must be acknowledged to contextualize the findings and inform future research directions.

Firstly, the sample was limited to future teachers enrolled at the ENS in the Fez-Meknes region of Morocco. This restriction was primarily due to practical constraints, including financial limitations, logistical challenges, and time constraints that prevented access to other training centers. As a result, the generalizability of the findings to other institutions or regions within Morocco, as well as to diverse educational systems globally, may be limited. Future studies should aim to include a broader and more representative sample from diverse institutions and geographical areas to enhance the external validity of the findings and ensure their applicability across varied educational contexts.

Secondly, the study exclusively relied on quantitative data collected via structured questionnaires grounded in established motivational frameworks (ARCS and the AMS). While this approach facilitated efficient data collection and statistical analysis, it may have limited the depth of participants' responses and failed to capture the full range of nuanced perspectives and experiences. Incorporating qualitative methods, such as semi-structured interviews or open-ended survey questions, in future research could provide a richer, more comprehensive understanding of the motivational dynamics surrounding GenAI adoption.

Moreover, while the present analysis focused on a specific motivational constructs, it is important to acknowledge that other potentially influential factors were not explored. Factors such as technology-related anxiety, concerns about data privacy and security, perceived enjoyment, and institutional support, among other relevant factors could also play a critical role in shaping motivation. Exploring these dimensions in future investigations would contribute to a more holistic, nuanced understanding of the motivational landscape, and facilitate the development of more targeted, contextually appropriate strategies for adopting GenAI into initial teacher education programs.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M.L is the main author of this scientific contribution; H.F reviewed the draft and contributed to the final manuscript by refining the conception and design; N.E provided contributions to the final manuscript. K.E.K. and L.A. served as the supervisors for this research article. All authors had approved the final version.

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References

[1] S. Ou, "Transforming education: The evolving role of artificial intelligence in the students academic performance," *International Journal of Education and Humanities*, vol. 13, pp. 163–173, Apr. 2024. doi: 10.54097/cc1x7r95

[2] D. Gm *et al*., "Enhancing education with ChatGPT: Revolutionizing personalized learning and teacher support," *EAI Endorsed Transactions on Internet of Things*, Aug. 2024. doi: 10.4108/eetiot.6998

[3] C. B. Fontao, M. L. Santos, and A. Lozano, "ChatGPT's role in the education system: Insights from the future secondary teachers," *IJIET*, vol. 14, no. 8, pp. 1035–1043, Aug. 2024. doi: 10.18178/ijiet.2024.14.8.2131

[4] Ö. Aydın, E. Karaarslan, F. Erenay, and N. Bacanin, *Generative AI in Academic Writing: A Comparison of DeepSeek, Qwen, ChatGPT, Gemini, Llama, Mistral, and Gemma*, 2025. https://doi.org/10.48550/arXiv.2503.04765

[5] DeepSeek. (Feb. 11, 2025). DeepSeek Into the unknown. [Online]. Available: https://www.deepseek.com/

[6] S. Mercer, S. Spillard, and D. P. Martin, "Brief analysis of DeepSeek R1 and it's implications for generative AI," arXiv: arXiv:2502.02523, Feb. 04, 2025. doi: 10.48550/arXiv.2502.02523

[7] xAI. (Mar. 05, 2025). *Grok 3 Beta—The Age of Reasoning Agents*. [Online]. Available: https://x.ai/blog/grok-3

[8] K. Wangsa, S. Karim, E. Gide, and M. Elkhodr, "A systematic review and comprehensive analysis of pioneering AI chatbot models from education to healthcare: ChatGPT, Bard, Llama, Ernie and Grok," *Future Internet*, vol. 16, no. 7, Art. no. 7, Jul. 2024. doi: 10.3390/fi16070219

[9] L. Doris, R. Shad, and P. Broklyn, "Intelligent tutoring systems using AI for personalized learning," *International Journal of Artificial Intelligence Tools*, Nov. 2024.

[10] O. Onesi-Ozigagun, Y. J. Ololade, N. L. Eyo-Udo, and D. O. Ogundipe, "Revolutionizing education through AI: A comprehensive review of enhancing learning experiences," *International Journal of Applied Research in Social Sciences*, vol. 6, no. 4, Apr. 2024. doi: 10.51594/ijarss.v6i4.1011

[11] UNESCO, "Recommendation on the ethics of artificial intelligence—UNESCO bibliothèque numérique," United Nations Educational, Scientific and Cultural Organization, France, Nov. 2021.

[12] R. Collie and A. Martin, "Teachers' motivation and engagement to harness generative AI for teaching and learning: The role of contextual, occupational, and background factors," *Computers and Education Artificial Intelligence*, vol. 6, 100224, Jun. 2024. doi: 10.1016/j.caeai.2024.100224

[13] L. Alvarez *et al*., "Future teachers' beliefs about generative AI. Assessing technology acceptance as students or as aspiring professionals," *Journal of Technology and Teacher Education*, vol. 32, no. 3, pp. 383–408, 2024. doi: 10.70725/379206cljimb

[14] A. M. Mohamed, T. S. Shaaban, S. H. Bakry, F. D. Guillén-Gámez, and A. Strzelecki, "Empowering the faculty of education students: applying AI's potential for motivating and enhancing learning," *Innov High Educ*, pp. 1–23, Oct. 2024. doi: 10.1007/s10755-024-09747-z

[15] W. K. Monib, A. Qazi, R. A. Apong, M. T. Azizan, L. Silva, and H. Yassin, "Generative AI and future education: A review, theoretical validation, and authors' perspective on challenges and solutions," *PeerJ Comput Sci,* vol. 10, e2105, Dec. 2024. doi: 10.7717/peerj-cs.2105

[16] UNESCO, "Guidance for generative AI in education and research," UNESCO, 2023. doi: 10.54675/EWZM9535.

[17] E. L. Deci and R. M. Ryan, "A motivational approach to self: Integration in personality," *Nebraska Symposium on Motivation*, Lincoln, NE, US: University of Nebraska Press, vol. 38, pp. 237–288, 1991.

[18] H. Zou, J. Yao, Y. Zhang, and X. Huang, "The influence of teachers' intrinsic motivation on students' intrinsic motivation: The mediating role of teachers' motivating style and teacher-student relationships," *Psychology in the Schools*, vol. 61, Aug. 2023. doi: 10.1002/pits.23050

[19] M. Vandewaetere and G. Clarebout, "Advanced technologies for personalized learning, instruction, and performance," *Handbook of Research on Educational Communications and Technology*, Springer, New York, NY, 2014, pp. 425–437. doi: 10.1007/978-1-4614-3185-5_34

[20] L. Laurens and H. Valdés, "M-learning adapted to the ARCS model of motivation and applied to a kinematics course," *Computer Applications in Engineering Education*, Jun. 2021. doi: 10.1002/cae.22443

[21] L. Laurens-Arredondo, "Mobile augmented reality adapted to the ARCS model of motivation: A case study during the COVID-19 pandemic," *Educ Inf Technol*, vol. 27, no. 6, pp. 7927–7946, Jul. 2022. doi: 10.1007/s10639-022-10933-9

[22] K. Li and J. M. Keller, "Use of the ARCS model in education: A literature review," *Computers & Education*, vol. 122, pp. 54–62, Jul. 2018. doi: 10.1016/j.compedu.2018.03.019

[23] J. M. Keller, "Using the ARCS motivational process in computer-based instruction and distance education," *New Directions for Teaching and Learning*, vol. 1999, no. 78, pp. 37–47, 1999. doi: 10.1002/tl.7804

[24] H. Fakhar, M. Lamrabet, N. Echantoufi, K. Ouadrhiri, K. El Khattabi, and L. Ajana, "ChatGPT as an intelligent self-continuous professional development tool for teachers IMMS -ARCS," *Statistics Optimization & Information Computing*, vol. 13, pp. 0–19, Oct. 2024. doi: 10.19139/soic-2310-5070-2145

[25] P.-Y. Lin, C.-S. Chai, M. S.-Y. Jong, Y. Dai, Y. Guo, and J. Qin, "Modeling the structural relationship among primary students' motivation to learn artificial intelligence," *Computers and Education: Artificial Intelligence*, vol. 2, 100006, 2021. doi: 10.1016/j.caeai.2020.100006

[26] R. Vallerand, L. Pelletier, M. Blais, N. Brière, C. Senécal, and E. Vallieres, "The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education," *Educational and Psychological Measurement*, vol. 52, pp. 1003–1003, Dec. 1992. doi: 10.1177/0013164492052004025

[27] R. Burgueño, Á. Sicilia, J. Medina-Casaubon, M. Alcaraz-Ibañez, and M.-J. Lirola, "Revisión de la Escala de Motivación Educativa. Inclusión de la Regulación Integrada para Medir la Motivación en la Formación Inicial del Profesorado," *AN PSICOL-SPAIN*, vol. 33, no. 3, p. 670, Jul. 2017. doi: 10.6018/analesps.33.3.249601

[28] M. Ardeńska, A. Ardeńska, and R. Tomik, "Validity and reliability of the polish version of the academic motivation scale: A measure of intrinsic and extrinsic motivation and amotivation," *Health Psychology Report*, vol. 7, no. 3, pp. 254-266, 2019. doi: 10.5114/hpr.2019.86198

[29] J. Li, R. B. King, C. S. Chai, X. Zhai, and V. W. Y. Lee, "The AI Motivation Scale (AIMS): A self-determination theory perspective," *Journal of Research on Technology in Education*, pp. 1–22. doi: 10.1080/15391523.2025.2478424

[30] J. Li *et al*., "Analyzing the network structure of students' motivation to learn AI: a self-determination theory perspective," *NPJ Sci Learn*, vol. 10, p. 48, Jul. 2025. doi: 10.1038/s41539-025-00339-w

[31] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 43, Jul. 2023. doi: 10.1186/s41239-023-00411-8

[32] DeepSeek-AI *et al*., DeepSeek-V3 Technical Report, Dec. 27, 2024. doi: 10.48550/arXiv.2412.19437

[33] F. Semeraro, M. Cascella, J. Montomoli, V. Bellini, and E. G. Bignami, "Comparative analysis of AI tools for disseminating CPR Guidelines: implications for cardiac arrest education," *Resuscitation*, 110528, Feb. 2025. doi: 10.1016/j.resuscitation.2025.110528

[34] H. S. Sætra, "Generative AI: Here to stay, but for good?" *Technology in Society*, vol. 75, 102372, Nov. 2023. doi: 10.1016/j.techsoc.2023.102372

[35] A. Hazzan-Bishara, O. Kol, and S. Levy, "The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants," *Educ Inf Technol*, Feb. 2025. doi: 10.1007/s10639-025-13393-z

[36] L.-H. Wong and C.-K. Looi, "Advancing the generative AI in education research agenda: Insights from the Asia-Pacific region," *Asia Pacific Journal of Education*, vol. 44, no. 1, pp. 1–7, Jan. 2024. doi: 10.1080/02188791.2024.2315704

[37] H. Bae, J. Hur, J. Park, G. W. Choi, and J. Moon, "Pre-service teachers' dual perspectives on generative AI: Benefits, challenges, and integrating into teaching and learning," *OLJ*, vol. 28, no. 3, Sep. 2024. doi: 10.24059/olj.v28i3.4543

[38] C.-C. Lin, A. Y. Q. Huang, and O. H. T. Lu, "Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review," *Smart Learning Environments*, vol. 10, no. 1, p. 41, Aug. 2023. doi: 10.1186/s40561-023-00260-y

[39] R. Khazanchi and P. Khazanchi, "Artificial intelligence in education: A closer look into intelligent tutoring systems," *Handbook of Research on Critical Issues in Special Education for School Rehabilitation Practices, in Advances in Early Childhood and K-12 Education (AECKE)*, Hershey, PA, US: Information Science Reference/IGI Global, 2021, pp. 256–277. doi: 10.4018/978-1-7998-7630-4.ch014

[40] L. Guo, D. Wang, F. Gu, Y. Li, Y. Wang, and R. Zhou, "Evolution and trends in intelligent tutoring systems research: a multidisciplinary and scientometric view," *Asia Pacific Educ. Rev*., vol. 22, no. 3, pp. 441–461, Sep. 2021. doi: 10.1007/s12564-021-09697-7

[41] V. J. Shute and D. Zapata-Rivera, "Intelligent Systems," in *International Encyclopedia of Education* (Third Edition), P. Peterson, E. Baker, and B. McGaw, Eds., Oxford: Elsevier, 2010, pp. 75–80. doi: 10.1016/B978-0-08-044894-7.00247-5

[42] M. Zhou, N. Duan, S. Liu, and H.-Y. Shum, "Progress in neural NLP: Modeling, learning, and reasoning," *Engineering*, vol. 6, no. 3, pp.

275–290, Mar. 2020. doi: 10.1016/j.eng.2019.12.014

[43] A. Rayhan, R. Kinzler, and R. Rayhan, *Natural Language Processing: Transforming How Machines Understand Human Language*, 2023. doi: 10.13140/RG.2.2.34900.99200

[44] K. M. Alhawiti, "Natural language processing and its use in education," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 5, no. 12, Feb. 2015. doi: 10.14569/IJACSA.2014.051210

[45] T. Hong, Z. Wang, X. Luo, and W. Zhang, "State-of-the-art on research and applications of machine learning in the building life cycle," *Energy and Buildings*, vol. 212, 109831, Apr. 2020. doi: 10.1016/j.enbuild.2020.109831

[46] S. K. Singh, A. K. Tiwari, and H. K. Paliwal, "A state-of-the-art review on the utilization of machine learning in nanofluids, solar energy generation, and the prognosis of solar power," *Engineering Analysis with Boundary Elements*, vol. 155, pp. 62–86, Oct. 2023. doi: 10.1016/j.enganabound.2023.06.003

[47] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *SN COMPUT. SCI.*, vol. 2, no. 3, pp. 1–21, May 2021. doi: 10.1007/s42979-021-00592-x

[48] T. Kabudi, I. Pappas, and D. H. Olsen, "AI-enabled adaptive learning systems: A systematic mapping of the literature," *Computers and Education: Artificial Intelligence*, vol. 2, 100017, Jan. 2021. doi: 10.1016/j.caeai.2021.100017

[49] T. Tran and N. De, "Developing an adaptive learning platform based on Artificial Intelligence (AI) to personalize the learning experience," *International Journal of Management and Organizational Research*, vol. 03, pp. 34–38, May 2024. doi: 10.54660/IJMOR.2024.3.3.34-38

[50] X. Zhang and B. Wang, "Research on cognitive computing model based on machine learning algorithm in artificial intelligence environment," *Applied Mathematics and Nonlinear Sciences*, vol. 9, Oct. 2024. doi: 10.2478/amns-2024-2741

[51] S. Aghav-Palwe and A. Gunjal, "Chapter 1—Introduction to cognitive computing and its various applications," in *Cognitive Computing for Human-Robot Interaction*, M. Mittal, R. R. Shah, and S. Roy, Eds., Academic Press, 2021, pp. 1–18. doi: 10.1016/B978-0-323-85769-7.00009-4

[52] M. T. Irfan and V. N. Gudivada, "Chapter 9—Cognitive computing applications in education and learning," in *Handbook of Statistics*, V. N. Gudivada, V. V. Raghavan, V. Govindaraju, and C. R. Rao, Eds., vol. 35, Elsevier, 2016, pp. 283–300. doi: 10.1016/bs.host.2016.07.008

[53] S. Rawas, "AI: The future of humanity," *Discov Artif Intell*, vol. 4, no. 1, pp. 1–14, Dec. 2024. doi: 10.1007/s44163-024-00118-3

[54] G. E. Gignac and E. T. Szodorai, "Defining intelligence: Bridging the gap between human and artificial perspectives," *Intelligence*, vol. 104, 101832, May 2024. doi: 10.1016/j.intell.2024.101832

[55] A. B. Rashid and M. A. K. Kausik, "AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications," *Hybrid Advances*, vol. 7, 100277, Dec. 2024. doi: 10.1016/j.hybadv.2024.100277

[56] S. Umirov, *Focus on Teaching: AI for Mundane Tasks*, 2024. doi: 10.13140/RG.2.2.27264.65284

[57] Z. Xu, "AI in education: Enhancing learning experiences and student outcomes," *Applied and Computational Engineering*, vol. 51, pp. 104–111, Mar. 2024. doi: 10.54254/2755-2721/51/20241187

[58] K. Chetry, "Transforming education: How AI is revolutionizing the learning experience," *International Journal of Research Publication and Reviews*, vol. 5, pp. 6352–6356, May 2024. doi: 10.55248/gengpi.5.0524.1277

[59] R. Luckin, M. Cukurova, C. Kent, and B. Boulay, "Empowering educators to be AI-ready," *Computers and Education: Artificial Intelligence*, vol. 3, 100076, Jan. 2022. doi: 10.1016/j.caeai.2022.100076

[60] C. V. Felix, *The Role of the Teacher and AI in Education*, 2020, pp. 33–48. doi: 10.1108/S2055-364120200000033003

[61] N. J. Kim and M. K. Kim, "Teacher's perceptions of using an artificial intelligence-based educational tool for scientific writing," *Front. Educ.*, vol. 7, 755914, Mar. 2022. doi: 10.3389/feduc.2022.755914

[62] E. Frank and E. Ok, *The Influence of Artificial Intelligence on Education: Enhancing Personalized Learning Experiences*, Sep. 2024.

[63] OpenAI. (Feb. 07, 2025). Introducing ChatGPT. [Online]. Available: https://openai.com/index/chatgpt/

[64] OpenAI. (Feb. 08, 2025). OpenAI o3-mini. [Online]. Available: https://openai.com/index/openai-o3-mini/

[65] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, vol. 61, no. 3, pp. 460–474, May 2024. doi: 10.1080/14703297.2023.2195846

[66] G. Cooper, "Examining science education in ChatGPT: An exploratory study of generative artificial intelligence," *J Sci Educ Technol*, vol. 32, no. 3, pp. 444–452, Jun. 2023. doi: 10.1007/s10956-023-10039-y

[67] H. Fakhar, M. Lamrabet, N. Echantoufi, K. E. Khattabi, and L. Ajana, "Towards a new artificial intelligence-based framework for teachers' online continuous professional development programs: Systematic review," *IJACSA*, vol. 15, no. 4, 2024. doi: 10.14569/IJACSA.2024.0150450

[68] J. Filgona, J. Sakiyo, D. Gwany, and A. Okoronka, "Motivation in learning," *Asian Journal of Education and Social Studies*, vol. 10, pp. 16–37, Sep. 2020. doi: 10.9734/AJESS/2020/v10i430273

[69] N. Davidovitch and R. Dorot, "The effect of motivation for learning among high school students and undergraduate students—A comparative study," *IES*, vol. 16, no. 2, p. 117, Mar. 2023. doi: 10.5539/ies.v16n2p117

[70] J. Martínez-Moreno and D. Petko, "What motivates future teachers? The influence of Artificial Intelligence on student teachers' career choice," *Computers and Education: Artificial Intelligence*, vol. 7, 100296, Dec. 2024. doi: 10.1016/j.caeai.2024.100296

[71] G. Gorozidis and A. G. Papaioannou, "Teachers' motivation to participate in training and to implement innovations," *Teaching and Teacher Education*, vol. 39, pp. 1–11, Apr. 2014. doi: 10.1016/j.tate.2013.12.001

[72] J. Brophy, "Toward a model of the value aspects of motivation in education: Developing appreciation for particular learning domains and activities," *Educational Psychologist*, vol. 34, no. 2, pp. 75–85, 1999. doi: 10.1207/s15326985ep3402_1

[73] K. Capunitan, J. Lirado, and C. Gregana, "Motivational factors in science learning, learner's satisfaction and learning outcomes of pre-service teachers," *International Journal of Scientific and Management Research*, vol. 6, pp. 72–115, May 2023. doi: 10.37502/IJSMR.2023.6504

[74] J. M. Keller, "Use of the ARCS model of motivation in teacher training," *IDD&E Working Paper No. 10*', Mar. 1983.

[75] J. M. Keller, "Development and use of the ARCS model of instructional design," *Journal of Instructional Development*, vol. 10, no. 3, pp. 2–10, Sep. 1987. doi: 10.1007/BF02905780

[76] X. Fang, D. T. K. Ng, J. K. L. Leung, and H. Xu, "The applications of the ARCS model in instructional design, theoretical framework, and measurement tool: a systematic review of empirical studies," *Interactive Learning Environments*, pp. 1–28, Aug. 2023. doi: 10.1080/10494820.2023.2240867

[77] A. Møgelvang, C. Bjelland, S. Grassini, and K. Ludvigsen, "Gender differences in the use of generative artificial intelligence chatbots in higher education: Characteristics and consequences," *Education Sciences*, vol. 14, no. 12, Art. no. 12, Dec. 2024. doi: 10.3390/educsci14121363

[78] M. Nyaaba, P. Kyeremeh, E. K. Majialuwe, C. Owusu-fordjour, E. Asebiga, and B. A-ingkonge, "Generative AI in academic research: A descriptive study on awareness, gender usage, and views among pre-service teachers," *Journal of AI*, vol. 8, no. 1, pp. 45–60, Dec. 2024. doi: 10.61969/jai.1400867

[79] H. Fakhar, M. Lamrabet, N. Echantoufi, K. Khattabi, and A. Lotfi, "Artificial intelligence from teachers' perspectives and understanding: Moroccan study," *IJIET*, vol. 14, no. 6, pp. 856–864, 2024. doi: 10.18178/ijiet.2024.14.6.2111

[80] M. Lamrabet, H. Fakhar, N. Echantoufi, K. El Khattabi, L. Ajana, and S. Ben Fares, "AI-based tools: Exploring the perceptions and knowledge of Moroccan future teachers regarding AI in the initial training—A case study," *IJIET*, vol. 14, no. 11, pp. 1493–1505, 2024. doi: 10.18178/ijiet.2024.14.11.2180

[81] A. Darayseh, "(PDF) Acceptance of artificial intelligence in teaching science: Science teachers' perspective," ResearchGate, Apr. 2025. doi: 10.1016/j.caeai.2023.100132

[82] N. G. Otis, K. Cranney, S. Delecourt, and R. Koning, *Global Evidence on Gender Gaps and Generative AI*, Oct. 14, 2024. doi: 10.31219/osf.io/h6a7c

[83] B. L. Moorhouse and L. Kohnke, "The effects of generative AI on initial language teacher education: The perceptions of teacher educators," *System*, vol. 122, 103290, Jun. 2024. doi: 10.1016/j.system.2024.103290

[84] J. Jeon, "Exploring AI chatbot affordances in the EFL classroom: young learners' experiences and perspectives," *Computer Assisted Language Learning*, vol. 37, no. 1–2, pp. 1–26, Jan. 2024. doi: 10.1080/09588221.2021.2021241

[85] T. K. F. Chiu, B. L. Moorhouse, C. S. Chai, and M. Ismailov, "Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot," *Interactive Learning Environments*, vol. 32, no. 7, pp. 3240–3256, Aug. 2024. doi: 10.1080/10494820.2023.2172044

[86] J. K. M. Ali, M. A. A. Shamsan, T. A. Hezam, and A. A. Q.

Mohammed, “Impact of ChatGPT on learning motivation: Teachers and students’ voices,” *Journal of English Studies in Arabia Felix*, vol. 2, no. 1, Mar. 2023. doi: 10.56540/jesaf.v2i1.51

[87] A. Mizumoto and M. Eguchi, “Exploring the potential of using an AI language model for automated essay scoring,” *Research Methods in Applied Linguistics*, vol. 2, no. 2, 100050, Aug. 2023. doi: 10.1016/j.rmal.2023.100050

[88] B. Memarian and T. Doleck, “ChatGPT in education: Methods, potentials, and limitations,” *Computers in Human Behavior: Artificial Humans*, vol. 1, no. 2, 100022, Aug. 2023. doi: 10.1016/j.chbah.2023.100022

[89] N. A. Mhamdi, “Questioning the narrative of generative AI and the metaverse in education: A mixed-methods study of Moroccan teachers’ perceptions and behavioural intentions,” in *Proc. the Second International Symposium on Generative AI and Education (ISGAIE’2025)*, Cham: Springer Nature Switzerland, 2025, pp. 471–486. doi: 10.1007/978-3-031-98476-1_37

[90] S. Ha, “Exploring the practical applications of ChatGPT for simulation teaching by preservice physics teachers,” *New Physics: Sae Mulli*, vol. 73, no. 9, pp. 734–749, Sep. 2023. doi: 10.3938/NPSM.73.734

[91] M. Lamrabet, H. Fakhar, N. Echantoufi, E. K. Khalid, and A. Lotfi, “Revolutionizing teachers’ professional development: The critical role of AI-based tools from initial training to lifelong learning—a case study,” *IJIET,* vol. 15, no. 4, pp. 696–715, 2025. doi: 10.18178/ijiet.2025.15.4.2277