Gifted Education in the Age of AI: A Proposal for an Integrated Conceptual Model

Simge Karakaş Mısır – Universidad de Tokat Gaziosmanpşa Üniversitesi 0000-0003-4358-9647

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Correspondencia a través de **ORCID**: Simge Karakaş Mısır **0000-0003-4358-9647**

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Abstract: The distinct cognitive and socio-emotional characteristics of gifted students necessitate differentiated educational approaches tailored to their unique needs. This study aims to address the integration of Artificial Intelligence (AI) and Deep Learning (DL) technologies into this field through a human-centered perspective, moving beyond a purely technical viewpoint. Rather than analyzing specific applications, the study presents a theoretical framework focusing on the potential role of AI in supporting both academic and emotional development. Drawing on interdisciplinary literature, the proposed conceptual model integrates four interrelated components: talent identification, personalized learning design, process monitoring, and socio-emotional support. This model positions AI and DL-based systems as elements that support objectivity in identification, deepen personalization, and provide real-time feedback, while emphasizing that these processes must be bounded by pedagogical judgment and ethical principles. Ultimately, this study aims to establish a coherent conceptual foundation capable of guiding future research, pedagogical designs, and policy development regarding the responsible use of technology in gifted education.

Keyword: Gifted Education

Introduction

The rapid advancement of technology necessitates that societies adapt to this pace. To keep up with these changes, it is essential to integrate technological innovations into all levels of education. Artificial intelligence (AI), one of the most widely discussed technological advancements today, has the potential to reshape learning and teaching processes. AI cannot be considered merely as a technology. When examining its component such as deep learning, machine learning, image processing, natural language processing, and neural networks it becomes evident that AI is not only used for training machines but also serves as a tool for human development (Russell and Norvig, 2021). Advances in these AI subfields provide innovative solutions to various educational challenges, ranging from enhanced personalized learning experiences to the development of higher-order thinking skills. In this context, understanding the role of AI in education and effectively utilizing this technology has become an unavoidable necessity for modern education systems.

The role of AI in education goes beyond being just a technological tool; it enables a deeper transformation. AI can personalize learning processes by offering content tailored to students' individual learning needs, allowing them to learn at their own pace and in their preferred style. This personalization has a particularly significant impact on the education of gifted students. Gifted students are individuals who learn faster than their peers, possess creative thinking skills, demonstrate exceptional abilities in specific areas, and often develop innovative solutions to complex problems (Renzulli and Gaesser, 2015). These students require a different approach than standard education programs, as conventional curricula may fail to meet their learning speed, depth, and creativity. To fully unlock the potential of gifted individuals, a specially designed learning experience beyond standard educational programs is necessary (VanTassel-Baska and Brown, 2007). AI can optimize the development of gifted students by providing content and activities tailored to their interests, learning speeds, and cognitive capacities (Kim, Park, and Lee, 2022).

Artificial intelligence (AI) and technologies such as deep learning have the potential to bring revolutionary changes to education (Kaplan and Haenlein, 2019). Deep learning algorithms can analyze how a student solves mathematical problems, determine which topics require additional support, or automatically adjust difficulty levels according to the student's interests. These technologies hold significant potential, especially in the education of gifted students.

AI's contribution to gifted education is not limited to personalized learning content. It can also provide specialized tools and simulations to help these students develop advanced problem-solving, analytical thinking, and creative potential. AI-powered learning platforms can enable gifted students to understand complex mathematical models, conduct scientific research, or develop new methods in art and design. This not only supports their academic growth but also nurtures their creative and innovative capacities.

In this context, there remains a need for AI to contribute to gifted education in ways that integrate both cognitive and socio-emotional dimensions. This study seeks to address this gap by (i) examining the potential of AI and deep learning to create sustainable and personalized learning environments for gifted students, (ii) integrating cognitive and socio-emotional perspectives into the analysis, and (iii) proposing a conceptual framework that connects these dimensions through four interrelated components: talent identification, personalized learning, monitoring and improvement, and socio-emotional support. Together, these contributions are aligned with the long-term goals of sustainable and inclusive education. Accordingly, the paper investigates in detail the role and contributions of AI and deep learning in the education of gifted students.

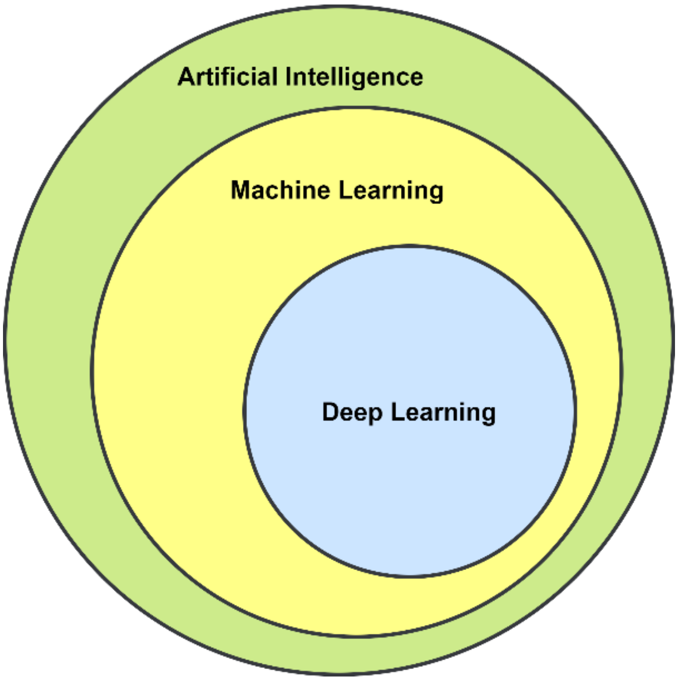
In emerging and rapidly evolving fields such as AI-supported gifted education, empirical findings alone are insufficient to guide sustainable educational design. Before technologies can be meaningfully evaluated or implemented, there is a need for theoretically grounded models that clarify core concepts, define relationships among key dimensions, and provide a coherent framework for interpreting both opportunities and risks. Conceptual model development thus represents a necessary step for structuring future research and informing educational practice. Addressing this need, the present study adopts a theoretical and conceptual approach to develop an integrative model for the sustainable and inclusive education of gifted students through artificial intelligence and deep learning. Drawing upon interdisciplinary literature in gifted education, AI-supported learning, and sustainability-oriented education, this study proposes a conceptual framework that articulates four interrelated dimensions: talent identification, personalized learning, the monitoring and enhancement of learning processes, and socio-emotional support. the present study aims to contribute to conceptual discussions and develop a theoretical perspective in this field of rapid technological transformation. Accordingly, the proposed model is expected to prepare the ground for future research and decision-making processes regarding the integration of AI and deep learning in gifted education by offering an alternative perspective for researchers, educators, and policymakers.

Artificial Intelligence and Deep Learning

Artificial intelligence (AI) is an interdisciplinary research field aimed at developing systems that mimic human intelligence and perform cognitive functions (Russell and Norvig, 2021). AI is based on algorithms and mathematical models designed to simulate cognitive processes such as learning, reasoning, problem-solving, perception, and language processing (Goodfellow, Bengio and Courville, 2016). The key components of artificial intelligence include machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision (CV), and robotics (Kaplan and Haenlein, 2019).

Deep learning stands out as a significant subfield of AI in analyzing complex data. It is a machine learning technique that utilizes artificial neural networks to learn complex models and analyze intricate data structures. Figure 1 illustrates the position of deep learning within the field of artificial intelligence. This technique is designed to discover patterns and relationships within large datasets. Deep learning employs artificial neural networks that are structured to mimic the functioning of the human brain. These networks consist of layers of mathematical processing units. Input data is fed into the initial layer of the network and then processed through weighted connections between layers. This process allows for the gradual abstraction and representation of the features that define the data.

Figure 1.
AI subfields and Deep Learning.

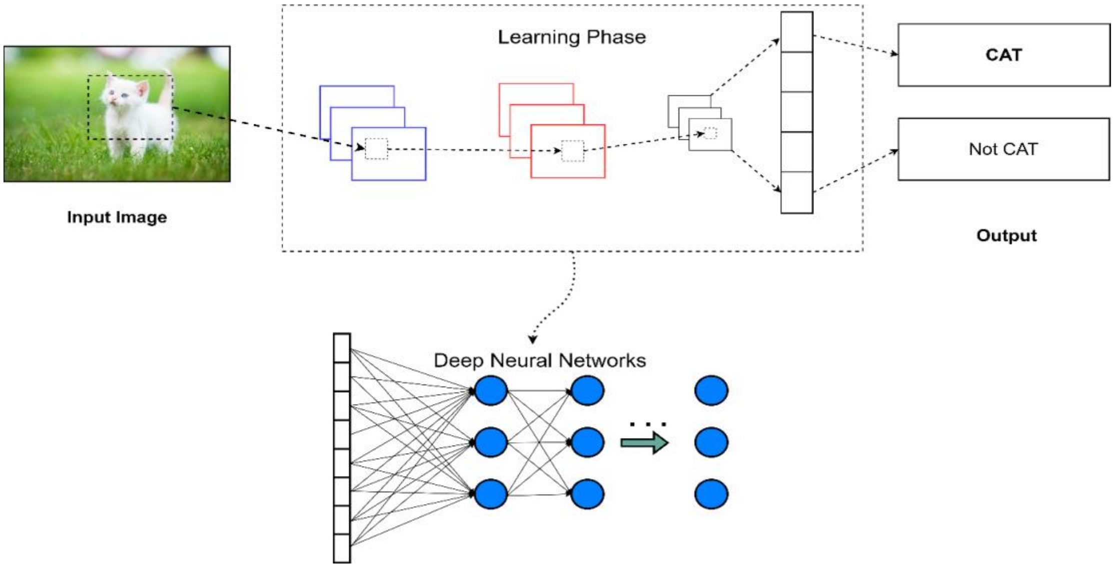


The concept of artificial neural networks, which forms the foundation of deep learning, was inspired by biological nervous systems. Early studies, such as the McCulloch-Pitts model, defined the fundamental mathematical structures of neural networks (McCulloch and Pitts, 1943).

One of the core components of deep learning is deep neural networks. These networks are typically multi-layered, where each layer takes the outputs of the previous layer as input. In this way, each layer further abstracts the features represented by the previous layer and constructs more complex representations. This multi-layered structure provides great flexibility in modeling complex relationships and learning more generalizable features. Frank Rosenblatt's work on the "Perceptron" introduced single-layer neural networks and created one of the first artificial neural networks used for solving classification problems (Rosenblatt, 1958).

The backpropagation algorithm, proposed by Paul Werbos, provided an effective method for training neural networks (Werbos, 1990). This algorithm was a significant step in deepening neural networks and solving more complex problems. Figure 2 illustrates a neural network model composed of deep layers.

Figure 2.
Deep Neural Network Model.



The availability of large datasets and high computational power has made it necessary to train neural networks using complex models that often involve millions of examples and hundreds of thousands of parameters. As a result, research in this field was stagnant for a period. However, the increase in large datasets, the accessibility of more powerful computing resources, and the development of new training techniques have led to the resurgence of deep learning. The deep neural network model AlexNet (Tan et al. 2018) won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) using the ImageNet dataset, contributing to the renewed popularity of deep learning. AlexNet demonstrated the effectiveness of deep neural networks in complex tasks such as image classification. Deep learning methods have achieved remarkable success in various complex problems, including visual recognition, disease diagnosis (Celik and Inik 2024), natural language processing (Arkhangelskaya and Nikolenko, 2023), and speech recognition (Mehrish et al., 2023). Deep neural networks are used to understand complex data structures, offering higher accuracy and better performance compared to previous methods. Today, deep learning techniques are widely applied across multiple disciplines and have become an essential part of artificial intelligence research and applications. In the future, deep learning techniques are expected to further evolve and become even more widespread.

The Historical Process of Identifying Gifted Individuals

For many years, evolving and developing intelligence theories have been proposed to explain the concept of giftedness. Today, it is well understood that being gifted is not solely determined by a high IQ level. However, various intelligence theories are still used as the foundation for identifying gifted students. While traditional IQ tests have long been the dominant method for determining giftedness, modern intelligence theories propose more comprehensive and multidimensional assessment processes. Understanding different intelligence theories is crucial for fully uncovering the potential of gifted individuals. Historically, intelligence was initially studied from a single-dimensional perspective.

Thurstone's Primary Mental Abilities Theory views intelligence as a multidimensional construct. According to Thurstone (1973), intelligence consists of seven distinct abilities: verbal comprehension, verbal fluency, numerical ability, spatial visualization, memory, perceptual speed, and reasoning. This model suggests that individuals may excel in certain cognitive areas rather than across all domains, emphasizing that intelligence and giftedness can take different forms.

A significant shift in intelligence theories was introduced with Gardner's Theory of Multiple Intelligences. Gardner conceptualized intelligence as a multidimensional structure and defined eight distinct intelligence types: verbal-linguistic, logical-mathematical, visual-spatial, bodily-kinesthetic, musical-rhythmic, interpersonal, intrapersonal, and naturalistic intelligence (Gardner, 1983). This model emphasizes that gifted individuals are not solely defined by academic achievement but may possess strengths in different types of intelligence. Therefore, identifying gifted individuals should not be limited to traditional tests but should also involve performance assessments across various domains.

A similar multidimensional approach is presented in Sternberg's Triarchic Theory of Intelligence. Sternberg categorizes intelligence into three components: analytical, creative, and practical intelligence (Sternberg, 1985). Analytical intelligence refers to problem-solving and logical thinking abilities, which can be measured by traditional IQ tests. Creative intelligence, on the other hand, involves generating new ideas and innovative thinking skills, while practical intelligence represents an individual's ability to handle real-world challenges. This theory marks a significant distinction by emphasizing that gifted individuals should be evaluated not only based on their academic achievements but also through their creative and practical intelligence. Lastly, Carroll's Three-Stratum Theory of Intelligence conceptualizes intelligence within a hierarchical structure at three levels: general intelligence (g factor), broad cognitive abilities (such as fluid intelligence, crystallized intelligence, and memory capacity), and narrow abilities (such as vocabulary knowledge and rapid thinking skills) (Carroll, 1993). This model provides a more detailed cognitive analysis in the assessment of gifted individuals, allowing for a comprehensive evaluation of both their general intellectual capacity and their specific cognitive strengths and weaknesses.

When all these theories are considered together, it becomes evident that a more holistic and individualized assessment approach should be adopted in identifying gifted students. Although traditional IQ tests remain a valuable tool, they need to be supplemented with alternative evaluation methods to fully uncover an individual's diverse cognitive abilities and potential. Various methods are used for identifying gifted students. One of the most common methods is the use of standardized intelligence tests. Tests such as the WISC-IV (Wechsler Intelligence Scale for Children) and the Stanford-Binet Intelligence Test are widely utilized to measure cognitive abilities (Wechsler, 2003; Roid, 2004). While these tests help determine students' general intelligence levels, they have been criticized for offering a limited perspective (Warne, 2012). Since relying solely on intelligence tests is insufficient for identifying gifted individuals, additional assessment methods such as teacher observations of classroom performance, problem-solving approaches, and creative thinking skills can be used (Pfeiffer and Blei, 2008; Gentry, Pereira, Peters, McIntosh and Fugate, 2015; McCarney and Arthaud, 2009). Moreover, individual interviews and self-assessment forms can provide insight into how gifted individuals perceive and express themselves (Paulhus and Vazire, 2007; Vazire and Mehl, 2008) Alternative approaches, such as project-based assessments and portfolio evaluations, allow for the observation of students' creative and critical thinking skills, making them effective tools for identifying gifted students (Renzulli and Gaesser, 2015). Particularly in alignment with Gardner's and Sternberg's theories, these methods are increasingly being used to assess gifted students' diverse talents across multiple domains (Sternberg, 1999).

Today, neuropsychological assessments and computer-assisted tests are becoming increasingly common. Brain imaging techniques offer a more detailed examination of students' cognitive processes, while computer-based dynamic assessment methods analyze students' problem-solving processes in real time (Feinstein, 2011). Techniques such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) provide valuable insights into the neurobiological foundations of cognitive processes. For example, fMRI can help identify which brain regions are more active during the problem-solving processes of gifted students (Jung and Haier, 2007). EEG, on the other hand, can analyze brain waves to examine neural activities related to quick thinking abilities and creativity (Geake and Hansen, 2005). Adaptive testing and AI-assisted analyses are introducing next-generation approaches to identifying gifted students by determining their individual learning profiles (McGrew, 2015). AI-based systems can continuously track students' cognitive processes and provide personalized feedback. Machine learning algorithms can analyze students' problem-solving processes to identify their strengths and areas for improvement. Deep learning techniques, working with large datasets, can examine the cognitive profiles of gifted students in detail and create personalized learning maps. Dynamic assessment methods aim not only to measure students' current performance but also to evaluate their learning potential. For example, cognitive games and virtual reality-assisted tests are among the tools that can analyze students' real-time problem-solving abilities (Shute and Ventura, 2013).

These theories and methods highlight the necessity of adopting a more holistic and individualized approach in the identification of gifted students. While traditional IQ tests remain a valuable tool, alternative assessment methods are essential to fully reveal individuals' multifaceted cognitive abilities and potential.

Challenges in the Education of Gifted Students

Gifted students may be cognitively, socially, and emotionally more advanced than their peers. While a gifted student may be far ahead of their peers in cognitive abilities, their social and emotional development may progress at the same level as their peers. Therefore, addressing the needs arising from the individual differences of gifted students requires special strategies. These students exhibit extraordinary intellectual abilities and skills; however, they often struggle in traditional educational settings that do not provide sufficient stimulation, support, or resources. Without appropriate intervention, gifted students are at risk of disengagement, underachievement, or social-emotional difficulties. Research shows that the lack of an adequately challenging curriculum often leads to boredom and frustration among gifted students (Colangelo and Assouline, 2009). Many school systems prioritize grade-level education, making it difficult for gifted students to progress at a pace that matches their abilities (VanTassel-Baska and Brown, 2007). Traditional education systems generally follow a curriculum that presents the same content to all students. This approach limits the development of gifted students and may lead to their disengagement from education. In many schools, programs such as grade skipping or subject-based acceleration are not offered. This causes academically advanced students to become bored and lose motivation in the learning process (VanTassel-Baska and Brown, 2007). Standard curricula do not adequately support skills such as critical thinking, problem-solving, and creative exploration. However, gifted students need to explore topics in greater depth and engage with complex problems. In some regions, specialized programs for gifted students either do not exist or are offered with limited resources due to insufficient funding (Ford, 2013).

One of the key aspects to consider in addressing the curriculum deficiencies for gifted students is the challenge level of course content. Although the students may have different levels of understanding, they often receive the same level of difficulty in lessons. Each student progresses at their own pace and requires individualized lesson plans and challenges that match their level to enhance their skills. When gifted students face a traditional education approach that does not challenge them appropriately, they may fail to reach their potential, experience boredom, or exhibit behavioral issues (Reis and McCoach, 2000). One of the deficiencies encountered in the implementation of standard curricula is the lack of encouragement for the development of higher-order thinking skills. Most educational programs prioritize covering a broad range of topics superficially rather than allowing gifted students to explore subjects in depth. This preference for breadth over depth can suppress intellectual curiosity and limit opportunities for higher-order thinking skills, such as synthesis and evaluation, as outlined in Bloom's Taxonomy (VanTassel-Baska, 2014). Although gifted students often excel in creative thinking—one of the higher-order thinking skills—many curricula emphasize standardized tests and compliance rather than open-ended exploration. This restricts their ability to engage in independent projects, original research, or innovative problem-solving efforts. The suppression of creativity can hinder the development of skills crucial for future success, such as entrepreneurship and scientific discovery (Renzulli, 2012).

Although academic achievement is the central focus in identifying and educating gifted individuals, they may also encounter various social and emotional challenges. These challenges can negatively impact their overall well-being and academic performance. The cognitive development of gifted children does not always progress in parallel with their emotional maturity. This discrepancy can make it difficult for them to fit in with their peers and lead to frustration (Neihart et al., 2016). Gifted students may struggle to find peers who can think at their level and share their interests, which can make them feel lonely and misunderstood (Cross, 2018). Social and emotional challenges, such as asynchronous development and heightened sensitivity, can make it difficult for gifted students to maintain peer relationships and develop self-esteem (Neihart et al., 2016). Another critical issue is that due to biases in assessment methods, gifted students from culturally and economically diverse backgrounds are often under identified (Ford, 2013). Traditional methods used in identifying gifted individuals may overlook many students. This issue is particularly significant for students from specific socioeconomic and cultural groups. Standard IQ tests and conventional assessment methods fail to adequately detect the abilities of students from disadvantaged backgrounds. Consequently, students from low-income and diverse cultural backgrounds have limited access to gifted programs (Ford, 2013*)*. Particularly in STEM (science, technology, engineering, and mathematics) fields, gifted female students may not be adequately identified and supported due to societal expectations (Rinn and Bishop, 2015).

In some cases, the different learning styles of gifted students may not be supported by teachers. This issue often arises when teachers lack sufficient knowledge in the field or do not have training in identifying and educating gifted students (Ford, 2013; Plucker and Callahan, 2014). Creating a differentiated or individually personalized education plan is essential for the education of gifted students (Renzulli, 2012; Subotnik, Olszewski-Kubilius and Worrell, 2011). However, traditional teacher training programs and in-service education do not sufficiently cover instructional strategies for this differentiation (VanTassel-Baska and Stambaugh, 2008). This deficiency leads to inadequacies in differentiated instruction, fostering higher-order thinking, and creating creativity-enhancing learning environments (Tomlinson, 2014). To address these gaps, teachers must develop themselves by using updated resources that incorporate differentiation strategies suitable for the diverse learning styles of students. Utilizing current technology to align with gifted students' interests can help teachers enrich their lessons and enhance student motivation.

One of the most up-to-date technologies, artificial intelligence (AI) and its subcomponents, can be used in the education of gifted students for various tasks. AI can serve as an assistant for teachers or students, monitor students' academic performance, predict student behaviors, implement personalized learning, and provide feedback to students (Brink, 2023). Scientists also emphasize that one of AI's potential applications as a teacher's assistant lies in developing and selecting the most appropriate, engaging, and valuable educational materials that correspond to and extend beyond the curriculum's boundaries for the target audience (Viznuk et al., 2021). Using AI to assist in curriculum differentiation and enriching course content for gifted students can offer teachers new perspectives

Methodology

The Proposed Conceptual Model for AI-Supported Gifted Education

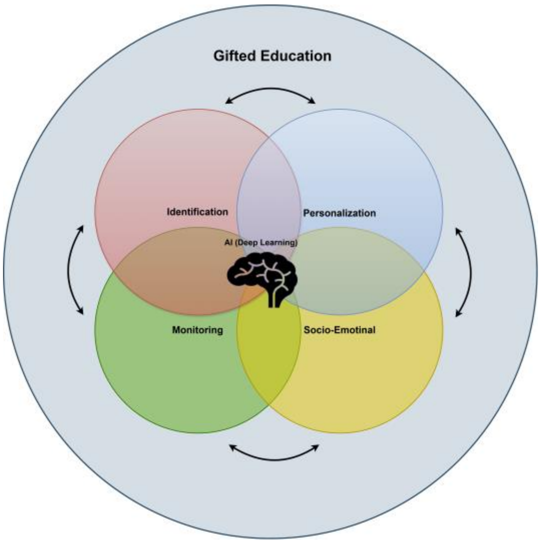
Overview and Rationale of the Model

The model proposed in the present study conceptualizes the integration of Artificial Intelligence (AI) and Deep Learning (DL) technologies into gifted education not as a collection of isolated technological applications, but as a systemic and process-oriented integrated educational framework. Grounded in the theoretical synthesis detailed in the methodology section, this construct aims to address the multi-layered cognitive, socio-emotional, and organizational dimensions of gifted education through a sustainability perspective. Diverging from purely outcome-driven or technology-centered approaches prevalent in the literature, the model positions AI and DL as supportive elements that reinforce pedagogical decision-making mechanisms, deepen learner engagement, and enhance responsiveness to individual differences. Within this context, the developed framework is designed to function as an explanatory and heuristic tool, elucidating how the dynamic components of AI-supported gifted education interact over time and under varying contextual conditions

Gifted students possess learning speed, depth, and creativity that go far beyond the standard curriculum offered by traditional education systems. Deep learning, a subfield of artificial intelligence (AI), presents numerous opportunities to maximize these students' individual potential, nurture their creativity, and support their social-emotional needs. In this context, the potential contributions of AI in better understanding students' abilities, creating personalized learning experiences, supporting socio-emotional development, and monitoring educational processes are examined.

Building on the literature and the dimensions discussed, this study proposes a conceptual framework (Figure 3) that integrates four interrelated dimensions: (i) talent identification and classification through AI-based data analysis, (ii) the design of personalized learning materials supported by adaptive algorithms, (iii) the monitoring and improvement of learning processes via real-time analytics, and (iv) socio-emotional support through AI-powered emotion recognition and virtual advisors. Collectively, these dimensions contribute to the development of sustainable and inclusive gifted education practices. The model is structured around four interrelated dimensions that collectively represent the primary mechanisms through which AI and DL can contribute to sustainable and inclusive gifted education. These dimensions are not hierarchical; instead, they operate as mutually reinforcing processes within a dynamic system. The development process of this model is based on an iterative conceptual synthesis approach, resulting in the framework presented in Figure 3.

Figure 3.
An integrative conceptual framework for gifted education supported by artificial intelligence.



Talent Identification and Classification

Early identification of gifted individuals and directing them to appropriate educational environments is crucial for maximizing their potential. However, this process often relies on standard tests (IQ tests, academic achievement tests) and teacher observations. These methods alone may not be sufficient, as talent can manifest in different ways. Traditional methods used to identify gifted individuals include intelligence tests, academic achievement tests, and observations from teachers and parents (Kuznetsova et al., 2024).

Gifted students are typically identified using standard intelligence tests (such as WISC, Stanford-Binet), and individuals who exceed a certain IQ threshold (usually 130+) are categorized as gifted. However, these tests do not fully measure creativity, problem-solving skills, or emotional intelligence. Academic achievement tests assess fields such as mathematics, science, and language, but they may create the misconception that gifted individuals must always be top performers academically. Additionally, teachers and parents may assess students' potential through observation, but this method is subjective and may not encompass all types of abilities (Sambuis *and* Bourdin, 2024). Traditional methods do not adequately evaluate skills such as cognitive flexibility, creativity, and problem-solving. Furthermore, environmental factors such as a student's socioeconomic status and access to educational resources can influence results. Standardized tests can also cause stress, making it difficult for students to fully demonstrate their true potential (Gabrys et al., 2018).

Deep learning can analyze data from various sources, such as test results, creative works (drawings, writings), and behavioral records, to identify gifted individuals. This is particularly useful for assessing creativity and problem-solving skills, which standard tests fail to measure. In a study by Franceschelli and Musolesi (2022), a new measurement method called "DeepCreativity" was introduced. This method applies deep learning techniques to measure creativity skills through a case study on the production of 19th-century American poetry. DeepCreativity is an innovative assessment system that integrates deep learning techniques to objectively analyze fundamental characteristics such as value, novelty, and surprise in produced works. Value measurement is performed using the discriminator component of a Generative Adversarial Network (GAN) model. Novelty measurement determines the originality and distinctiveness of a structure using a neural network-based style classification method, while surprise measurement quantitatively evaluates unexpected and extraordinary aspects of a structure through sequential generative models (Gs). Deep learning models, particularly those utilizing recurrent neural networks (RNNs), which can process time-series data, are well-suited for analyzing students' developmental processes. For example, compared to one-time assessments, this approach offers a more dynamic evaluation, enabling a more accurate assessment of students' potential. Similarly, Kang et al. (2024) developed a deep learning model using a Gated Recurrent Unit (GRU) network to predict students' academic performance. By analyzing historical academic data, this model identified patterns in students' performance, reducing reliance on single-instance evaluations. Such models provide the opportunity to detect potentially gifted students earlier by monitoring their development over time.

A recent systematic literature review by Alnasyan, Basheri, and Alassafi (2024) emphasized that deep learning techniques are used to predict student performance in virtual learning environments and that longitudinal data, such as prior academic performance, plays a significant role. This suggests that analyzing students' development over time can reduce dependency on one-time evaluations. The contributions of deep learning and artificial intelligence tools in identifying and classifying gifted students can be examined in areas such as visual ability classification, handwriting analysis, problem-solving skills, and recommendation systems. Visual ability classification involves analyzing visual materials such as drawings, artwork, or graphic designs using deep learning, a subfield of artificial intelligence, to assess students' visual-spatial skills. In this context, a study conducted by Panfilova, Valueva, and Ilyin (2024) applied deep learning-based AI models to automatically evaluate creativity levels and used explainable artificial intelligence (XAI) methods to understand the decision-making processes of these models. Their research particularly aimed to analyze drawings from the Urban Creativity Test and identify the specific drawing features that the model relies on.

Therefore, this dimension extends the scope of talent identification beyond mere cognitive performance measures, envisioning a holistic structure that encompasses creativity, motivation, and contextual factors. Within the model's approach, AI is positioned not as an independent decision-maker, but as a support tool designed to reinforce the educator's expertise and decision-making capabilities. This facilitates the synthesis of AI-generated data with human reasoning; thereby, minimizing potential errors and risks of over-reliance associated with technology acting as the sole determinant. Ultimately, this approach aims to establish an ethical and sustainable identification process

Personalized Learning Materials

Deep learning and machine learning provide powerful tools for adapting the learning process to individual needs in personalized educational environments. In this process, learning objectives, content, methods, and pace can vary for each student; therefore, personalization involves both differentiation and individualization. Personalized learning can be designed not only based on students' cognitive and behavioral characteristics but also by adapting to their learning styles, knowledge levels, and individual preferences (Yun, Lee, and Choi 2024). Deep learning algorithms can detect these differences through big data analysis and provide the most suitable learning path for each student, thereby ensuring a more effective and efficient educational experience. Machine learning, which also encompasses deep learning, is frequently used in image processing, natural language processing, and engineering problems. However, it has also been shown to help address classification problems in gifted education. Machine learning methods go beyond traditional statistical approaches, and deep neural networks can analyze complex data relationships more accurately. In this context, a study by Hodges and Mohan (2019) explored how machine learning can assist in personalized learning, material development, and the classification of gifted students. Their research demonstrated that machine learning can be used in evaluating student products, reducing biases, classifying students, and modeling complex relationships for gifted individuals.

Generative language models (such as ChatGPT) and adaptive learning technologies, which frequently employ deep learning methodologies, have been highlighted as potential tools for enhancing gifted students' digital skills. A study by Bayly-Castaneda, Ramirez-Montoya, and Morita-Alexander (2024) demonstrated that AI and deep learning methodologies present significant opportunities for creating personalized learning processes for gifted students. The positive impact of deep learning on personalized learning is particularly evident in improving efficiency in e-learning environments. A study by Liu et al. (2022) emphasized the effectiveness of recommendation systems based on deep learning in this field. In this context, multilayer networks, recurrent neural networks, convolutional neural networks, neural attention mechanisms, and deep reinforcement learning methods play crucial roles in enhancing personalized learning.

AI-powered adaptive learning environments adjust materials and learning pace according to students' individual needs, track data to provide content recommendations, and highlight engaging topics. This approach personalizes the learning process, addresses learning gaps, and strengthens students' abilities. Additionally, it helps in forming detailed student profiles. Strengthening e-learning processes with deep learning presents a viable opportunity for gifted students as well. Deep learning methods have achieved significant success in processing and classifying student-specific data. In a study conducted by Zeki, Karanfiller, and Yurtkan (2022), a model was developed using a Convolutional Neural Network (CNN) to learn and classify individually collected handwriting samples through a deep network. The model achieved 94.5% accuracy in classifying numerical handwriting samples collected from special education students and was trained and utilized specifically for each student. For gifted students, the training data and parameters of the model can be optimized to include the more complex and diverse handwriting characteristics of this group. This adaptation would allow the model to be personalized in a way that reflects the creativity and analytical abilities of gifted students. AI systems can create individualized learning plans based on a student's prior knowledge, interests, and learning style. For gifted students, this can enable them to progress faster than standard materials and advance to more complex topics, such as early computational skills (Zhai, Wibowo, and Li 2024).

Within the context of the proposed model, personalized learning is conceptualized as a dynamic and adaptive process that is responsive to learner profiles, interests, and developmental needs. In this framework, Artificial Intelligence (AI) and Deep Learning (DL) systems are positioned as facilitating tools that differentiate instruction and provide flexibility in content and pacing, without compromising pedagogical principles. Rather than reducing personalization to mere 'acceleration' or 'efficiency gains,' the model adopts an approach that fosters depth of learning, learner autonomy, and sustained engagement. Consequently, instructional adaptations are structured to serve the goals of meaningful learning and long-term development, rather than focusing on short-term performance indicators.

Monitoring and Improving Learning Processes

Monitoring and improving students' learning processes is an important tool to maximize their academic and personal development. For gifted students, who possess the ability to solve complex problems and deeply understand concepts, personalizing and continuously monitoring their learning experiences is of great importance (Rincon-Flores et al. 2024). Deep learning supports the effective monitoring and improvement of learning processes by developing these students' critical thinking, creativity, and independent learning skills. This method shifts students from being passive recipients of information to active participants in the learning process, enhancing their critical thinking, creativity, and independent learning abilities. At the same time, it increases their cognitive flexibility, helping them consciously manage their own learning processes (Tofel-Grehl, Feldon, and Callahan 2018). Deep learning is effective in evaluating complex data collected from a variety of student-related data sources in the learning process. In a study conducted by Thao et al. (2024), a deep learning network model called EduViT was developed to enhance students' attention using wireless sensor networks. With EduViT, a camera in the classroom tracks students' attention levels by observing their facial expressions, and this attention level is indicated through colored lights (RGB LEDs) placed on each student's desk. EduViT is built on the MobileViT architecture and uses the "Squeeze and Excitation (SE)" module to better capture facial features. In the training of the model, the SSL-Barlow Twins method was used, and the model made a good prediction with an accuracy of 66.51% on the FER2013 dataset.

Among the effective environments where learning processes are monitored are e-learning environments. E-learning platforms are particularly suitable for the real-time tracking of recent developments in data collection. (Ahamed and Kerana Hanirex 2024) developed a deep learning (DL)-based approach to monitor student behavior in e-learning environments in real-time. In this method, metrics such as learning progress, time spent, exam performance, completion rates, and average participation were collected before and during evaluations. To accurately model student behavior and predict learning outcomes, deep learning architectures such as recurrent neural networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) were used. RNN and LSTM networks were employed for time-dependent and periodic data in student activities, while CNNs were used for analyzing visual content.

The tracking and assessment of AI-based learning processes create differences for students requiring special education and in analyzing the data collected from students. In a study addressing these differences, the learning processes of gifted students were comprehensively examined through artificial intelligence-supported and traditional classroom discussion experiences, interviews, observations, and content analysis methods (El Naggar, Gaad, and Inocencio 2024). The data, evaluated through thematic analysis, revealed the effects of different discussion methods on learning processes in dimensions such as information quality, information quantity, personalization, practical learning, and accessibility. AI has achieved significant outputs in providing a personalized and intellectually stimulating learning experience for gifted students. These outputs include the adaptation of content to individual needs, the promotion of practical learning, and ensuring uninterrupted access to information. Additionally, students were allowed to learn at their own pace, rapid feedback mechanisms were developed, and a safe environment was created where they could express themselves without judgment or social anxiety. Furthermore, offering new and challenging topics that align with the student’s interests and learning pace was an important gain in this process.

The monitoring and improvement of learning processes can be significantly enhanced through the integration of AI performance prediction models and learning analytics (LA). AI-based prediction models can foresee students' academic performance in advance, allowing for the creation of personalized learning pathways and optimization of teaching processes. However, these models must not only focus on prediction accuracy but also be implemented in a way that provides timely and continuous feedback to students, thereby improving the quality of learning. The integration of AI and LA has created a dynamic structure that combines quantitative performance data with qualitative feedback, supporting students' learning processes. This integration has been shown to increase student engagement, strengthen collaborative learning processes, and improve the overall learning experience (Ouyang et al. 2023).

The monitoring dimension addresses learning analytics and feedback mechanisms through a process-oriented approach designed to support continuous improvement. Within the proposed model, monitoring is defined not as a mere instrument of control or surveillance, but as a reflective process that guides instructional interventions and fosters learner self-regulation. In this context, AI-supported tools are positioned as sources of real-time and context-specific feedback that enhance metacognitive awareness and instructional responsiveness. The model emphasizes that generating genuine educational value from these technologies is contingent upon interpreting the data through the lens of pedagogical expertise and aligning it with process-oriented learning objectives.

Contribution to Socio-Emotional Development

Traditional educational models primarily focus on the academic potential of gifted students. However, it should not be forgotten that their socio-emotional development must not be neglected (Blaas, 2014). At this point, artificial intelligence and deep learning technologies have the potential to open new horizons in more effectively identifying student-centered individual needs and implementing appropriate interventions. AI and deep learning can be integrated with applications that support socio-emotional development to enhance the emotional intelligence and self-awareness of gifted students. This section aims to present perspectives on how AI- and deep learning-based educational approaches can contribute to the socio-emotional development of gifted students and to evaluate studies within this scope from a theoretical perspective.

Various techniques, such as facial expressions, EEG signals, and speech data, are utilized to detect and analyze students' emotional development. In the emotion assessment process, visual, auditory, and signal-based data collection tools are used, and these data are analyzed using deep learning architectures such as CNNs and RNNs. Emotion recognition studies based on multi-channel EEG signals employ machine learning-based prediction methods, such as Long Short-Term Memory (LSTM) networks and Graph Convolutional Networks (GCN). These methods can generate highly accurate predictions based on previously collected datasets or the temporal past information of signals (Rojas Vistorte et al. 2024). These techniques aim to analyze students' emotional states, optimize learning processes, and develop more individualized learning environments. With advancements in deep learning, automatic emotion recognition from video materials has become more effective. In a study conducted by Bohm et al. (2017), a methodology with a semi-automatic labeling feature was proposed to extract emotional characteristics from human faces in video images. Using existing emotion recognition systems, a targeted emotion classification method was developed through the transfer learning technique used in deep learning. The evaluation of human behaviors from video images using deep learning techniques paves the way for their application in detecting students' behaviors.

Emotion analysis can also be performed using electroencephalography (EEG) signals, which capture brainwave patterns. However, obtaining these data is more challenging compared to other methods, requiring clinical cases or settings. EEG signals serve as effective data for identifying reflections of human emotions. In their study, Chakravarthi et al. (2022) developed a hybrid model that employs CNN and LSTM deep learning models for emotion detection using EEG signals. The complex data patterns in EEG signals can be effectively processed through deep learning techniques. Since EEG is a strong indicator of emotion detection, deep learning demonstrates superior performance in this field. This approach shows that EEG signals can be used to classify different emotions.

The visual classification success of AI and deep learning has proven to be an effective tool for measuring emotional states and responses across different age groups. In their study, Xu et al. (2024) demonstrated that within the framework of the China Baby Connectome Project (CBCP), an intelligent coding system was developed to assess children's socio-emotional development using CNN and LSTM-based deep learning methods. They addressed factors such as behavioral inhibition, adaptation, self-control, and socio-emotional regulation in different age groups, including early childhood.

AI and deep learning provide advanced inference mechanisms that allow the processing of auditory, visual, and signal-based data types, either individually or in an integrated manner. These technologies facilitate the analysis of the cognitive and affective characteristics of gifted individuals through AI and deep learning supported assessments, laying the groundwork for new approaches in their education. Particularly in the context of identifying and evaluating socio-emotional development, considering gifted individuals, these technologies contribute to the creation of personalized education models, enabling the full support of their potential.

A distinguishing feature of the proposed model is the explicit integration of socio-emotional support as a core dimension of AI-supported gifted education. Acknowledging the asynchronous development and heightened sensitivities often experienced by gifted learners, the model foregrounds emotional well-being, motivation, and social connectedness as indispensable components of sustainable learning. AI and DL-based systems may contribute to this dimension through reflective feedback, adaptive guidance, and emotion-aware learning environments. However, the model defines the role of technology as a complementary support mechanism and clearly delineates its boundaries. Proceeding from the premise that socio-emotional development is an inherently relational process, the sustainability of this dimension is grounded not in technological tools, but in quality human interaction, ethical responsibility, and the professional sensitivity demonstrated by the educator.

Discussion

The proposed conceptual model (Figure 3) redefines the role of artificial intelligence and deep learning in gifted education not as isolated technological applications, but as a systemic and process-oriented whole. This framework offers a coherent perspective on how educational processes can be transformed by integrating technology with pedagogical judgment, ethical principles, and a sustainability perspective.

Within the model, talent identification moves beyond static and single-point measures, being conceptualized as a dynamic and continuous process that is supported by human judgment. By longitudinally monitoring learning behaviors and developmental trajectories, this approach aims to overcome the limitations of deficit-oriented models and safeguard professional agency against the risks of algorithmic bias.

Similarly, personalized learning is addressed not as mere acceleration or efficiency optimization, but as a developmental process prioritizing learner autonomy and depth of learning. Here, AI systems are positioned as facilitating tools aligned with pedagogical goals, encouraging exploration and creativity rather than short-term performance gains.

The model transforms the monitoring and evaluation dimension from a mechanism of surveillance into a formative and reflective practice. Rather than serving accountability metrics, learning analytics contributes to sustainable development by generating meaningful feedback that supports self-regulation and metacognitive awareness.

Socio-emotional support at the center of the process. Recognizing the sensitivities of gifted individuals, the model acknowledges the supportive role of technology but draws a clear line against technocentric approaches by emphasizing that human interaction, ethical responsibility, and professional care lie at the foundation of this dimension.

Currently, traditional methods are used to identify and assess gifted students. These methods, based on standardized intelligence tests, academic achievement evaluations, teacher observations, and parental reports, often contain subjective judgments and may not sufficiently account for individual differences (Subotnik, Olszewski-Kubilius *and* Worrell 2011). AI- and DL-based systems, utilizing big data analytics and advanced modeling techniques, offer a more precise, objective, and multidimensional evaluation process, overcoming these limitations (Chen et al. 2020). While teacher or parental observations are essential in identifying students' talents, they can be subjective and influenced by biases (McBee, Peters *and* Waterman 2014). These systems can identify students' strengths and weaknesses, proposing different evaluation methods according to their developmental progress. Based on these recommendations, lesson content can be deepened according to students' areas of interest. Personalized learning prevents a one-size-fits-all approach, allowing students to discover themselves and evaluate their learning outcomes in real time through data-driven insights (Pane et al. 2015). Personalized learning for gifted students supports their cognitive development by offering academic acceleration, differentiated instruction, and independent learning opportunities (Reis *and* Renzulli, 2010).

Since it is practically difficult for teachers to develop specialized content and teaching strategies for each student's individual needs in traditional classroom settings, AI-supported learning systems bridge this gap by providing customized educational experiences through big data analytics and machine learning (Luckin et al., 2016). AI-based adaptive learning systems dynamically deliver content by analyzing students' learning speeds, mistakes, comprehension levels, and areas of interest (Brusilovsky *and* Millán, 2007). These systems can create personalized content based on students' learning history, interests, and strengths. Using text mining and natural language processing (NLP) techniques, AI-supported learning environments can recommend lesson materials, articles, and problems suitable for students' levels. AI-based learning environments can track students' progress in real time, providing instant feedback (Gierl, Lai, *and* Turner, 2012). This process accelerates learning while helping students learn from mistakes and enhance their comprehension levels. AI- and DL-supported personalized learning systems aim to maximize the individual potential of gifted students by responding more effectively to their cognitive needs. Adaptive learning algorithms, personalized content development through deep learning, and real-time feedback mechanisms make the educational process more flexible, effective, and student-centered.

Although gifted students are often recognized at an early age due to their academic potential, their socio-emotional development is equally important (Cross, 2018). Despite their high cognitive capacities, gifted students may encounter various emotional and social challenges (Pfeiffer et al., 2012). Research indicates that supporting their emotional development is as critical as academic success. Gifted students may experience higher levels of stress, anxiety, and motivation compared to their peers (Neihart et al. 2016). AI-supported emotion recognition and real-time feedback systems, such as computer vision and NLP techniques, can analyze students' stress levels, anxiety, and low motivation through facial expressions, voice tones, or written expressions, evaluating their emotional states and providing appropriate psychological support recommendations (Calvo and D'Mello 2019). These systems not only provide instant feedback on students' emotional states but also enable teachers and education administrators to develop policies and strategies that support students' psychological well-being (Siemens *and* Baker 2012). AI-based virtual counselors and chatbots, which go beyond the limitations of traditional counseling services in addressing students' socio-emotional development, can provide students, particularly those with low emotional awareness or social anxiety, access to recommendations based on cognitive behavioral therapy (CBT) techniques (Fitzpatrick, Darcy *and* Vierhile, 2017).

Conclusion

Aiming to contribute to the field by synthesizing existing findings, this study proposes a sustainable and human-centered conceptual model for the integration of artificial intelligence and deep learning into gifted education. By addressing the interaction between talent identification, personalized learning design, process monitoring, and socio-emotional support within a holistic structure, the study aims to bridge the disconnect often found in the literature, where AI applications are typically examined in isolation or through outcome-oriented perspectives. In this context, rather than offering empirical generalizations, the proposed model functions as a conceptual framework capable of guiding future research, informing pedagogical design, and supporting policy-level decision-making processes. Therefore, the original value of this study lies in the systematic integration of fragmented theoretical approaches within a consistent and explanatory framework, rather than in empirical validation.

This study addresses the potential of artificial intelligence (AI) and deep learning (DL) in supporting the cognitive and socio-emotional development of gifted students. A review of intelligence theories and identification methods reveals that traditional approaches remain limited in reflecting the multidimensional potential of these students. In contrast, AI- and DL-based systems can provide more objective and personalized evaluation and learning processes through big data analytics, adaptive algorithms, and real-time feedback mechanisms. The findings highlight the contribution of developing more objective and multidimensional approaches for identifying gifted students, enhancing personalized learning materials, and strengthening socio-emotional support processes through AI-based tools.

Future research should focus on ethical use, student privacy, and data security, while also developing inclusive solutions for students from diverse socio-cultural and economic backgrounds and examining how teachers can effectively integrate these technologies into pedagogical practices. In this regard, AI and DL emerge as critical tools that can contribute to the development of more flexible, personalized, and inclusive models in the education of gifted students.

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