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Research Article

Ethical and Cognitive Impacts of Machine Learning in Education: A Stakeholder-Centric Analysis

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Abstract

This study explores machine learning (ML) in education, focusing on its effects on creativity, critical thinking, and a human-centered approach to learning. It addresses ethical issues and the risk of dehumanizing education, stressing the importance of balanced frameworks that maintain human interaction and essential pedagogical principles. The research utilizes a quantitative approach, examining online data analytics and stakeholder engagement metrics from platform X. The stakeholder analysis shows differing engagement levels: students displayed a high level of interest, while teachers showed mixed responses. Quantitative findings, such as the average views and standard deviation (882.5) for teachers, highlight the complex dynamics of stakeholder interest. By integrating these insights with an analysis of stakeholder discussions, the study uncovers significant gaps and opportunities in ML-enhanced learning environments. It underscores the necessity of equipping educators with the skills to effectively incorporate ML and promoting inclusive, reflective practices to enhance cognitive engagement. The results contribute to the ongoing conversation about the responsible and meaningful implementation of ML in education, providing strategies to tackle ethical, pedagogical, and stakeholder-related challenges. This study concludes on the ethical use of machine learning processes and recommends for more stakeholders and educational institutions active engagement.

Keywords

Machine, Learning, Ethics, Cognition, Stakeholders

1. Introduction

Machine learning (ML) is a branch of artificial intelligence (AI) that allows systems to learn from data, enhance performance over time, and make decisions without being specifically programmed. It utilizes algorithms and statistical models to analyze large datasets, uncover patterns, and leverage these insights for predictions or task automation. ML can be divided into supervised learning, where the system learns from labelled data; unsupervised learning, where it discovers hidden patterns in unlabelled data; and reinforcement learning, where it learns through trial and error. By continuously refining its

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algorithms with new data, ML systems can adapt and improve accuracy, making room for essential tools in various fields such as education, healthcare, finance, and more (Sanusi et al, 2024).

Machine learning (ML) is transforming numerous sectors worldwide, including education, by improving efficiency, personalization, and accessibility. While developed countries have quickly embraced ML technologies to change traditional educational methods, the adoption in developing nations is still limited due to challenges related to infrastructure, culture, and policy. This gap underscores a significant need for research to understand the specific effects of ML in different educational environments (Martins, von Wangenheim, Rauber & Hauck, 2024).

In developed countries, machine learning (ML) is widely utilized to enhance adaptive learning platforms, streamline administrative tasks, and facilitate data-driven decision-making. The emphasis in these areas often lies in improving technologies for better personalization and scalability. However, important conversations about the ethical concerns, overreliance, and possible cognitive drawbacks stemming from the excessive use of ML are not as thoroughly examined. These challenges become increasingly urgent as ML adoption grows, highlighting the need for research into frameworks that strike a balance between technological advancement and the maintenance of critical thinking and human-centered education (Oraif, 2024).

In contrast, the situation in developing countries is quite different. Limited access to digital infrastructure, inconsistent teacher training, and a shortage of localized content hinders the effective incorporation of ML into education. Additionally, while ML presents potential solutions to close educational gaps, there is limited research on how these technologies can tackle socio-economic inequalities without worsening issues. The tendency to copy models from developed countries often overlooks the distinct cultural, economic, and institutional contexts of developing nations (Rane, Kaya & Rane, 2024).

The incorporation of machine learning in education offers considerable advantages, but it also brings forth crucial ethical and cognitive issues. While machine learning can enhance administrative efficiency and facilitate personalized learning experiences, an overdependence on these technologies may hinder students' critical thinking and problem-solving skills. There are growing concerns regarding data privacy, algorithmic bias, and the potential sidelining of educators in the educational process. Additionally, the risk of dehumanizing education—where machines take over vital human interactions—threatens the relational elements of teaching and learning, which are essential for effective education (Siram, Chikati Srinu & Tripathi, 2024).

This study is significant because it thoroughly examines the cognitive, ethical, and practical aspects of machine learning (ML) in education. It offers important insights into how ML influences critical thinking, problem-solving, and creativity, especially for novice learners, and suggests methods to promote cognitive engagement and reflective practices in ML-enhanced learning settings. By tackling urgent ethical issues like data privacy, algorithmic bias, and the risk of dehumanizing education, the study provides a solid framework for the responsible use of ML in educational environments. Additionally, it emphasizes the need to close the digital divide, proposing strategies to make ML technologies accessible to learners in low-resource areas through localized solutions that consider the specific socio-economic and cultural contexts of developing countries. Lastly, the research highlights the changing role of educators, showing how ML can assist teachers by automating routine tasks and offering valuable insights, while also stressing the importance of professional development to help educators acquire the skills needed to effectively integrate ML into teaching practices. The findings of this study aim to guide both policy and practice, ensuring that the adoption of ML enhances education in an ethical, inclusive, and meaningful way (Liu, 2024).

Machine Learning Concept

Machine learning is an area of expertise that premise on two different semantic antecedents, which are machine and learning. Dissecting machine learning connote machine first and learning second. Machine learning is imbued with machining education processes for faster and more efficient process (Priya, Bhadra, Chimalakonda & Venigalla, 2024).

The machine learning acceptance and a face of humanity entails adjusting to the change that comes with machining education processes to ethically fit human existence. An adjustment that allows concurrent existence of humanity and machines without conflicting issues (Asnicar, Thomas, Passerini, Waldron & Segata, 2024).

Educational technology as a discipline affords the educationist and secondly technologist point of view to machine learning. As an educationist the humanity view comes to play to address the issue of keeping teachers' job and learning relevance with active human engagement. Secondly, the technology point of view considers the engineering and machining aspect of machine learning, with serious concern on robotics role in education and balancing the interference of this technology in teaching. Educational technology diversifies thought of machining towards considering the human aspect of machine learning concurrently with humanity (Li, 2024).

Machine Learning and the theory of experienced versus inexperienced learners

Machine learning is inhibiting for inexperienced learners that are young and at budding stage. For instance, the theory of experienced states that experience is the best teaching prowess in education as it premise over maturity gathered overtime. However, inexperienced theory premise on immaturity and inability towards handling new operations. Inexperienced finds it hard to adjust quickly to new changes and accepting new changes alters behaviour. Experienced knows when to reject or accept new knowledge. However, inexperienced accepts virtually all that comes around due to immaturity and low level attained in the learning cone. Inexperienced learners are learners without maturity comprising of early career students (Kisahwan, Winarno & Hermana, 2024).

Machine Learning and the Theory of Addiction versus Inhibition

The theories of addiction versus the inhibition. Based on the theory of addiction. Students are bound to attach too much interest to machine learning for solving learning problems due to addiction. Based on inhibition. The learners in turn inhibit personal senses through critical thinking and engagement with learning task using cognitive endowment and capabilities. The theory of addiction states that an individual is excessively tied to using a substance with repetitive tendencies in the absence of control mechanism. Besides, the theory of inhibition states that an action that is mastered due to addicted act becomes habitual and takes prominence over prior habits and actions learnt (Ferrer-Pérez, Montagud-Romero & Blanco-Gandía, 2024).

Machine Learning and the theory of overdependence versus dependence

The overdependence theory states that an individual is too tired for a practical engagement routine due to automated overlearning and excessive reliance. However, the dependence theory is simply the reliance without the over-reliance antecedent to a routine (Xu, Saffarizadeh & Lee, 2024).

The machine learning excessive use vs critical thinking

Machine learning excessive use is presently being discouraged by some publishing companies using software detectors on the internet. The excessive use of machine learning products is being controlled by publishing companies to reduce overdependence. Assessment comes with grading. It is the grading of the level of right or wrong of either responses, situation or phenomenon. Nowadays, high impact journals assess papers quality using machine learning detectors. This implies that high impact journals introduced checks and balances to ensure that critical thinking is prioritised concurrently with machine learning (Sargsyan, 2024).

The ethical concern machine learning brings to education in the face of humanity

Adopting machine learning in this era for education calls for ethical review of standards as education is a unique field run by teachers that are saddled with teaching responsibilities. Human beings are in the fore of education and introducing robotics and machine learning calls for ethical checks to ensure that stakeholders concerns are considered in the course of introducing machine learning for instruction. Education holds unique ethical issues in the face of using machine learning due to the fact that machine learning replicates virtually teacher-like activities from teaching, writing, discussion and questioning (Rane, Kaya, Mallick & Rane, 2024).

Machine learning adoption for mining, surgical and space explorations in other scientific fields are ethical due to remote nature of the environment where it is being adopted. However, in education machine learning is taking up the spaces occupied by human beings, which calls for big concerns. From the cloud computing to big data concept. Data breach and data security concerns become prominent matter that needs to be prioritised to safeguard stakeholders' online data (Abdullah & Basheer, 2024).

Machine Learning versus critical thinking in the Nigeria Context

Some Nigeria students are now too dependent on computational machines for solving critical cognitive operations, which is a threat to critical thinking. In the past, students writing final year senior school certificate examination were disallowed from using digital mathematical calculators, which promoted the mastery of cognitive operations off hand through critical engagement. Machine learning is a mark of civilisation and its acceptance should not inhibit humanity's critical thinking development (Okunade, 2024).

Machine Learning SWOT Analyses

According to Farrokhnia, Banihashem, Noroozi and Wals (2024) SWOT analyses is an acronym that analyses strengths, weaknesses, opportunities and threats. This study SWOT analyses is conducted as follows.

Strengths

- It is fast
- Efficient
- Valid
- Free of charge
- Saves labour cost

Weaknesses

- Concerns for it to stand the test of time for reliability.
- Concerns as threat to teacher's role in the face of education.
- Concerns for its commercialisation in future university education.

Opportunities

- It paves way for more independent learning
- It helps with brainstorming activities
- It is easy to use in an environment with internet facilities

Threats

- It is a threat to teaching job
- It is a threat to critical thinking engagement
- It is going to require high cost of maintenance

2. Methods

This study adopts quantitative methodology by gathering online data analytics from X. The data analytics consist of metrics derived from the number of tweet re-post, comments, and likes.

Besides, machine learning stakeholder analyses was conducted comprising of metrics gathered from X regarding the interest level of Nigerian teachers and students. The metrics was likewise drawn on evidences sighted in the X discourses based on number of tweet's re-post, views, comments and likes.

	Stakeholder's classification	Interest levels	Views	Comment	Re-post	Like	Mean views	Standard deviation views
1	Teachers	High-Low	1.9K	1	1	1	1017.5	882.5
2	Students	High-High	135	0	0	0		

Table 1. Stakeholders' analyses

The teachers interest level in machine learning is High-low as some teachers in the field of engineering, medicine and pure sciences apply machine learning for remote operations like mining, surgical and space exploration. Except for distant learning the application of machine learning by teachers in education for remote operation is rare. The teachers' High-Low interest suggest that some teachers' have ethical concerns regarding the adoption of machine learning for teaching and learning. However, students' High-High interest reveals high affinity to adopt machine learning for instruction.

This research adopted random sampling technique in gathering tweets for this research. Besides, five (5) set of tweets were gathered randomly using inclusion and exclusion criteria on X. By using a target population technique and goodness of best fit two tweets were chosen from the five sets of data for analyses using the statistical package for social sciences (SPSS).

Teachers and students' high standard deviation in number of views reveal varied engagement (see table 1). It implies teachers engage more with machine learning discourse on X than students. This scenario causes asymmetrical alignment of interest in machine learning discourse on X. The result also marginalises interest in students' voices on X with regards to machine learning for education. Hence, this study findings reveals that the machine learning discourse in education is mainly of stakeholders' interest from teacher centred position as it gains higher views on X than students' tweets.

3. Result and Discussion

Machine learning is very important technology in this 21st century for educational activities. Machine learning has made complex and painstaking task easier. For instance, machine learning needs minimal technicalities to use for rigorous activities by lay man without complex programming skills. Machine learning presents an all-encompassing opportunity to a beginner to master difficult task within a very short time. This research investigates machine learning as a technology that has the potential of challenging human existence in the face of education with a need to create awareness on the implementation of ethical standards (Okatta, Ajayi & Olawale, 2024).

By blending computational efficiency with the nuanced understanding of human needs, ML serves as a "machine with the face of humanity." ML combines fast computing with a deep grasp of people's requirements, acting as a "human-like machine." This principle embodies the harmony of tech progress with compassionate beliefs, guaranteeing that scholastic enhancements adhere to moral integrity and teach efficiently (Otoum, Gottimukkala, Kumar & Nayak, 2024).

A fundamental trait of Machine Learning (ML) in academia involves its capability to execute instructor-like roles, including evaluating, offering critiques, and tailoring educational engagements. These stated features make things work faster and handles more student's engagement task. There is more to teachers' role in education than being a facilitator, which ML has reduced teachers to nowadays. Using machines for certain school tasks might make education feel less personal, making it more about exchanges than learning. Machine learning (ML) should work with people, not just take over individual's tasks. ML tools can aid instructors by spotting pupils' comprehension deficits, thus allowing instructors to concentrate on more substantial and inventive interaction (Kommisetty & Nishanth, 2024).

The integration of machine learning in education requires careful ethical consideration. Data privacy is a major issue, as machine learning systems depend on large quantities of data from students and teachers to function effectively. Any breaches in data security can threaten the dignity and independence of those involved in education. Additionally, biases present in algorithms can reinforce existing inequalities, which goes against the principles of fairness and inclusivity that education aims to uphold (Bakariya et al, 2024).

Ethical deployment requires clear communication about data collection and usage policies, along with strong governance frameworks. For machine learning (ML) to truly represent humanity, it must focus on ethical integrity, ensuring that its advantages are shared fairly without infringing on individual rights (Haliburton, Ghebremedhin, Welsch, Schmidt & Mayer, 2024).

A common concern regarding ML in education is its potential to undermine critical thinking. Relying too heavily on automated solutions can hinder students' abilities to analyze, synthesize, and apply knowledge independently. This issue is especially pronounced in situations where ML tools are used for simple problem-solving or content generation without promoting a deeper understanding (Kadhim & Abdulameer, 2024).

To tackle this, educators and technologists need to work together to create ML systems that foster inquiry and exploration. For example, rather than simply providing answers, ML tools can be designed to guide students through problem-solving processes, encouraging questions and offering resources that promote critical engagement. Such systems maintain human agency, allowing students to actively participate in learning (Bappy, Ahmed & Rauf, 2024).

The incorporation of ML into education represents a significant shift from traditional teaching models. By enabling personalized learning pathways, ML allows students to progress gradually and according to individual needs. However, this transition also necessitates that educators take on new roles as facilitators and co-learners (Anokhina & Przedpelski, 2024).

For ML to align with humanistic educational values, it is essential to provide professional development for teachers. Educators need to be equipped with the skills to understand ML-generated insights and effectively integrate using instructional strategies. This approach ensures that technology enhances rather than dictates pedagogical practices (Bozkurt & Sharma, 2024).

One of the most exciting possibilities of machine learning (ML) in education is its ability to close access gaps. In areas that are often overlooked, ML-driven platforms can offer resources and learning opportunities that were previously out of reach due to issues like poor infrastructure or lack of staff. However, this potential can only be realized if government ensure that everyone has fair access to technology (Ajala, Okoye, Ofodile, Arinze & Daraojimba, 2024).

If researchers do not tackle the digital divide, ML could end up deepening existing inequalities. It is crucial for policymakers and educational institutions to invest in infrastructure, training, and affordable access so that the advantages of ML can be shared by all. Only then can ML genuinely embody the "face of humanity," acting as a means of empowerment instead of exclusion (Yang et al., 2024).

The idea of a "machine with the face of humanity" highlights the need to align technological advancements with human-centered values. In education, this means creating ML systems that emphasize ethical integrity, encourage critical thinking, and support equity. By finding a balance between automation and human interaction, addressing ethical issues, and ensuring accessibility, ML can become a powerful tool that enriches education while upholding its fundamental humanistic values. This balance is vital for shaping an educational future where machines act as partners in our pursuit of knowledge and understanding (MunishKhanna, Singh & Garg, 2024).

Machine learning (ML) is a game changer in education, offering the potential for greater efficiency and personalized learning experiences. However, as we consider its adoption and integration, we must address some fundamental questions that can be explored through established theories. The theory of experience versus inexperience, the dependence and overdependence theory, the concept of use versus overuse, and the law of inhibition provide useful perspectives for critically assessing ML's influence on education. These frameworks help us understand the necessary balance for integrating ML in a way that enhances, rather than undermines, educational objectives (Bello, Ige & Ameyaw, 2024).

The distinction between experienced and inexperienced individuals highlights the differences between learners and educators regarding familiarity with evolving tools like machine learning (ML). Experienced educators, who often possess pedagogical expertise and professional maturity, are able to critically evaluate the role of ML in education, using it to enhance traditional teaching methods. For example, they might utilize ML-driven analytics to pinpoint students who are struggling and provide personalized interventions, ensuring that the technology aligns with overall teaching objectives (Urrutia & Araya, 2024).

On the other hand, inexperienced educators or students may find it challenging to recognize the limitations of ML. This can lead to an uncritical acceptance of ML outputs, resulting in shallow learning experiences or an excessive dependence on automation. For instance, students who are new to advanced problem-solving tools might rely solely on automated solutions, missing out on valuable opportunities to cultivate critical thinking and problem-solving abilities (Low, Keikhosrokiani & Pourya Asl, 2024).

To tackle this issue, training programs should aim to bridge the divide between experienced and inexperienced participants. Both educators and learners need to be exposed to the strengths and weaknesses of ML, promoting a balanced approach that focuses on enhancement rather than replacement

(Alslaity & Orji, 2024).

The dependence and overdependence theory explores the range of reliance on machine learning (ML) tools in education. Healthy dependence means using ML as a supportive resource that enhances learning outcomes. For example, adaptive learning platforms can modify content difficulty based on a student's progress, offering a scaffolded learning experience that stays connected to human cognitive engagement (Timpe-Laughlin, Sydorenko & Dombi, 2024).

On the other hand, overdependence signifies an excessive reliance on ML, where both educators and learners completely rely on algorithms for decision-making. This can undermine human agency, creativity, and adaptability. In a classroom where teachers depend solely on ML-generated lesson plans, there is a risk of losing the nuanced understanding of students' unique needs that only human insight can provide. Likewise, students who are overly reliant on ML tools may struggle to internalize essential skills, such as mental arithmetic or critical analysis (Nguyen-Tat, Bui & Ngo, 2024).

To counteract overdependence, strategies like promoting blended learning models can be effective, where ML supports rather than dominates the learning process. Encouraging activities that require manual effort and critical thinking helps ensure that learners remain engaged and active participants in education (Hohman, Kery, Ren & Moritz, 2024).

The difference between appropriate use and overuse is crucial for understanding the role of machine learning (ML) in education. When used correctly, ML can significantly improve educational processes by automating repetitive tasks, enabling personalized learning, and offering data-driven insights. For instance, ML can simplify administrative tasks like grading, allowing teachers to concentrate on more interactive and creative teaching methods (Núñez, Gómez-Pulido & Ramírez, 2024).

On the other hand, overuse can lead to a mechanical approach to education that lacks human interaction. For example, relying too heavily on ML for delivering content may reduce educators to mere technology facilitators, which can diminish the essential relational elements of teaching. Moreover, excessive dependence on ML can dampen students' intrinsic motivation, as learning experience becomes too reliant on external prompts and feedback (Nozari, Ghahremani-Nahr & Szmelter-Jarosz, 2024).

To avoid overuse, educational institutions should create guidelines for integrating ML. These guidelines must emphasize the human elements of education, such as mentorship, collaboration, and social-emotional learning. Additionally, regular assessments of ML usage can help ensure that its application aligns with educational objectives (Hossain, Mazumder, Bari & Mahi, 2024).

The law of inhibition, when applied to machine learning (ML), indicates that over-reliance on automation can hinder the growth of cognitive skills. For example, when students utilize ML tools to tackle math problems, they might skip the process of grasping fundamental concepts, resulting in superficial learning. This issue can also affect teachers, that depends on ML for curating content without thoroughly assessing its suitability for students (Panagoulias, Virvou & Tsihrintzis, 2024).

To mitigate these inhibitory effects, ML systems should be designed to promote active participation instead of passive consumption. For instance, platforms could include features that require students to show understanding before moving on. Likewise, educators should be motivated to critically evaluate and tailor ML-generated suggestions to fit unique classroom environments (Shimaponda-Nawa & Nwaila, 2024).

Another strategy is to blend ML with hands-on learning experiences. By merging automated insights with practical learning opportunities, educators can ensure that ML enhances rather than obstructs cognitive growth (Susnjak, 2024).

The integration of machine learning in education is not necessarily a bad thing, but it does require thoughtful consideration of its effects. By examining concepts like experience versus inexperience, dependence versus overdependence, and the balance between use and overuse, stakeholders can better manage the challenges that come with adopting machine learning. The aim should be to create a collaborative relationship between humans and technology, where advancements enhance human capabilities without compromising the fundamental cognitive and social elements of education. This balanced perspective ensures that machine learning embodies the "face of humanity," upholding the essential values of education in a world that is becoming more automated (Mupaikwa, 2025).

5. Conclusions

Machine learning (ML) has become a transformative force in education, offering enhanced efficiency, personalization, and accessibility. Its true potential lies in its ability to work alongside traditional teaching methods, helping both educators and students reach new heights of engagement and productivity. However, as discussed, the implementation of ML must be approached thoughtfully, taking into account the complexities of human cognition, the nuances of the educational landscape, and the ethical implications involved.

Theoretical frameworks such as the experience versus inexperience, dependence versus overdependence, use versus overuse, and the law of inhibition provide valuable insights for assessing the effects of ML on education. These viewpoints highlight the need for balance utilizing ML to enhance human abilities while protecting the intellectual, emotional, and social aspects of the learning experience.

One of the most important effects of machine learning in education is the changing role of teachers. As machine learning takes over repetitive and administrative tasks, educators can concentrate on the more creative and interpersonal aspects of teaching. This shift allows teachers to become facilitators, mentors, and key interpreters of data generated by machine learning. However, this new role requires a rethinking of professional development. Teachers need to develop new skills to effectively incorporate machine learning into classrooms while preserving teaching autonomy. To ensure that educators remain central to the educational process, ongoing investment in training, resources, and collaborative platforms is essential.

The dependence and overdependence theory highlights the delicate balance between beneficial reliance on machine learning (ML) and harmful over-reliance. ML can significantly improve learning by offering personalized feedback, pinpointing areas for growth, and allowing for self-paced advancement. However, excessive reliance on it may weaken critical thinking, problem-solving abilities, and other cognitive skills.

Educational institutions need to set clear guidelines for ML usage, promoting a balanced approach. Both teachers and students should be encouraged to view ML as a tool for exploration and improvement, rather than a replacement for cognitive effort. By fostering a culture of reflective practice, educators can assist learners in developing a healthy relationship with technology, ensuring it acts as a means to an end rather than an end in itself.

One major concern regarding machine learning (ML) in education is its potential to stifle critical thinking. While automated solutions can be efficient, they may lead to a passive approach to information consumption instead of fostering active engagement. This issue is especially significant for inexperienced learners, who might not yet have the skills to question or critically assess ML outputs.

To address this, ML systems should be crafted to promote inquiry and exploration. For example, educational platforms could include interactive problem-solving activities, scenario-based learning, and reflective prompts that encourage students to think critically. Additionally, educators have a vital role in shaping learning environments that emphasize active participation rather than passive dependence.

By combining ML with constructivist teaching methods, educators can ensure that technology supports cognitive growth rather than hinders it. Encouraging students to analyze, question, and interpret insights generated by ML fosters deeper learning to tackle complex challenges in the real world.

Machine learning has the potential to transform assessment practices by allowing for more comprehensive and dynamic evaluations. Traditional assessments often concentrate on limited metrics, like test scores, which may not fully represent a learner's abilities. In contrast, assessments powered by machine learning can analyze a variety of data points to offer a more complete view of students' progress.

However, it is crucial to ensure that these machine learning-driven assessments are fair and unbiased. Relying too heavily on algorithmic evaluations could disadvantage learners who do not conform to established patterns or categories. By combining machine learning with human judgment, we can create a balanced approach that utilizes the strengths of both.

The future of assessment should focus on developing systems that are not only accurate and efficient but also equitable and inclusive. By aligning machine learning with humanistic educational principles, educators can create assessment practices that genuinely reflect the diverse talents and potential of all learners.

Theories like use versus overuse and the law of inhibition highlight the importance of finding a balance when incorporating machine learning (ML) into education. It's crucial that technology does not eclipse the primary goal of education: the comprehensive development of individuals.

Achieving a seamless integration of ML requires teamwork among educators, technologists, policymakers, and students. All parties need to maintain an ongoing conversation to ensure that ML supports the wider objectives of education, promoting empathy, creativity, and social connections alongside academic success.

Innovative approaches, such as co-teaching models where educators collaborate with ML systems, present promising opportunities for striking this balance. By merging the efficiency of automation with the meaningfulness of human interaction, these models showcase the potential for synergy.

As educational services increasingly embrace automation, the influence of machine learning (ML) in education will expand. However, its integration should be guided by ethical, pedagogical, and social factors. Policymakers need to create clear regulations for the use of ML in education, ensuring that it is transparent, accountable, and inclusive. Educational institutions should invest in training and resources to equip teachers and students for the challenges and opportunities presented by an ML-driven landscape. Simultaneously, technologists must focus on developing ML systems that embody human values, fostering equity, empathy, and critical thinking. By encouraging collaboration among all stakeholders, we can build an environment where ML enriches education while maintaining its humanistic core.

The metaphor of "a machine with the face of humanity" perfectly illustrates what machine learning (ML) in education ethically implies. Technology ought to be a means of empowerment, enhancing human potential while preserving the relational and ethical aspects of learning.

Integrating ML into education goes beyond just a technical task; it's a philosophical challenge. It prompts us to consider the true purpose of education, the essence of learning, and how technology influences our future. By adopting a balanced and thoughtful approach to ML, we can ensure it reflects the "face of humanity" and fosters a more inclusive, equitable, and transformative educational experience.

Achieving this vision calls for dedication, innovation, and teamwork. It's a journey that requires not just technical skills but also a deep respect for the values that make us human. Together, we can leverage the power of ML to build an educational system that genuinely embodies the best of both humanity and technology.

References

Abdullah, S. A., Basheer, K. I., & Sharif, S. I. (2024). The ethical and social implications of using artificial intelligence in social studies instruction. *Lark Journal for Philosophy, Linguistics and Social Sciences, 16*(1), 762-782. https://www.iraqoaj.net/iasj/article/295183

Ajala, O. A., Okoye, C. C., Ofodile, O. C., Arinze, C. A., & Daraojimba, O. D. (2024). Review of AI and machine learning applications to predict and thwart cyber-attacks in real-time. *Magna Scientia Advanced Research and Reviews, 10*(1), 312-320. https://doi.org/10.30574/msarr.2024.10.1.0037

Alslaity, A., & Orji, R. (2024). Machine learning techniques for emotion detection and sentiment analysis: Current state, challenges, and future directions. *Behaviour & Information Technology,43*(1),139-164. https://doi.org/10.1080/0144929X.2022.2156387

Anokhina, K., & Przedpelski, R. (2024). Addressing Possible Bias in AI Implementation within the Irish Immigration System: Strategies for Ethical Machine Learning. https://kseniiia.nl/data/pdf/Research%20Paper%20-%20AnokhinaKsenia.pdf

Asnicar, F., Thomas, A. M., Passerini, A., Waldron, L., & Segata, N. (2024). Machine learning for microbiologists. *Nature Reviews Microbiology, 22*(4), 191-205. https://doi.org/10.1038/s41579-023-00984-1

Bakariya, B., Singh, A., Singh, H., Raju, P., Rajpoot, R., & Mohbey, K. K. (2024). Facial emotion recognition and music recommendation system using CNN-based deep learning techniques. *Evolving Systems, 15*(2), 641-658. https://link.springer.com/article/10.1007/s12530-023-09506-z_

Bappy, M. A., (2024). Exploring the integration of informed machine learning in engineering applications: A comprehensive review. *American Journal of Science and Learning Development, 3 (2), 1-11.* https://dx.doi.org/10.2139/ssrn.4785058

Bello, H. O., Ige, A. B., & Ameyaw, M. N. (2024). Adaptive machine learning models: Concepts for real-time financial fraud prevention in dynamic environments. *World Journal of Advanced Engineering Technology and Sciences, 12(02),* 021-034. http://dx.doi.org/10.30574/wjaets.2024.12.2.0266

Bozkurt, A., & Sharma, R. C. (2024). Are we facing an algorithmic renaissance or apocalypse? Generative AI, ChatBots, and emerging human-machine interaction in the educational landscape. *Asian Journal of Distance Education, 19(1).* http://asianjde.com/ojs/index.php/AsianJDE/article/view/781

Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International, 61(3), 460-474.* https://doi.org/10.1080/14703297.2023.2195846

Ferrer-Pérez, C., Montagud-Romero, S., & Blanco-Gandía, M. C. (2024). Neurobiological Theories of Addiction: A Comprehensive Review. *Psychoactives, 3(1), 35-47.* https://doi.org/10.3390/psychoactives3010003

Haliburton, L., Ghebremedhin, S., Welsch, R., Schmidt, A., & Mayer, S. (2024). Investigating labeler bias in face annotation for machine learning. In *HHAI 2024: Hybrid Human AI Systems for the Social Good* (pp. 145-161). IOS Press. https://ebooks.iospress.nl/volumearticle/68008

Hohman, F., Kery, M. B., Ren, D., & Moritz, D. (2024). Model compression in practice: Lessons learned from practitioners creating on-device machine learning experiences. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (pp. 1-18). ACM. https://doi.org/10.1145/3613904.3642109

Hossain, M. A., Mazumder, M. S. A., Bari, M. H., & Mahi, R. (2024). Impact Assessment of Machine Learning Algorithms on Resource Efficiency and Management in Urban Developments. *International Journal of Business and Economics*, 1(2), 1-9. https://doi.org/10.62304/ijbm.v1i2.129

Kadhim, O. N., & Abdulameer, M. H. (2024). A multimodal biometric database and case study for face recognition based deep learning. *Bulletin of Electrical Engineering and Informatics*, 13(1), 677-685. https://doi.org/10.11591/eei.v13i1.6605

Kisahwan, D., Winarno, A., & Hermana, D. (2024). Implicit and social learning theory: an explanation of why experienced medical representatives have higher engagement and performance. *International Journal of Business Innovation and Research*, 33(3), 418-432. https://doi.org/10.1504/IJBIR.2024.137272

Kommisetty, P. D. N. K., & Nishanth, A. (2024). AI-Driven Enhancements in Cloud Computing: Exploring the Synergies of Machine Learning and Generative AI. *International Advanced Research Journal in Science, Engineering and Technology*, 9(10), 1-13. https://iarjset.com/papers/ai-driven-enhancements-in-cloud-computing-exploring-the-synergies-of-machine-learning-and-generative-ai/

Li, L. (2024). The Theoretical and Knowledge System of Educational Technology Discipline in China. *Journal of Educational Technology Development and Exchange (JETDE)*, 17(2), 1-29. https://doi.org/10.18785/jetde.1702.03

Liu, Y. (2024). Digital Human Innovation in Education Industry. In *Proceedings of the 3rd International Conference on Educational Innovation and Multimedia Technology, EIMT 2024, March 29–31, 2024, Wuhan, China*. http://dx.doi.org/10.4108/eai.29-3-2024.2347652

Low, H. Q., Keikhosrokiani, P., & Pourya Asl, M. (2024). Decoding Violence Against Women: Analyzing Harassment in Middle Eastern Literature with Machine Learning and Sentiment Analysis. *Humanities and Social Sciences Communications*, 11(1), 1-18.

Martins, R. M., von Wangenheim, C. G., Rauber, M. F., & Hauck, J. C. (2024). Machine Learning for All! — Introducing Machine Learning in Middle and High School. *International Journal of Artificial Intelligence in Education*, 34(2), 185-223. https://link.springer.com/article/10.1007/s40593-022-00325-y

Núñez, J. C. S., Gómez-Pulido, J. A., & Ramírez, R. R. (2024). Machine learning applied to tourism: A systematic review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, e1549.* https://doi.org/10.1002/widm.1549

Nguyen-Tat, B. T., Bui, M. Q., & Ngo, V. M. (2024). Automating attendance management in human resources: A design science approach using computer vision and facial recognition. *International Journal of Information Management Data Insights, 4(2), 100253.* Retrieved from https://www.sciencedirect.com/science/article/pii/S2667096823000920.

Okatta, C. G., Ajayi, F. A., & Olawale, O. (2024). Navigating the future: Integrating AI and machine learning in HR practices for a digital workforce. *Computer Science & IT Research Journal*, 5(4), 1008-1030. https://doi.org/10.51594/csitrj.v5i4.1085

Okunade, A. I. (2024). The role of artificial intelligence in teaching science education in secondary schools in Nigeria. *European Journal of Computer Science and Information Technology, 12(1), 57-67.* https://tudr.org/id/eprint/2679.

Oraif, I. (2024). Natural Language Processing (NLP) and EFL Learning: A Case Study Based on Deep Learning. *Journal of Language Teaching and Research*, 15(1), 201-208. https://doi.org/10.17507/jltr.1501.22

Otoum, Y., Gottimukkala, N., Kumar, N., & Nayak, A. (2024). Machine Learning in Metaverse Security: Current Solutions and Future Challenges. *ACM Computing Surveys*, 56(8), 1-36. https://doi.org/10.1145/3654663

MunishKhanna, Singh, L. K., & Garg, H. (2024). A novel approach for human diseases prediction using nature-inspired computing & machine learning approach. *Multimedia Tools and Applications, 83(6), 17773-17809.* https://link.springer.com/article/10.1007/s11042-024-14825-5

Mupaikwa, E. (2025). The Application of Artificial Intelligence and Machine Learning in Academic Libraries. In *Encyclopedia of Information Science and Technology, Sixth Edition* (pp. 1-18). IGI Global.

Nozari, H., Ghahremani-Nahr, J., & Szmelter-Jarosz, A. (2024). AI and machine learning for real-world problems. In *Advances in Computers (Vol. 134, pp. 1-12).* https://doi.org/10.1016/bs.adcom.2023.02.001

Panagoulias, D. P., Virvou, M., & Tsihrintzis, G. A. (2024). A novel framework for artificial intelligence explainability via the Technology Acceptance Model and Rapid Estimate of Adult Literacy in Medicine using machine learning. *Expert Systems with Applications, 248, 123375.* https://doi.org/10.1016/j.eswa.2024.123375

Priya, S., Bhadra, S., Chimalakonda, S., & Venigalla, A. S. M. (2024). ML-Quest: A game for introducing machine learning concepts to K-12 students. *Interactive Learning Environments*, 32(1), 229-244. https://doi.org/10.1080/10494820.2022.2084115

Rane, N. L., Kaya, O., & Rane, J. (2024). Human-centric artificial intelligence in Industry 5.0: Enhancing human interaction and collaborative applications. In *Artificial Intelligence, Machine Learning, and Deep Learning for Sustainable Industry*, Vol. 5, pp. 2-95. https://www.researchgate.net/publication/372895103.

Rane, N., Shirke, S., Choudhary, S. P., & Rane, J. (2024). Artificial Intelligence in Education: A SWOT Analysis of ChatGPT and Its Impact on Academic Integrity and Research. *Journal of ELT Studies*, *1*(1), 16–35. https://doi.org/10.48185/jes.v1i1.1315

Sanusi, I. T., Sunday, K., Oyelere, S. S., Suhonen, J., Vartiainen, H., & Tukiainen, M. (2024). Learning machine learning with young children: Exploring informal settings in an African context. *Computer Science Education*, 34(2), 161-192. https://doi.org/10.1080/08993408.2023.2175559

Sargsyan, L. (2024). Fostering critical thinking skills in the HEIs of Armenia in the age of AI-driven transformation. *Foreign Languages in Higher Education*, 28(1(36)), 200-215. https://doi.org/10.46991/FLHE/2024.28.1.200

Shimaponda-Nawa, M., & Nwaila, G. T. (2024). Integrated and intelligent remote operation centres (I2ROCs): Assessing the human–machine requirements for 21st-century mining operations. *Minerals Engineering, 207, 108565.* https://doi.org/10.1016/j.mineng.2023.108565

Siram, J., Chikati Srinu, D. S. V., & Tripathi, A. (2024). Towards a framework for performance management and machine learning in a higher education institution. *Journal of Informatics Education and Research*, 4(2). https://doi.org/10.52783/jier.v4i2.844

Susnjak, T. (2024). Beyond predictive learning analytics modelling and onto explainable artificial intelligence with prescriptive analytics and ChatGPT. *International Journal of Artificial Intelligence in Education, 34(2), 452-482.* https://link.springer.com/article/10.1007/s40593-023-00352-8

Timpe-Laughlin, V., Sydorenko, T., & Dombi, J. (2024). Human versus machine: Investigating L2 learner output in face-to-face versus fully automated role-plays. *Computer Assisted Language Learning*, 37(1-2), 149-178. https://doi.org/10.1080/09588221.2022.2032184

Urrutia, F., & Araya, R. (2024). Who's the Best Detective? Large language models vs. traditional machine learning in detecting incoherent fourth-grade math answers. *Journal of Educational Computing Research*, 61(8), 187-218. https://journals.sagepub.com/doi/abs/10.1177/07356331231191174_

Xu, L. Z., Saffarizadeh, K., & Lee, J. (2024). Fast Forward, as Copilot Becomes the Pilot: Examining GenAI Dependence and Problematic Use. *AMCIS 2024 TREOs*, 102, 1-2. https://aisel.aisnet.org/treos_amcis2024/102/

Yang, S., Yang, J., Zhou, M., Huang, Z., Zheng, W. S., Yang, X., & Ren, J. (2024). Learning from human educational wisdom: A student-centered knowledge distillation method. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 46(6), 4188-4205.* https://doi.org/10.1109/TPAMI.2024.3354928.