https://rijournals.com/engineering-and-physical-sciences/
RESEARCH INVENTION JOURNAL OF ENGINEERING AND PHYSICAL SCIENCES 3(1):89-101, 2024
©RIJEP Publications ISSN: 1597-8885

Advancing Personalized Learning through Educational Artificial Intelligence: Challenges, Opportunities, and Future Directions

Afiya Dembe H.

Faculty of Education Kampala International University Uganda

ABSTRACT

Educational Artificial Intelligence (EAI) holds immense promise in transforming traditional learning paradigms by integrating artificial intelligence and learning science to create personalized learning systems. This paper explores the critical role of EAI in advancing personalized learning, addressing challenges, highlighting opportunities, and proposing future directions. Leveraging insights from learning science and AI, EAI systems aim to tailor learning experiences to individual student needs, preferences, and learning styles. However, the complexity of data, ethical considerations, and scalability issues pose significant challenges. Addressing these challenges requires a multidimensional approach involving stakeholders such as educators, policymakers, and learners themselves. The paper discusses the foundational principles of personalized learning, the role of machine learning and AI algorithms, adaptive learning technologies, and ethical considerations surrounding data privacy and bias. Furthermore, it examines the evolving landscape of AI in education, emphasizing the need for transparency, fairness, and scalability in AI-powered personalized learning systems. Finally, the paper outlines future directions, emphasizing the importance of integrated assessment features, continuous improvement in AI algorithms, and bridging the gap between research and real-world implementation.

Keywords: Educational Artificial Intelligence, Personalized Learning, Machine Learning, Adaptive Learning Technologies, Data Privacy, Bias and Fairness, Challenges, Opportunities, Future Directions

INTRODUCTION

It is vital to leverage the theory of learning science and artificial intelligence to design and develop new and improved educational practices [1]. Because of the substantial computational resources needed and the complexity of data from both sides of teachers and learners, EAI systems and their components demand more research. In general, just like recommender systems and in-depth student data analysis, it is critical to maintain transparency and trust in EAI-driven smart learning systems for their acceptance and large-scale use by stakeholders, such as teachers and students [2-5]. Raising awareness, training, and conducting practical workshops for a variety of stakeholders, particularly in developing countries, to provide appropriate and compliant recommendations, is another essential concern in the region. Future researchers may examine how personalization can be facilitated and devised in EAI systems in a right-to-left integrated way [6-10]. Different students have different learning behaviors and skills, which makes personalized learning essential for stakeholders, including K-12 schools and universities. Personalized recommendation and learning features based on predictable trends have shown significant effectiveness in supporting instructional design [11-14], while motivation remains the essential theoretical framework of EAI. Specifically, adaptive learning environments based on individual profiling, track progress and adjust learning paths to promote self-regulated learning and academic success. For instance, web-based and AI-driven personalized mathematics software suggest mathematics problems for individual students that present the greatest gains in student learning. On the other hand, the one-size-fits-all curriculum may lead to a lack of attraction to a few students' interests. In response, the AI-driven personalized learning system adjusts the contexts of content, covering students' interest in learning and their preferred modalities, while keeping readily available communication and support for students [15-19].

Educational Artificial Intelligence (EAI) is a promising and emerging field that integrates artificial intelligence and learning science to create personalized learning systems using machine learning algorithms [20, 21]. EAI-based personalized learning systems collect data describing student learning behaviors (e.g., solving problems and interacting with their peers), predict student learning performance, and provide real-time feedback, accurate review, and collaborative supervision. Specifically, KHAN Academy with over 120 million active users worldwide, is an influential EAI system with a suite of personalized learning features (e.g., student learning progress, knowledge mastery, and teacher recommendations) [22, 23].

Background and Significance

Teaching everyone the same way means that it won't reach the same standards as often. In recent years large-scale individualized learning has become viable via advances in technology. Personalized learning eventually responds to the specific learning needs of each student. AI algorithms can be responsible for developing such customized learning experiences that require a complex computational analysis of a student's circumstances. AI provides instruction and instruction material at the required intensity based on learners ' needs. It differs from traditional learning in that it provides the explanations and instructions individually tailored and is not limited by time. Information and explanations are reviewed repeatedly at the moment when they fail to understand the information once upon a time. Personalized learning is crucial for a successful learning experience [24-28]. Personalized learning is the revolution that our world needs since personalized learning directly addresses the increasing needs for learning in the 21st century. The primary aim of AI in education is to elevate the personalization of learning and promote self-paced learning. Different students have different learning abilities, and sometimes spending the same amount of time to learn the same thing does not give equitable results for everyone. To promote self-education efficiently, tutorials on matters of pupil interest can be chosen. To help the instructors to give personalized learning in a larger group, it needs the tutor's pupil model that shows the learning needs, preferences, and capabilities of students [29-34]. AI systems may recognize all students ' ways of learning. Today, with the diversity of thought, interest, prior knowledge, learning style, and learner's age, all instructors need to move on from the traditional, and now obsolete one-size-fits-all teaching and learning-focused mode to an individualized one. AI-supported technologies can be an effective solution to this problem even for online settings, which makes it easy to collect the necessary data and provide personalized learning experiences to each learner. AI can help educators offer tailored content to students and automate the assessment process, allowing teachers to focus more on teaching and tutorials [35-39].

Foundations of Personalized Learning

At heart, personalization is a computationally inexpensive form of experimental design – It is about choosing decision points (content, pathways, strategies) based on historical data and then updating our understanding of our students and our educational materials based on our actions and their results. Personalized educational systems in high school or college education are known in the industry as adaptive learning systems; in addition, in various subdomains adaptive mathematical tutoring and open learning materials have been online for years, although many of these were rule-based systems [40-44]. Implementing personalized learning in schools is not straightforward, as it is contradictory to the principles and practices of the traditional factory-model classroom and much of the logistics of large-scale educational systems, including the design of educational content and the knowledge and skills of many educators. One of the enablers of personalized learning in recent years is a new generation of algorithm-powered educational platforms [45-49]. These platforms enable students to learn at different speeds and via different forms of content adjusted to personal preferences. Achieving personalization requires having content and learning activities that can scale. This means taking advantage of various forms of digital content that measure the learners' understanding and their degree of confusion. This work requires educators to understand the diversity of learning strategies, diverse data types, and diverse computing systems that make personalization possible, however, also makes personalization analytics systems complex and vibrant [50-54].

Definition and Principles of Personalization

Though personalized systems have an upper hand over age-old lectures or one-size-fits-all systems, direct communication/interactions between instructors and learners, and among the learners are generally not replaced by personalized systems. Instead, these systems take data from multiple communication channels of distributed learning platforms, including instructor feedback, assignments, sessions attendance, learning and knowledge assessment data generated by different learner interactions, and the content used for these interactions, to help instructors in making better decisions concerning personalization. AI-driven personalized systems come with a trade-off between the precision of predictions and the system's ease of use [55-60]. To maintain the system's ease of use, only partial personalization is normally done.

Such AI-driven personalized systems in educational research are called “AI-driven tutoring systems” “AI-based advisor systems” or “AI-driven facilitator systems” [61-65]. Personalization can be approached in different ways. One of the most frequently employed methods is individualization. Individualization refers to either of the following: (i) individual instruction and (ii) individual learning. In individual instruction, the content, structure, and pacing of learning are tailored to the learning preferences and profile of individual students. However, an instructor constructs all or most, tasks, instructions, or assessments for the different learners. On the other hand, individual learning refers to self-planned aspects of education or free, informal learning. In such cases, students usually do not have a formal instructor but are allowed to pursue their learning using different learning resources [66-69]. Over the last decade, personalization has attracted much attention in AI and educational technology research. Personalized learning systems, tools, and platforms are now available at different levels of education, including K-12 and higher education institutions. p.2 AI-Driven Personalized Learning System, Advisor, and Tutoring System [70, 71]

Traditional vs. Personalized Learning Approaches

Few of the systems identified the prior knowledge gaps in students and tried to remove those dynamically based on the learner's performance. Systems consider various attributes such as learning styles, learning preferences, learning strategies, and learner’s demographics including nationality, psychological factors, and emotional states to treat the learner for it’s engagedness [72-75]. Each learner can have his/her strengths, weaknesses, interests, and preferred ways of learning, and AI-powered personalized education can significantly improve education quality by adapting to each learner's unique characteristics and expectations. The traditional learning approach focuses on mass education by following a session-based (online class) model. With this approach, the instructor follows the one-size-fits-all approach, which means the same type of content will be displayed to all learners irrespective of their educational background, learning style, or preferences whereas in personalized learning, the system recognizes these constraints and provides a learning plan exclusively designed for the student, using AI algorithms. The related literature on personalized learning emphasizes the potential of providing the best possible learning experience for each student [73-78]. Personalized e-learning considers individual student variations and customizes the virtual training environment. The factors of professors' competence, teaching style, and assistance are related to positive student emotions and trigger flow. Various theoretical models, such as FAUCLE, aim to connect elements of the e-learning process and create relationships among them. Recently, Artificial Intelligence (AI) algorithms have been introduced in e-learning systems to support personalized learning approaches. It is designed to adapt to learners' requirements based on their preferences. Providing learners with the right content, and personalized learning environments can support learners in aspects such as close interaction with course content, a variety of multimedia content types, technical skills, and the level of depth of a presentation of the content [79-82]. Personalized learning systems, also known as adaptive learning platforms or intelligent tutoring systems, use AI to provide students with access to different learning materials based on their individual needs and subjects [83-86].

Role of AI in Personalized Learning

FUNDAMENTAL OPPORTUNITIES

The goal of the next generation of LA is to get learner learning trajectories. Learning trajectories are the prediction of how learners should improve to reach their learning goals and aspirations. Although the learning trajectory is one of the key findings in the field of learning sciences and human cognition, the form creation and direct prediction of this information from the data is an open question. To make a first step towards this goal, we offer a new trace-based modeling approach for the time series in the features of the learners such as assessments for how well learners had acquired specific knowledge, how accurately the learners had been able to generalize this knowledge and how efficiently the learners had been able to apply this knowledge in solving problem [87-90].

DEPICTION OF AI IN PERSONALIZED LEARNING

These are typically integrated with intelligent tutors (ITSs) to provide customized learning. In a feedforward system, AI can learn associations from LMS data and bottlenecks and pre-empower feedback. A primary contribution is a growing emphasis on data-driven AI capable of nominally adaptive responses. As a result, it becomes plausible to personalize learning at a high proficiency and work based on achievement level or prior knowledge. While even calling for adaptive support, the question is whether this sector is prepared to exploit these advancements. To outline key achievements and strategies to sense and respond, adapt, and anticipate digital trace data are used. The operating characteristics of AI applications currently are reinforced; both the technology and infrastructure readiness desired to execute such interventions are still largely driven by research opportunities and less by commercially viable software options [91-96]. The role of AI in personalized learning has gained momentum in recent years, as it holds the potential to revolutionize the traditional learning paradigm. The term personalized learning is not new, but with the emergence of AI, knowledge can be tailored or personalized and delivered to individual learners based on their unique specific learning needs. Personalized learning helps in recognizing, creating awareness, and enabling the moving parts of a supportive learning environment. It is very important to have an intelligent presence, creating functionality and helping in the next level of personalized learning. The involvement of technology and a massive amount of data has led to the development of complex intelligent systems. AI has partially been able to digest these enriching data and plays a fundamental role in improving the process of personalized learning [97, 98].

Machine Learning and AI Algorithms

Using artificial intelligence in teaching and learning, such as algorithmic transparency, bias, discrimination, equity, privacy, and security, can be subject to ethical concerns. Teachers should be able to select the algorithmic model that is best suited for the task, configure its parameters, choose how data comes in terms of feedback, and understand the conditions under which new models are to be built. Unintended biases inside students' data collection methods, missing information, imprecision, and lack of control over the data they gather can be mitigated by teachers through these concerns. Specifically, data minimization, data dispersion, decay of data, differential privacy, and data curation are techniques and strategies that can be applied to limit these concerns [99, 100]. Teachers should be able to explain how their algorithmic recommendations have been created to students and answer questions about how these recommendations are made. A way to build up this explainability is feature engineering, a technique where some statistical details of the features are provided, and the result of feature extraction should be interpretable, so the teacher can comprehend the properties of each feature and shape the data for the model in such a way that it is not unique. Machine learning (ML) and artificial intelligence (AI) algorithms are the underlying tools in today's technology-based products and services, and they have been applied in various sectors including education, especially in personalized learning platforms and intelligent tutoring systems (ITS) [101, 102]. Given the variety of different pedagogical models, algorithms, and components that can be used in an ITS, the use of ML and AI-enhanced ITS enables the platform to collect, process, interpret, and use data in real-time. Specifically, kernel methods are the most common way of analyzing the performance of the system about the user actions concerning the system's recommendations. Furthermore, these models can use different sources of information to make predictions and adapt to the user's features on the fly [103].

Adaptive Learning Technologies

These systems are based less on a one-size-fits-all educational strategy and further on bespoke client or group-tailored interactions, promoting true Customer-Centric Personalized Learning (CCPL) Technology. In comparison, they are helpful for educators who struggle in today's distributed educational environment since they may guarantee that students in need are not overlooked in large educational frameworks. AI-enabled databases give individualized, adaptive assignments that may recommend homework questions based on the student's NTO (number of times open) answer and NTSC (number of times submit choice). Artificial intelligence (AI) studies have the potential to yield new adaptive learning paths for learners by considering their learning habits and outcomes, and user understanding of the question [104]. The adaptive learning system would also recommend learning pathways and knowledge-point marking according to the adaptiveness of the students, displaying pace allocations, and carrying out personalized learning historical data. Therefore, AI possesses the potential to customize educational content to a specific pupil's requirements, learning styles, tempo; labels, and statistics related to online learning interactions; Predicting the failure of the student in any topic [105]. Adaptive learning technologies implement a teaching method and emphasize customized practice questions. Prescriptive analytics works on historical data and suggests an individualized learning path, constraints, and prescriptive advice [106]. Adaptive learning technologies that collect real-time user data, such as a user's learning patterns, time between questions, accuracy of questions answered, correctness, and bias of each question, user understanding of the question without options (e.g., fill in the black), difficulty of each question, and confirms the long-term memory of questions. The system then selects the next question based on the adaptive results from real-time user data [107].

Challenges and Ethical Considerations

Issues related to developing systems that are scientifically valid, educationally effective, acceptable to key stakeholders, and scalable. There are also several ethical challenges related to potential harm to learners or teachers, confidentiality of user data, surveillance of learning anywhere and all the time, potential bias in teaching and learning resources, and inequitable access to AI-powered personalized learning systems. In particular, the wider deployment of AI technologies is enabling rapid and large-scale development and delivery of affordable, effective personalized learning systems. For instance, AI tools, such as user input automation, chatbots, tutoring systems, and various gamified systems, can advise on and/or make decisions about, a range of aspects of learning, from learning companions to embedded assessment, and all aspects of the curriculum [108, 109]. They can also provide new forms of support, such as automating administrative tasks. For many learners, including those far removed from formal education, and those in high or low-income countries, AI-powered learning systems promise much in terms of low-cost, personalized learning. While AI-powered personalized learning systems have much potential, the road to their large-scale adoption is not without significant and deep-seated challenges. Personalized learning, or individualized instruction, refers to instruction that is paced to the learning needs of students and tailored to the specific learning preferences of different learners [110]. It also involves using different forms of technology and digital content to allow for learning opportunities that are flexible, adaptable, and responsive to student needs. From simple pathways through learning material tailored to each student's ability to adaptive learning systems that use AI to identify areas where students struggle and then offer extra help in those areas [111]. Personalized learning has grown in recent years, thanks to advances in technology, and in particular, personalized learning has benefited from one specific technology: AI.

Data Privacy and Security

It is impossible to discuss AI in education without discussing big data. One of the virtues of the big data movement is the ability to aggregate separately stored datasets for all purposes. Yet, once this data is integrated, it becomes vulnerable to leaks, hacks, and unauthorized access, and if one dies, all the others die. Many components have made the personalization renaissance possible in the last few years from deep learning algorithms' improved predictive capabilities to faster microprocessors that enable faster algorithms [112]. However, the single most critical element has been the coalescence of educational big data, which in turn has been, enabled by the birth and expansion of massive online open courses. Major technology companies, such as Google, Apple, and Amazon, have each established a presence in the personalization market. Their unique selling proposition is that students interact with their applications in school and at home so that they can collect more data. Thus, their systems have the potential to facilitate year-round, all-the-time surveillance of students. AI-powered personalized learning systems require vast amounts of data, both personal and sensitive, to operate. From the personalization model to the adaptive learning engine to the predetermined curriculum or lesson generator, underlying algorithms require large datasets [113]. These datasets typically include but are not limited to, a bevy of sensitive, educational, and noneducational student data including biographic, demographic, academic, social, emotional, biometric data, health, behavioral attributes, searchable, personal, attendance, enrolling objects, course enrollment, extracurricular activity participation, transport, and meal eligibility, and disciplinary records. They require vast quantities of data about academic performance and a student's behavior and choices inside an educational environment. From national student clearinghouses to educational records bureaus to credit bureaus to state Departments of Education to institutional departments, most higher education institutions have a multiplicity of data sources that store student data. Student records not captured in the data store are often plentiful in public records, institutional notes, and online records [114].

Bias and Fairness in AI Algorithms

Bias can arise in AI content through factors such as data selection, algorithm design, or other human-elected factors. For example, if training data doesn't represent the diversity of the population, AI systems can implicitly "write out" minority perspectives when using such disproportionate datasets. It can be useful to promote diverse datasets that represent the evenness of the situation being measured, e.g. a facial recognition algorithm built from populations including representative genders, skin shades, ages, etc., to help develop mindsets that reflect parity [115]. This training data should balance likely functional and frequency values as well as avoid relying too heavily on perspectives coming from unjust power distributions. These datasets can also be chosen to represent the problem space from multiple angles and perspectives, beyond a narrow scope of a single perspective leader. This may be likened to researchers working on a certain type of bacterial engineering using multiple models and variables to avoid losing sight of certain reminders, etc. However, data collection will not necessarily prevent bias from entering an AI system. This data is not neutral, coming from a world born of oppressive structures, historical legacies, and power disparities as in the Kuenssberg example above. Biases in data can include over- or underrepresentation of something within relevant historical data because of bigotry widespread in a given population or could have complex causes [116]. Bias in data collection might mean that a trainer model is privileging certain patterns of regularity over others. An AI system can only replicate inequalities inherent in historical data that influence how we frame a problem, define a situation, or evaluate conditions of certain situations or populations and biases in how the AI system affects AI output. This means the way a system is trained and the data it is trained on can strengthen existing biases if developers fail to account for history and context. AI for learning has the potential to generate different opportunities, resources, and outcomes for different learner groups through human-computer interactions, and technological and infrastructural specificities [117, 118]. It is crucial to have a deeper engagement with actors who are involved in AI-for-learning platforms (beyond just developers and instructional designers) since they influence the design choices being made. Besides top-bottom coordination, educators (who employ AI-driven instructional materials in educational settings), policymakers (articulate AI-for-learning goals; design and enforce regulations, standards, and policy guidelines), and students (interact with AI-driven content) should also be involved. This will enhance readiness for the challenges and opportunities that result from AI integration in educational contexts. As a naive application of AI algorithms in the learning environment can exacerbate disparities in inner educational contexts, for example, pitfalls of flawed models, unintended consequences of using AI in educational systems, and bias, and fairness issues in AI-generated educational content. There are challenges associated with integrating AI into learning. Toward preventing the exacerbation of certain disparities, some scholars put forward a forward-looking design focusing (e.g.) on more equitable future scenarios, as opposed to optimization, problem-solving, or generalizing algorithms based on limited and prior data akin to the science fiction approach that lampooned [119].

Future Directions and Conclusion

As said earlier, AIEd proliferation faced legitimate concerns regarding student data privacy. Therefore, future AIEd systems must focus on transparency. The hypothesis is that the more transparent an AIEd system is seen, the more user buy-in we can get from educators, parents, and students. At least two pressing real-world improvement concerns have not been paid a lot of deep AIEd research attention. First, long-term adaptive feedback fatigue. One experiment with a utility optimizer for the deliberately boring item presentation order did not show a lot of (meaningful) learning gains. What works is a rich AI-enabled space with counter-frustration feedback, but there is a roadmap of tens of partially autonomous pet projects ahead. Second, the scalability of AI-powered personalization. We have some results in gamified areas, but we lack scalable approaches that do not rely heavily on manually designed educational ontologies and meta-labels [120]. Well, mainstream CBT suffers from a similar issue; the blurry boundary between these 2 existing paradigms of improving education (in slight exaggeration) is a big business that received a lot of focus in future research. No EdTech system is complete without an integrated assessment feature. Therefore, AIEd systems capable of designing, delivering assessments with feedback, and providing adaptive learning suggestions are necessary. The most significant evolution in education gaps will happen when we have AI algorithms working on some form of (automated) content analysis and feedback. Examples may include automated essay assessment, automated feedback on individual homework answers, personalized adaptive highlighting in STEM exercises or exams, summative assessments (like exams) based on individual meta-questions, and many others [121]. There is a wide variety of content assessment areas. There is an increasing body of evidence accumulating that AI-powered Adaptive Learning Systems can outperform traditional systems. There is no doubt among leading AIEd-ists that the personalized learning trajectory can only be achieved by highly sophisticated AI algorithms continuously analyzing a lot of student data. Most of the (plausible) future studies are focused on closing the remaining knowledge and skill gaps in AIEd business intelligence and the abilities to smoothly use that BI in complex real-life EdTech ecosystem multi-stakeholder projects [122, 123].

CONCLUSION

Educational Artificial Intelligence (EAI) presents a transformative opportunity to revolutionize traditional learning practices through personalized learning experiences tailored to individual student needs. While EAI systems offer significant potential, they also face various challenges, including data privacy concerns, bias in algorithms, and scalability issues. Addressing these challenges requires collaborative efforts from educators, policymakers, researchers, and technologists. By prioritizing transparency, fairness, and continuous improvement, EAI systems can enhance educational outcomes and empower learners worldwide. Moving forward, future research should focus on developing integrated assessment features, improving AI algorithms, and bridging the gap between theory and practice to realize the full potential of personalized learning in the digital age.

REFERENCES

1. Chaudhry, Muhammad & Kazim, Emre. (2021). Artificial Intelligence in Education (AIEd): a high-level academic and industry note 2021. AI and Ethics. 2. 1-9. 10.1007/s43681-021-00074-z.
2. Olaide Olutola Fagbolu, Azizi Wasike. (2019). Model for Translation of English Language Noun Phrases to Luganda. London Journal of Research in Computer Science and Technology. 19(3), 1-14.

3. Vincent Kayindu, Zahara Faridah Kiggundu, Azizi Wasike (2023). Religion as a Correlate of Administrative Staff's Adoption of Information and Communication Technology (ICT) In Primary Schools of Bukomansimbi District, Uganda. International Journal of Advance Research and Innovative Ideas in Education. 9(4), 1220 – 1228.
4. Vincent Kayindu, Zahara Faridah Kiggundu, Azizi Wasike. (2023). Administrative Staff's Age and Their Adoption of Information and Communication Technology (ICT) In Secondary Schools, Kampala District, Uganda. International Journal of Advance Research and Innovative Ideas in Education. 9(4), 1229 – 1235.
5. Barongo E. K, Busingye J. D., Tom Mulegi, Lubaale G (2023). Gendered Economic Gap In Uganda: Education Attainment and Women's access to, and Land ownership in Bunyoro Sub-Region. Idosr Journal of Arts and Management. 8(2), 1-10.
6. Eleanor Kirahora Barongo, Tom Mulegi, Mary Tunde Nalubega (2023). Evaluation of the relationship between Job Safety and Employee Productivity in Public and Private Organizations in Kampala, Uganda. IAA Journal Arts and Humanities 10(1), 62-75.
7. Rukundika Francois, Mwaniki Roseann, Tom Mulegi, Eleanor Kirahora Barongo (2023). The effect of Health service interventions on re- integration of ex-combatant children in Haute-Kotto Prefecture of the Central African Republic. Newport International Journal of Research in Education 3(2), 108-119.
8. Mary tunde nalubega, tom mulegi, eleanor kirahora barongo. (2023). evaluation of the level of job safety in some selected organizations in kampala, uganda. Idosr journal of current issues in arts and humanities. 9(1), 60-73.
9. Robert Mpiira, Patrick Okello. (2020). A Multisectoral Approach To Eradication Of Malnutrition In Vulnerable Groups: A Cluster-Randomized Trial. Acta Scientific Nutritional Health. 4(2), 1-7.
10. Ashirafu Masudi Kule, Mugizi Wilson, Kariisa Henry Ampeire, Victor Turiabe. (2012). Teacher characteristics and the Use of ICT in Rural Secondary Schools of Bwera Sub County, Kasese District, Uganda. Interdisciplinary Journal of Rural and Community Studies. 3(2), 30-40.
11. Sudar Rheina Romadhoni, Tatik Suryani. (2023). The relationship of workplace spirituality, job characteristics employee engagement, and employee wellbeing. Enrichment: Journal of Management. 12(6), 4780-4787.
12. Ismail Bello, Asmau Isyaku Dutse, Sophia Kazibwe, Muzaare Gerald. (2022). Multinational Corporations, Knowledge and Technology Transfer in Nigeria: An examination of Etisalat Telecommunications Engineering Postgraduate Programme (ETEPP). International Journal of Research and Innovation in Social Science. 6(5), 508-513.
13. Gerald Muzaare. (2017). Management of Integrated Development Programmes in Ibanda and Kiruhura districts in Western Uganda. NIU Journal of Social Sciences. 2(2), 7-17.
14. Nakate Sylvia, Muzaare Gerald, Katunguka Aaron, Adam Matiko Charles, Mainrad Haule Lembuka, Samanya John, Mutebe Janet. (2019). Job Satisfaction and Organizational Citizenship Behavior (OCB) in Multinational Telecommunication in Uganda. Journal for Studies in Management and Planning 5(9), 49-52.
15. Blessing Etukudo Ogunjimi, Aniebiet Inyang Ntui, Uduak Enang, Undie Felicia Nkatv. (2022). Socio-demographic variables and utilization of ict among members of staff of university libraries in cross-river and akwa-ibom state nigeria. Global Journal of Educational Research. 21(2), 159-171.
16. Osim Tina Alam, Felicia Nkatv Undie. (2023). Students Industrial Work Experience scheme in enhancing employable skills in Library and Information Science students in Tertiary Institutions in Cross River State, Nigeria. International Research Journal of Education and Technology. 5(9), 251-264.
17. Mugizi, W., Mujuni, B. T., & Dafiewhare, O. A. (2019). Ethical leadership and job performance of teachers in secondary schools in Kyabugimbi Sub-County in Bushenyi District in Southwestern Uganda. *Direct Research Journal of Education and Vocational Studies, 1*(1), 11-22.
18. Abimbola Labake Agboke, Rose Ezeibe, Felicia Nkat v Undie, Ahiaoma Ibegwam. (2021). The Adoption of Microsoft Excel in Resource Processing (Cataloguing and Classification) Section and Readers' Services (Circulation) Section of University Library …International Journal of Research in Library Science (IJRLS). 7(2), 54-64.
19. Felicia Nkatv Undie, Rose Ezeibe and Abimbola Labake Agboke. (2020). Computer Literacy Skills and Utilisation of Information Resources in Federal University Libraries by Post-Graduate Students in South–South, Nigeria. International Journal of Advanced Library and Information Science. 8(1), 470-478.

20. Franklin Muhereza T. Ukaidi Chris U. A, Ssekajugo Derrick, Ukaidi Evelyn. (2024). Road Merchants and Socio-Economic Development: A Study of Cross River State of Nigeria. Nigerian Journal of Management Sciences. 25(1), 319-328.
21. Edwine Atukunda, Owen McOnyango, Deborah Amukowa. (2022). Mchango wa Mashairi ya Kiganda katika Kuendeleza Muundo wa Ushairi wa Kiswahili Kupitia Ufunzaji na Ujifunzaji. 5(1), 171-182.
22. Mugizi, W., Musinguzi, M. N., & Dafiewhare, O. A. (2019). Human resource career development practices and retention of secondary schools' teachers in Rubabo County, Rukungiri District, Uganda. *Journal of Education Research and Rural Community Development*, *1*(2), 18-37.
23. Manyange, M. M. N., Abuga, I. M., & Nyambane, D. O. (2015). Investigating the financial knowledge management in selected Ngo's in Yei County, Republic of South Sudan.
24. Ceaser, J. B., Daniel, O., Innocent, E. E., Akiyode, O. O., Brenda, M. G., & Danson, M. (2019). Youth" s Awareness of Climate Change in Nakuru Town, Kenya. *International Journal of Scientific Engineering and Science*, *3*(11), 19-24.
25. Mwebesa, E., Sumil, N., Hassan, A. H., & Cephus, D. (2017). Antecedents of statistics anxiety in a higher education system.
26. Bengat, J., Odenyo, M., & Rotich, J. (2015). Organizational change and resistance dilemmas resolution approaches and mechanisms. *International Journal of Economics, Commerce and Management*, *3*(2), 1-17.
27. Jovita Nnenna Ugwu, Asiat Mbabazi, Tom Mulegi, Chidinma Esther Eze, Jude Uchechukwu Aleke, Rachel Okwaja Puche, Eric Mabonga. Evaluation of Factors that Affect Teachers' Job Satisfaction and the Impact on Student Academic Performances NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION 2023. 3(3), 6-9.
28. Jovita Nnenna Ugwu, Asiat Mbabazi, Tom Mulegi, Chidinma Esther Eze, Jude Uchechukwu Aleke, Rachel Okwaja Puche, Eric Mabonga. Effect of Cultural Values on Character Formation: Implication for Education NEWPORT INTERNATIONAL JOURNAL OF EDUCATION RESEARCH. 2023 3(3), 1-5.
29. P.A & Ashong M Betiang. Adult Education: a remedy for the mis-educated and dysfunctional Nigerian. Niger Delta Journal of Education. 2013 1(1), 263-270.
30. Peter Betiang. Adult Education and Empowerment of Rural Women in Bette Communities of Cross River State. International Journal of Research in Education. 2011, 3(5), 109-113.
31. E I Betiang, P.A & Ibiang. Community Education and Community Development in Nigeria. Journal of Educational Innovators. 2010, 8(2), 88-92.
32. P.A & Ashipu B Betiang. Adult Education for poverty reduction and sustainable development: applying the political economy analysis from the systems theory perspective. International Journal of Research and Administration. 2010, 5(9), 58-73.
33. E I Betiang, P.A & Ibiang. Community Education and Community Development in Nigeria. Journal of Educational Innovators. 2010, 8(2), 88-92.
34. P.A & Ashipu B Betiang. Adult Education for poverty reduction and sustainable development: applying the political economy analysis from the systems theory perspective. International Journal of Research and Administration. 2014, 5(9), 58-73.
35. Peter Nsiimire Mwesigye, Patrick Mbyemeire, Raphael Kombi. Academic Performance of Learners by Education Level of Parents in Primary Schools in Ibanda Municipality. INOSR Arts and Management. 2022, 8(1), 27-34.
36. American Journal of Academic Research. Leadership practices and productivity of academic staff in polytechnics in Nigeria. American Journal of Academic Research. 2016, (1)2 56-67.
37. A Mugyenyi, I Anumaka, S Gaite. Entry qualifications and teacher trainees' competencies in primary teachers' colleges of Wakiso and Kampala Districts, Uganda. American Journal of Academic Research. 2017, 2 A31-A45.
38. Asanairi Bwambale, Tom Mulegi, Samanya Bulhan. The Effect of Transactional Leadership on Academic Performance of Primary School Pupils in Social Studies in Munkunyu Sub County Kasese District. IAA Journal of Education. 2024, 10(1), 17-22.
39. Bulhan Samanya, Seezi Kusemererwa. English language and Academic Performance among Learners in Inclusive Schools of Mabaale Sub County, Kagadi District. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION (NIJRE) 2023, 3(2), 81-90.

40. Ambrose Beluaye Anashie, Veronica Kulo. Conflict resolution strategies of Nigerian secondary schools' administrators for peace and economic development. African Education Indices. 2014, 7(1), 1-12.
41. Ambrose Beluaye Anashie, Erasmus Eyang Ebuta, Linus Adie. Influence of students' population pressure and class size on the academic performance of secondary school students in Cross River State. Multidisciplinary Journal of Research Development. 2014, 22(1), 1-17.
42. Ambrose Beluaye Anashie, Patricia Nguwasen Mando. INFLUENCE OF SCHOOL SUPERVISION ON TEACHER-EFFECTIVENESS IN PRIMARY SCHOOLS. Journal of Teacher Perspective. 2014, 8(1).
43. Ambrose Beluaye Anashie, Mark Terlumun Ijov. management of primary education for transformation and Sustainable Development in Ogoja Education zone of Cross River State, Nigeria. Knowledge Review. 2015, 33(2), 67-75.
44. Benson Tukundane, Muhammad Kibuuka, Arthur Sunday (2020). New Product Development Practices and the Growth of Small and Medium Enterprises in Kampala Metropolitan, Uganda. International Journal of Research and Innovation in Social Science. 4(4), 266-271.
45. Abura Samuel Pirir, Ongodia Ekomolot, Kiweewa Emmanuel, Tukundane Benson (2022). Assessment of Recruitment Methods and Employees Performance in local Governments, Karamoja Sub Region, Uganda. International Journal of Research and Innovation in Social Science. 6(7), 410-427.
46. Tukundane Benson, Kibuuka Muhammad, Sunday Arthur (2020). Information Technology Adoption and Growth of Small and Medium Enterprises in Greater Kampala Metropolitan Area, Uganda. International Journal of Advanced Research and Publications. 4(4), 69-74.
47. Tukundane Benson, Emuron Lydia (2023).The Role Played by Research and Development in Uganda's MSME toward Promoting SDGs. Springer Nature Singapore. 155-173.
48. Mbyemeire Patrick, Deusdedit Byabashaija, Tumwesigye Mathias, Muhindo Tadeo, Beyongyera Julius, Nyabuhuzi M Donatien. (2016). Human Resource Planning and Employee Performance in Rwanda: A Perspective of Peoples Bank of Rwanda. Scholars Journal of Economics, Business and Management. 3(6), 316-320.
49. CALVINE CHEPLETING SEREM, TOM ONGESA. (2023). Opportunity for advancement strategy on performance of non-academic staff in the university of Eldoret, Kenya. Reviewed Journal International of Business Management. 4(1), 516-529.
50. FRED SIAMBE OMWERI, WILSON MUNA, JANE NJOROGE. (2023). An analysis of how politics stream affects the implementation of road safety policy measures in Nyanza Region, Kenya. Reviewed Journal International of Business Management. 4(1), 13-21.
51. Omweri, F. S., Muna, W., & Njoroge. (2023). EFFECTS OF PROBLEM STREAM ON IMPLEMENTATION OF ROAD SAFETY POLICY MEASURES IN NYANZA REGION, KENYA. The Strategic Journal of Business & Change Management. 10(1), 269-285.
52. Fred Omweri Siambe Dr. Thomas Otieno Juma. (2022). Bureaucratic Corruption on Devolved Units on Hard - Core Infrastructural Service Delivery: Case of Lake Region Economic Block, Kenya. American Based Research Journal. 11(5), 01-26.
53. Thomas Gisemba Onsarigo, Gladys Nyaiburi Ogaro. (2015). Gender based violence: An examination of ITS effect on women's social economic status a survey of Langas estate, Uasin Gishu County. International Journal of Advanced Research in Management and Social Sciences. 4(4), 281-290.
54. Kobusinge Aida. (2023). The Effect of Risk Management on Financial Performance in Centenary Bank Masindi Branch. EURASIAN EXPERIMENT JOURNAL OF HUMANITIES AND SOCIAL SCIENCES (EEJHSS). 4(1), 17-25.
55. Joseph Ekpang, Godwin Omelagah. (2018). Advertising and the Culture of Consumerism in Nigeria: An Analysis of the "Black Friday" Sales of SPAR Nigeria. Journal of Humanities, Management and Social Sciences, 1(1), 36-52.
56. Nyambane, D. O., & Ouma, B. O. (2017). Cash Management and Profitability of cement Industries in Kenya.
57. Byabashaija, D., Aluonzi, B., Karoro, E. A., Manyage, M. N., Nyambane, D. O., & Besigye, O. (2015). Group Formation Criteria of Money lending Associations in Rubirizi District, Western. Uganda.
58. DUSHIMIMANA GERARD (2016). Agricultural support projects and coffee production in rwanda: a case study of price project in huye district.
59. Hannington, T., Asuman, B., & Mary, B. (2022). Loans and women involvement in business in Kasese District: A Case of Women Entrepreneurs in Hima Town Council. *INOSR Humanities and Social Sciences*, *8*(1), 11-18.

60. Mbyemeire Patrick, Deusdedit Byabashaija, Tumwesigye Mathias, Muhindo Tadeo, Beyongyera Julius, Nyabuhuzi M Donatien. Human Resource Planning and Employee Performance in Rwanda: A Perspective of Peoples Bank of Rwanda. Scholars Journal of Economics, Business and Management. 2016, 3(6), 316-320.
61. Fred Ssemugenyi, Augustine Amboka Asumwa, Sophia Kazibwe. Balancing the delicate space between organizational culture and customer service quality: An empirical review for systemic excellence in the electrical energy sector in Kenya. Asian Research Journal of Arts & Social Sciences. 2020, 10(4), 20-32.
62. Kibuuka Muhammad, Novembrieta Sumil, Byamukama Eliab Mpora, Sophia Kazibwe, Manuel Sumil, Fred Ssemugenyi, Tindyebwa Wilberforce. Managerial skills and success of small-scale entrepreneurs in Kampala Uganda. Canadian International Journal of Social Science and Education. 2015, 3, 546-552.
63. Emurugat Immaculate Azabo, Sofia Sol Gaite, Blessing Ijeoma Anumaka, Yakubu Ibrahim Wunti. Remuneration and discipline of employees in private universities in Uganda. Advances in Social Sciences Research Journal. 2020, 7(1), 438-451.
64. Enoch Oluwatomiwo Oladunmoye. A regression analysis of perceived organizational support, interpersonal relationship and employee turnover intention in southwest Nigeria. International Journal of Information, Business and Management. 2017, 9(3), 147.
65. Oladunmoye E. O, A Rasaq Toyin, Adegunle SO, Chibuzor E ONYEMA. Mediation analysis of Pre-Marital Sexual behaviour in Nigeria: The direct and indirect effects of peer pressure, socioeconomic status, and parent-child relationship. International Journal of Humanities Social Science and Management. 2022, 2(4), 140-148.
66. Samanya Bulhan, Nagaruka Deborah. Non-monetary incentives and employee relations in homes of hope non-government organisation (Mbarara district) IDOSR JOURNAL OF ARTS AND MANAGEMENT. 2023, 8(2), 22-30.
67. Kukundakwe Rosen, Samanya Bulhan. Decentralization and service delivery in government aided primary schools of Buremba Sub-County. IAA Journal of Management. 2023, 10(1), 78-88.
68. Kusingiza Christine, Samanya Bulhan. Women's Participation and Management of Primary Schools in Ibare Sub-County: Bushenyi District, Uganda. IAA JOURNAL OF SOCIAL SCIENCES. 2023, 9(1), 55-61.
69. Samanya Bulhan, Beyogyera Naboth. Record keeping and operational accountability in Mutara sub-county Mitooma district, Western Uganda. IDOSR JOURNAL OF ARTS AND HUMANITIES. 2023, 9(1), 55-61.
70. Bulhan Samanya, Tom Mulegi, Ramadhan Badru Malinga, Hussein Muhaise, Wallen Atwijukire. Examining the Influence of Regulatory Governance on Service Quality in Bwera District Hospital, Kasese District, Western Uganda. IAA Journal of Management. 2023, 10(2), 17-31.
71. Bulhan Samanya, Tom Mulegi, Ramadhan Badru Malinga, Hussein Muhaise, Wallen Atwijukire. Exploring the Impact of Decentralization on Service Quality at Bwera District Local Government Hospital in Kasese District. IAA Journal of Management. 2023, 10(2), 1-16.
72. Bulhan Samanya, Umurungi Musiime Florence. Quality management system in Corporate business: A case study of a Customer focus approach in Kimironko Sector-Gasabo District. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION. 2023, 3(2), 23-37.
73. Bulhan Samanya, Seezi Kusemererwa. English language and Academic Performance among Learners in Inclusive Schools of Mabaale Sub County, Kagadi District. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION (NIJRE) 2023, 3(2), 81-90.
74. Bulhan Samanya, Elias Amanya. Evaluation of Youth Empowerment and Community Development: A Case Study of Kamunganguzi Sub County, Kabale District, Uganda. IDOSR JOURNAL OF ARTS AND MANAGEMENT. 2023, 8(2), 11-21.
75. August, E. S. & Tsaima, A. (2021). Artificial Intelligence and Machine Learning: An Instructor's Exoskeleton in the Future of Education. ncbi.nlm.nih.gov
76. Baillifard, A., Gabella, M., Banta Lavenex, P., & S. Martarelli, C. (2023). Implementing Learning Principles with a Personal AI Tutor: A Case Study. [PDF]
77. Chen, S. Y. & Chien, W. C. (2022). Immersive Virtual Reality Serious Games With DL-Assisted Learning in High-Rise Fire Evacuation on Fire Safety Training and Research. ncbi.nlm.nih.gov
78. Chen, Z. (2022). Artificial Intelligence-Virtual Trainer: Innovative Didactics Aimed at Personalized Training Needs. ncbi.nlm.nih.gov
79. Karpouzis, K., Pantazatos, D., Taouki, J., & Meli, K. (2024). Tailoring Education with GenAI: A New Horizon in Lesson Planning. [PDF]

80. Kshirsagar, R. P., B. V. Jagannadham, D., Alqahtani, H., Noorulhasan Naveed, Q., Islam, S., Thangamani, M., & Dejene, M. (2022). Human Intelligence Analysis through Perception of AI in Teaching and Learning. ncbi.nlm.nih.gov
81. Kenwright, B. (2023). Exploring the Power of Creative AI Tools and Game-Based Methodologies for Interactive Web-Based Programming. [PDF]
82. Dimitriadou, E. & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. ncbi.nlm.nih.gov
83. Kamalov, F., Santandreu Calong, D., & Gurrib, I. (2023). New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution. [PDF]
84. Gaskins, N. (2022). Interrogating Algorithmic Bias: From Speculative Fiction to Liberatory Design. ncbi.nlm.nih.gov
85. Ali Chaudhry, M. & Kazim, E. (2022). Artificial Intelligence in Education (AIEd): a high-level academic and industry note 2021. ncbi.nlm.nih.gov
86. Hu, A. (2024). Developing an AI-Based Psychometric System for Assessing Learning Difficulties and Adaptive System to Overcome: A Qualitative and Conceptual Framework. [PDF]
87. Tom Mulegi(2022). Evaluation of the Skill Mix of Health Professionals in Government Regional Referral Hospitals in Uganda. International Digital Organization for Scientific Research.7(1): 43-68
88. Tom Mulegi.(2022). An Overview of Performance of Health Workers in Uganda. IDOSR JOURNAL OF HUMANITIES AND SOCIAL SCIENCES 7(1): 113-124.
89. **Jovita Nnenna Ugwu, Tom Mulegi, Mbabazi Asiati, Chidinma Esther Eze .** **(2023). Prospects and Challenges of Sustainsble Development in Africa.** **IDOSR JOURNAL OF COMMUNICATION AND ENGLISH. 8(1) . 6-12.**
90. Rachel Okwaja Puche and Eric Mabonga Ugwu Jovita Nnenna, Mbabazi Asiat, Tom Mulegi, Eze Chidinma Esther, Aleke Jude Uchechukwu.(2023). Mentorship and Increased Participation of Women in Politics: A Review. NEWPORT INTERNATIONAL JOURNAL OF CURRENT RESEARCH IN HUMANITIES AND SOCIAL SCIENCES.3(2). 10-13.
91. Rachel Okwaja Puche and Eric Mabonga Ugwu Jovita Nnenna, Mbabazi Asiat, Tom Mulegi, Eze Chidinma Esther, Aleke Jude Uchechukwu. (2023). The Impacts of Teaching Strategies and Skills for Effective Learning of English Language in Cameroon. NEWPORT INTERNATIONAL JOURNAL OF CURRENT RESEARCH IN HUMANITIES AND SOCIAL SCIENCES. 3(2). 6-9.
92. Tom Mulegi and Lubaale G. Barongo E. K., Busingye J. D. (2023). Gendered Economic Gap in Uganda: Education Attainment and Women's Access to and Land Ownership in Bunyoro Sub-region. IDOSR JOURNAL OF ARTS AND MANAGEMENT. 8(2): 1-10.
93. Rachel Okwaja Puche and Eric Mabonga Ugwu Jovita Nnenna, Mbabazi Asiat, Tom Mulegi, Eze Chidinma Esther, Aleke Jude Uchechukwu (2023). The Benefits of Emotional Intelligence to Healthcare in Nigeria. NEWPORT INTERNATIONAL JOURNAL OF CURRENT RESEARCH IN HUMANITIES AND SOCIAL SCIENCES. 3(2). 1-5
94. Rachel Okwaja Puche and Eric Mabonga Ugwu Jovita Nnenna, Mbabazi Asiat, Tom Mulegi, Eze Chidinma Esther, Aleke Jude Uchechukwu , (2023). Effect of Cultural Values on Character Formation: Implication for Education. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION 3(3). 1-5.
95. Mulegi Tom and Eleanor Kirahora Barongo Usman Bappi (2023). Examination of the level of governance in Gombe local government, Nigeria. IDOSR JOURNAL OF BANKING, ECONOMICS AND SOCIAL SCIENCES.8(1). 60-74.
96. Tom Mulegi, Usman Bappi and Bulus Jonah Saidu (2023). An Assessment of the Effect of Motivation and Affirmative Action on Employee's Performance in Gombe Local Government, Nigeria. IDOSR JOURNAL OF BANKING, ECONOMICS AND SOCIAL SCIENCES.8(1). 50-59.
97. Mulegi Tom and Eleanor Kirahora Barongo Usman Bappi. (2023). Examination of the level of community development in Gombe local government, Nigeria. IDOSR JOURNAL OF ARTS AND MANAGEMENT. 8(2): 48-62.
98. Rachel Okwaja Puche and Eric Mabonga Ugwu Jovita Nnenna, Mbabazi Asiat, Tom Mulegi, Eze Chidinma Esther, Aleke Jude Uchechukwu(2023). Evaluation of Factors that Affect Teachers' Job Satisfaction and the Impact on Student Academic Performances. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION 3(3) . 6-9
99. Mulegi Tom and Barongo Kirahora Eleanor Rukundika Francois, Mwaniki Roseann (2023). Evaluation of the effect of Education service interventions on re-integration of ex-combatant children in Haute-Kotto Prefecture of the Central African Republic. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION (NIJRE) 3(2): 120-131.

100. Tom Mulegi and Lubaale G. Barongo E. K., Busingye J. D. (2023). Gendered Economic Gap in Uganda: Education Attainment and Women's Access to and Land Ownership in Bunyoro Sub-region. IDOSR JOURNAL OF ARTS AND MANAGEMENT.8(2):1-10.
101. Hawton, K.; Harriss, L.; Hall, S.; Simkin, S.; Bale, E.; Bond, A. Deliberate self-harm in Oxford, 1990–2000: A time of change in patient characteristics. *Psychol. Med.* **2003**, *33*, 987–995. [**Google Scholar**] [**CrossRef**] [**Green Version**
102. Mulegi Tom and Barongo Kirahora Eleanor Rukundika Francois, Mwaniki Roseann, (2023). The effect of Health service interventions on the reintegration of ex-combatant children in Haute-Kotto Prefecture of the Central African Republic. NEWPORT INTERNATIONAL JOURNAL OF RESEARCH IN EDUCATION (NIJRE). 3(2):108-119.
103. Doyle, L.; Sheridan, A.; Treacy, M.P. Motivations for adolescent self-harm and the implications for mental health nurses. *J. Psychiatr. Ment. Health Nurs.* **2017**, *24*, 134–142. [**Google Scholar**] [**CrossRef**]
104. Mulegi Tom and Barongo Kirahora Eleanor Rukundika Francois, Mwaniki Roseann(2023). The influence of the family support interventions on re-integration of ex-combatant children in HauteKotto Prefecture of the Central African Republic (CAR). NEWPORT INTERNATIONAL JOURNAL OF CURRENT RESEARCH IN HUMANITIES AND SOCIAL SCIENCES (NIJCRHSS).3(1):24-34.
105. Mwaniki Roseanne and Eleanor Kirahora Barongo Tom Mulegi, Ndagire Laila. (2023). A situational analysis of Access to and utilization of sexual and reproductive health services under decentralization in Kampala, Uganda. INOSR HUMANITIES AND SOCIAL SCIENCES. 9(1):31-50.
106. Mwaniki Roseanne and Eleanor Kirahora Barongo Tom Mulegi, Ndagire Laila (2023). Social, economic, and cultural factors that influence access and utilization of sexual and reproductive health services under decentralization In Kampala, Uganda. INOSR HUMANITIES AND SOCIAL SCIENCES. 9(1): 15-30.
107. Meaney, Michael. (2023). Hegemonic Design Bias in Massive Open Online Courses (MOOCs): A Conceptual Framework Exploring Why MOOCs Struggle to Democratise Learning. 10.35542/osf.io/kcqm2.
108. Barongo Eleanor Kirahora and Tom Mulegi (2023). Empowerment and Participation of Women in Community Development in Lower Local Governments: A Case of Makindye Division, Kampala, Uganda. INOSR ARTS AND HUMANITIES 9(1): 48-61.
109. Mwaniki Roseanne and Eleanor Kirahora Barongo Tom Mulegi, Ndagire Laila (2023). Assessment of the level of knowledge and awareness of women on sexual and reproductive health services (SRH) under decentralization in Kampala Uganda. INOSR ARTS AND HUMANITIES 9(2): 35-47
110. Jovita Nnenna Ugwu, Tom Mulegi, Mbabazi Asiati, Chidinma Esther Eze(2023). Challenges Confronting Community Newspapers in Meeting Aesthetics Standards. IDOSR JOURNAL OF COMMUNICATION AND ENGLISH 8(1): 1-5
111. Jovita Nnenna Ugwu, Tom Mulegi, Mbabazi Asiati, Chidinma Esther Eze.(2023). Barriers to Women Leadership. IDOSR JOURNAL OF ARTS AND HUMANITIES 9(1): 6-10
112. Hawton, K.; Saunders, K.E.; O'Connor, R.C. Self-harm and suicide in adolescents. *Lancet* **2012**, *379*, 2373–2382. [**Google Scholar**] [**CrossRef**]
113. Tom Mulegi (2015). Skills and motivation of work performance of health professionals in government regional referral hospitals in Uganda :presented at the Canadian International Conference on Advances in Computer Science, Humanities and Education, April 1-2, 2015, Dubai, UAE.conference paper. http://hdl.handle.net/20.500.12306/1304.
114. Ehsan, Upol & Liao, Vera & Passi, Samir & Riedl, Mark & Daumé, Hal. (2024). Seamful XAI: Operationalizing Seamful Design in Explainable AI. Proceedings of the ACM on Human-Computer Interaction. 8. 1-29. 10.1145/3637396.
115. Beattie, M.; Atherton, I.; McLennan, B.; Lauder, W. Compassion or speed, which is a more accurate indicator of healthcare quality in the emergency department from the patients' perspective? *Int. J. Pers. Cent. Med.* **2012**, *2*, 647–655. [**Google Scholar**]
116. Kool, N.; van Meijel, B.; Koekkoek, B.; van der Bijl, J.; Kerkhof, A. Improving communication and practical skills in working with inpatients who self-harm: A pre-test/post-test study of the effects of a training programme. *BMC Psychiatry* **2014**, *14*, 64. [**Google Scholar**] [**CrossRef**] [**PubMed**] [**Green Version**]

117. Taylor, T.L.; Hawton, K.; Fortune, S.; Kapur, N. Attitudes towards clinical services among people who self-harm: Systematic review. *Br. J. Psychiatry* **2009**, *194*, 104–110. [**Google Scholar**] [**CrossRef**]
118. Hawton, K.; Bale, L.; Brand, F.; Townsend, E.; Ness, J.; Waters, K.; Clements, C.; Kapur, N.; Geulayov, G. Mortality in children and adolescents following presentation to hospital after non-fatal self-harm in the Multicentre Study of Self-harm: A prospective observational cohort study. *Lancet Child Adolesc. Health* **2020**, *4*, 111–120. [**Google Scholar**] [**CrossRef**]
119. Xie, H.; Jiang, D.; Zhang, D. Individuals with depressive tendencies experience difficulty in forgetting negative material: Two mechanisms revealed by ERP data in the directed forgetting paradigm. *Sci. Rep.* **2018**, *8*, 1113. [**Google Scholar**] [**CrossRef**] [**Green Version**]
120. Miranda-Mendizabal, A.; Castellvi, P.; Pares-Badell, O.; Alayo, I.; Almenara, J.; Alonso, I.; Blasco, M.J.; Cebria, A.; Gabilondo, A.; Gili, M.; et al. Gender differences in suicidal behavior in adolescents and young adults: Systematic review and meta-analysis of longitudinal studies. *Int. J. Public Health* **2019**, *64*, 265–283. [**Google Scholar**] [**CrossRef**] [**PubMed**] [**Green Version**]
121. Australian Bureau of Statistics. 3303.0—Causes of Death, Australia. 2018. Available online: **https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/3303.0~2018~Main%20Features~Intentional%20self-harm,%20key%20characteristics~3** (accessed on 12 December 2019).
122. Australian Bureau of Statistics. Intentional Self-Harm in Aboriginal and Torres Strait Islander People. 2019. Available online: **https://www.abs.gov.au/articles/intentional-self-harm-aboriginal-and-torres-strait-islander-people#-suicide-deaths-of-aboriginal-and-torres-strait-islander-children** (accessed on 10 March 2021).
123. Robinson, J.; McCutcheon, L.; Browne, V.; Witt, K. *Looking the Other Way: Young People and Self-Harm*; Orygen, The National Centre for Excellence in Youth Mental Health: Melbourne, Australia, 2016. [**Google Scholar**]

CITE AS: Afiya Dembe H. (2024). Advancing Personalized Learning through Educational Artificial Intelligence: Challenges, Opportunities, and Future Directions. RESEARCH INVENTION JOURNAL OF ENGINEERING AND PHYSICAL SCIENCES 3(1):89-101.