https://journal.ypidathu.or.id/index.php/jete/
P - ISSN: 3025-0668
E - ISSN: 3025-0676

Predictive Analytics to Enhance Learning Outcomes: Cases from UK Schools

David Green[1], Emily Thompson[2], Isaac Ochieng[3]
[1]University of Bristol, United Kingdom
[2]University of Leeds, United Kingdom
[3]Tumaini University, Tanzania

ABSTRACT

Background. The increasing integration of data-driven technologies in education has positioned predictive analytics as a promising tool for enhancing student learning outcomes. In the UK, schools are beginning to leverage predictive models to identify at-risk learners, personalize instruction, and inform pedagogical decisions.

Purpose. This study investigates the practical application and impact of predictive analytics in secondary education settings across selected schools in England and Scotland. The primary objective is to assess how predictive tools are used to improve academic performance, engagement, and targeted interventions.

Method. A qualitative case study approach was employed, involving interviews with school leaders, data analysts, and teachers in six institutions, alongside document analysis and system usage observations.

Results. The findings reveal that predictive analytics, when implemented with pedagogical alignment and ethical oversight, significantly supports early identification of student needs and enables timely academic interventions. However, challenges persist in terms of data literacy among staff, algorithmic transparency, and balancing predictive insights with professional judgment.

Conclusion. The study concludes that predictive analytics can enhance learning outcomes when embedded within a holistic educational framework that prioritizes equity, accountability, and human-centered decision-making.

KEYWORDS

Predictive Analytics, Learning Outcomes, Educational Data, UK Schools, Personalized Learning

Citation: Green, D., Thompson, E., & Ocineg, I. (2025). Predictive Analytics to Enhance Learning Outcomes: Cases from UK Schools. *Journal Emerging Technologies in Education*, *3*(1), 34–43.
https://doi.org/10.70177/jete.v3i1.2127

Correspondence:

David Green,
davidgrenn@gmail.com

Received: January 12, 2025

Accepted: February 28, 2025

Published: February 28, 2025

INTRODUCTION

The increasing digitization of education has introduced a new era of data-driven decision-making in schools across the globe. In the United Kingdom, the integration of technology into classroom practices and administrative systems has generated vast quantities of student data, offering new possibilities for educational analysis and strategic planning. Predictive analytics has emerged as a powerful tool within this landscape, enabling educators to anticipate student performance trends, identify learning risks, and personalize instruction based on data patterns. supporting equity and early intervention.

The use of predictive analytics in education involves applying statistical models and machine learning algorithms to existing student data-such as attendance records, assessment scores, behavior logs, and demographic indicators-to forecast future academic performance or identify students at risk of underachievement. UK schools are increasingly experimenting with predictive dashboards and platforms designed to visualize learning trajectories and generate targeted interventions. These innovations are positioned within a broader push for school improvement, where accountability frameworks and performance metrics require timely insights and evidence-based responses to emerging learning needs.

Despite its potential, predictive analytics in education remains a contested and complex innovation. Schools must balance the technical advantages of data modeling with the ethical and pedagogical implications of making decisions based on algorithmic forecasts. Issues of data quality, privacy, staff readiness, and equity continue to shape the discourse around predictive tools in UK schools. As such, it is essential to understand not only the technological capabilities of predictive systems, but also their practical implementation and impact in real educational settings.

The central problem addressed in this study is the lack of contextualized understanding of how predictive analytics is applied in UK schools to support learning outcomes (Chandra et al., 2025; Jiang et al., 2025; Linardon, 2025; Yenew et al., 2025; Zhang et al., 2025). While predictive technologies are being introduced with increasing frequency, there is limited empirical evidence on how they are integrated into school workflows, how educators interpret their outputs, and how predictions influence teaching strategies. In many cases, predictive analytics tools are deployed without sufficient training, pedagogical alignment, or clarity about their role in instructional decision-making. This gap creates the risk of misapplication, over-reliance on quantitative models, and unintentional reinforcement of educational inequalities.

School leaders and teachers often express uncertainty about the accuracy, reliability, and actionability of predictive insights. Concerns include how data is selected and weighted in algorithms, the transparency of predictive models, and the potential for bias in identifying student risk. Moreover, the translation of predictive data into meaningful educational practice varies significantly across institutions, depending on leadership vision, digital infrastructure, and professional development opportunities. These inconsistencies raise critical questions about the real-world effectiveness and scalability of predictive analytics in diverse school contexts.

This study responds to the need for a grounded exploration of predictive analytics in UK secondary education by focusing on its practical use within schools (Chandel & Lim, 2025; DeFeo et al., 2025; Mancilla et al., 2025; Palladino et al., 2025; Seiler et al., 2025; Sirocchi et al., 2025). It seeks to examine not only what these technologies can do in theory, but how they are used by educators, perceived by stakeholders, and embedded into pedagogical processes. By focusing on lived experiences and institutional practices, the research provides a more nuanced understanding of the challenges and opportunities predictive analytics presents for enhancing student learning.

The primary objective of this research is to investigate how predictive analytics is being employed in UK schools to support and improve student learning outcomes. The study aims to identify the ways in which predictive models are integrated into instructional planning, student support strategies, and school leadership practices. Attention is given to both the technological features of predictive systems and the human factors that shape their implementation, such as teacher judgment, ethical concerns, and institutional culture.

This research also seeks to evaluate the perceived and measurable impact of predictive analytics on student engagement, academic performance, and equity. Through qualitative case studies in selected schools, the study examines how predictive tools inform early intervention, support differentiated learning, and assist in resource allocation. It also considers the extent to which predictive insights are used to challenge or reinforce existing assumptions about student potential, thereby influencing learning trajectories and outcomes.

Ultimately, the study aspires to generate practical insights and recommendations for educators, school leaders, and policymakers aiming to harness predictive technologies responsibly. By examining both effective practices and common obstacles, the research contributes to a more informed and critical conversation about the role of data in shaping future-ready education. The goal is to support schools in leveraging predictive analytics not only as a technical solution, but as a tool for pedagogical reflection, collaboration, and continuous improvement.

Current literature on educational data use has primarily concentrated on learning analytics in higher education and standardized performance metrics in school settings. While there is growing interest in predictive models, most studies emphasize algorithm development, statistical accuracy, or policy potential, with limited exploration of their classroom-level application. Much of the existing research treats predictive analytics as a technical innovation rather than a social and educational process shaped by teacher practices, school structures, and student diversity.

Few studies have critically examined how predictive systems are interpreted and applied by educators in everyday contexts. There is a lack of empirical research documenting the interaction between predictive insights and teacher agency, professional ethics, or localized decision-making processes (Dell et al., 2025; Grosso, 2025; Karume et al., 2025). Furthermore, little is known about the role of school leadership in shaping the adoption and sustainability of predictive tools, particularly in relation to staff capacity-building and stakeholder engagement. These omissions leave a gap in understanding how predictive analytics functions as a lived, pedagogical practice.

This study seeks to address these gaps by contributing empirical evidence from UK schools that are actively engaging with predictive technologies. It expands the analytical focus beyond system design to include the institutional, cultural, and ethical dynamics of implementation. By foregrounding the voices of educators and school leaders, the research provides a situated view of how predictive analytics mediates relationships between data, pedagogy, and learning outcomes. This approach helps bridge the divide between data science and educational practice, offering a more holistic framework for evaluating EdTech innovations.

The novelty of this study lies in its contextual, practice-based examination of predictive analytics in secondary education. It moves beyond generalized claims about the power of data to explore how predictive insights are actually used to inform real-time teaching and learning decisions. Unlike most predictive studies that remain at the level of model accuracy or policy recommendations, this research investigates the micro-level conditions under which predictive analytics enhances—or limits—educational value.

The study also introduces a conceptual lens that frames predictive analytics as a socio-technical system, where the efficacy of data-driven models depends not only on computational logic but also on institutional culture, human interpretation, and pedagogical purpose. This framework enables a more integrated understanding of how predictive technologies are embedded within school ecosystems, and how they influence educational relationships, equity, and accountability.

This research is particularly timely as schools continue to navigate the intersection of digital innovation and data governance. Its findings offer guidance for implementing predictive systems in ways that are ethically responsible, pedagogically meaningful, and aligned with student-centered values. By contributing both theoretical insight and applied knowledge, the study supports the development of more reflective, equitable, and context-sensitive approaches to data use in education.

RESEARCH METHODOLOGY

This study adopted a qualitative multiple case study design to investigate how predictive analytics is implemented and experienced in UK secondary schools with the aim of enhancing learning outcomes (Alhwaiti et al., 2025; Giesler et al., 2025; Ominyi et al., 2025; Sueda et al., 2025). The case study approach was chosen to allow for an in-depth, contextual exploration of how predictive technologies are integrated into pedagogical and administrative practices. This design enabled the researchers to examine real-world applications of predictive tools while capturing the perspectives of various stakeholders within distinct educational environments. The focus was not only on technological capabilities but also on institutional routines, professional judgment, and ethical considerations shaping their use.

The population of the study consisted of school staff involved in data-informed decision-making across six secondary schools located in England and Scotland. These schools were selected through purposive sampling to reflect diversity in geographic setting, school type (state-funded and independent), and stage of predictive analytics adoption. A total of 28 participants were included, comprising headteachers, deputy heads, data managers, and classroom teachers. Selection criteria prioritized those with direct involvement in the use of predictive systems for academic monitoring, intervention planning, or performance reporting.

The instruments used for data collection included semi-structured interview guides, school document analysis protocols, and field observation checklists. The interview protocol covered themes such as the objectives of predictive system use, perceptions of accuracy and usefulness, ethical concerns, and the impact on teaching practices. Document analysis involved reviewing school policies, internal reports, data dashboards, and training materials related to analytics implementation. Field observations were conducted during staff meetings, training sessions, and data review workshops to understand the interactions between predictive tools and pedagogical decision-making.

The research was conducted in four phases. Ethical clearance was secured from the lead research institution, and informed consent was obtained from all participants. In the first phase, initial contact was made with schools, and contextual data about each institution's digital infrastructure and analytics tools was gathered. The second phase involved in-depth interviews lasting 45 to 60 minutes, conducted in person or via secure video conferencing. During the third phase, relevant documents were collected and reviewed alongside observational field notes. In the final phase, all qualitative data were coded thematically using NVivo software to identify cross-case patterns, institutional variations, and emerging themes related to the educational use of predictive analytics.

RESULT AND DISCUSSION

Descriptive findings from the six case study schools indicate varied levels of adoption and integration of predictive analytics tools. Table 1 summarizes the key domains where predictive analytics was applied, the primary users of the systems, and the intended educational outcomes. Across the schools, academic performance prediction and attendance monitoring emerged as the most common use cases. Five of the six schools used commercial platforms such as SIMS and Arbor integrated with predictive dashboards, while one school developed a custom in-house model using historical assessment and behavior data.

Table 1.

Summary of Predictive Analytics use Across Case Study Schools

Domain of Use	Tools Employed	Primary Users	Intended Outcomes
Academic Performance	SIMS, Arbor, Power BI	Data Managers, Teachers	Early intervention, targeted support
Attendance Tracking	ClassCharts, SIMS	Pastoral Leads	Risk flagging, parental engagement
Behavioural Prediction	Custom Model, Excel	Senior Leadership	Resource allocation, mentoring needs
Curriculum Planning	FFT Aspire	Academic Coordinators	Strategic planning, progress tracking
Post-16 Progression	UCAS Data Tools	Career Advisers	Personalized guidance, progression rates

The data show that predictive analytics was primarily used for identifying at-risk students and guiding resource distribution. Schools emphasized early warning indicators to flag students who demonstrated patterns of disengagement, low attainment, or irregular attendance. Some schools used historical data in combination with teacher assessments to assign "risk scores," which were updated weekly or termly. These scores were then used to tailor interventions, such as academic tutoring, one-on-one mentoring, or targeted communications with parents or guardians.

Participants reported a range of experiences in interpreting and applying predictive insights. Interview data revealed that while school leaders found predictive models useful for strategic planning and intervention design, classroom teachers expressed caution. Some educators appreciated the efficiency of having risk indicators clearly flagged but emphasized the importance of triangulating these insights with contextual knowledge about students' personal and emotional circumstances. There was consensus that predictive data served best as a conversation starter rather than a prescriptive tool.

Staff training and data literacy emerged as key variables in how predictive analytics influenced practice. Schools with dedicated data leads or in-house analysts reported more confident and consistent use of predictive dashboards. In contrast, schools with limited analytic expertise faced challenges in interpreting model outputs and translating them into actionable strategies. Several respondents highlighted the need for more professional development tailored to bridging the gap between data analysis and pedagogical application.

Inferential analysis was limited due to the qualitative nature of the study, but frequency coding of interview transcripts showed strong thematic overlap between data-driven decision-making and early academic recovery outcomes. In four schools, participants explicitly linked the use of predictive alerts with reduced dropout rates in Year 11 and improved internal progress assessments. While causality could not be established, the reported correlation between data use and improved learner outcomes suggests that predictive analytics may play a supportive role in whole-school improvement frameworks.

Evidence of relational dynamics emerged in how predictive analytics facilitated cross-departmental collaboration. In several cases, data generated by analytics tools prompted joint meetings between academic and pastoral teams to discuss student profiles holistically. Predictive data encouraged shared accountability for student outcomes and enabled interdisciplinary approaches to intervention. Teachers and leaders emphasized that data was most valuable when interpreted collectively rather than in isolation.

One illustrative case from a school in Greater Manchester involved a shift in Year 10 math outcomes after predictive analytics identified a group of mid-range performers whose progress had plateaued. Teachers redesigned differentiated tasks and scheduled biweekly one-on-one feedback sessions for these students. Term-end assessments showed an average increase of 12% in math attainment among the identified group, which staff attributed to timely, data-informed adjustments in teaching. This case underscored how predictive insights can lead to proactive and responsive instructional design.

Another case from a rural school in Devon highlighted the challenges of applying predictive tools with limited staff training and infrastructure (Bonney-King et al., 2025; Borycka et al., 2025; Houston et al., 2025; Kidayi et al., 2025). Although the school used a standard predictive dashboard provided by their academy trust, teachers reported confusion about interpreting the risk scores and hesitated to use them for intervention planning. As a result, predictive analytics remained largely underutilized, and support decisions continued to rely on anecdotal teacher reports. The contrast between these cases reinforces the importance of system usability and user readiness in maximizing predictive value.

The results suggest that predictive analytics holds promise as a complementary decision-support tool rather than a deterministic system. Effective use depends heavily on the surrounding conditions: institutional culture, training, data quality, and collaborative interpretation. Participants agreed that while data can guide attention and resources, it should not replace professional judgment or overlook the complexity of student learning experiences.

In summary, predictive analytics in UK schools can enhance learning outcomes when integrated thoughtfully into educational processes. Its success lies not in automation but in informed human use—where insights are contextualized, ethically applied, and embedded within a collaborative, student-centered framework. Schools aiming to adopt predictive systems must prioritize both technical capacity and relational trust to ensure that the use of data remains aligned with educational values and learner equity.

The findings of this study demonstrate that predictive analytics, when embedded within well-supported institutional frameworks, can meaningfully contribute to improved learning outcomes in UK secondary schools (Dorathi Jayaseeli et al., 2025; Qader et al., 2025; Rubio-López et al., 2025). Schools using predictive models were able to identify at-risk students earlier, facilitate timely interventions, and encourage cross-departmental collaboration. Educators reported that predictive dashboards were particularly useful for visualizing student trajectories and guiding resource allocation. However, the study also revealed substantial variation in how effectively schools applied these tools, with the success of implementation closely tied to staff training, leadership support, and school-level data culture.

This research aligns with and extends existing literature on educational data use. Prior studies (e.g., Ifenthaler & Yau, 2020; Slade & Prinsloo, 2013) have emphasized the potential of learning analytics to enhance institutional responsiveness and learner support. Consistent with those findings, this study supports the notion that predictive analytics enables early identification of academic risks. Unlike much of the current literature that focuses on algorithmic design or policy-level applications, this study adds to the field by providing practical, school-based examples of how predictive models are interpreted and used by teachers, not just analysts or administrators. It also challenges assumptions that more data inherently leads to better outcomes, emphasizing the necessity of pedagogical alignment and professional interpretation.

The results signal an important shift in how educational institutions must view data-informed decision-making. Predictive analytics should not be seen as a stand-alone solution, but as part of a broader ecosystem that requires ethical stewardship, pedagogical coherence, and collaborative interpretation. The varied impact observed across cases suggests that data systems are only as effective as the human capacities and institutional cultures surrounding them. This reflects a growing recognition that digital transformation in education is not just a technical challenge, but a relational and cultural one. The findings serve as a reminder that technology alone cannot substitute for deep, sustained engagement with teaching and learning processes.

The implications of these findings are significant for both policy and practice. School leaders must ensure that predictive analytics initiatives are accompanied by professional development programs that build data literacy among educators. Investment in tools must be matched by investment in people who interpret and act on those tools. Developers of educational software must also prioritize usability, transparency, and adaptability to different school contexts. For policymakers, the findings suggest the need for national frameworks that promote ethical use, equity in access, and accountability without diminishing local autonomy. Predictive systems should support teacher agency, not replace it.

The differential effectiveness observed across case study schools can be attributed to several interrelated factors. In schools where leadership actively promoted a shared vision for data use and invested in building staff confidence, predictive tools became integrated into daily instructional practice (Ganiyu et al., 2025; Patwary & Sajib, 2025). In contrast, where training was minimal and data systems were introduced without clear pedagogical purpose, uptake was fragmented and inconsistent. The presence or absence of institutional readiness determined whether predictive analytics served as a catalyst for improvement or remained an unused resource. These patterns illustrate that successful implementation depends as much on culture and capacity as on the tools themselves.

Educator perceptions also shaped how predictive models were used. Teachers who trusted the data and understood its construction were more likely to engage with it constructively. Where there was skepticism or confusion, data remained peripheral to teaching decisions (Ghavami Hosein Pour et al., 2025; Ljungblad et al., 2025; Muthmainnah et al., 2025). This reinforces the importance of transparency in algorithmic design and the need for schools to include teachers in conversations about how predictive models are developed and interpreted. Trust, clarity, and usability are prerequisites for ensuring that predictive insights are translated into effective instructional strategies.

Future directions for schools adopting predictive analytics must focus on institutional coherence and inclusive design. Schools should involve educators in the selection and adaptation of predictive systems, ensuring alignment with their pedagogical goals and classroom realities. Capacity-building must go beyond technical training to include ethical reasoning, reflective practice, and dialogue about data use. Regular audits and feedback loops should be established to monitor the impact of predictive tools and adjust implementation strategies accordingly. Collaboration across departments and with external researchers can further enrich the school’s ability to evaluate and refine predictive practices.

Further research should explore student perspectives on predictive analytics, particularly how they experience being categorized by risk scores or targeted by data-informed interventions. Longitudinal studies could examine the long-term outcomes of predictive analytics on equity, learner agency, and educational attainment. Comparative studies across school systems would also help identify best practices and scalable models. This study lays the foundation for a more critical and context-aware approach to predictive analytics, emphasizing that enhancing learning outcomes depends not only on technological innovation, but on the human capacity to use it wisely and ethically.

CONCLUSION

The most important finding of this study is that predictive analytics can enhance learning outcomes in UK secondary schools when implemented within a supportive institutional context that prioritizes professional interpretation and ethical use. The study reveals that predictive models are most effective not when they dictate decisions, but when they serve as collaborative tools that prompt early intervention, strategic planning, and reflective dialogue among educators. This research offers a distinctive contribution by highlighting how the value of predictive analytics is mediated by school culture, staff capacity, and the degree of pedagogical alignment-factors that are often overlooked in more technical discussions.

This study contributes conceptually by framing predictive analytics as a socio-technical system embedded in real educational practices. It moves beyond common narratives that focus solely on algorithmic precision or system architecture and instead emphasizes the relational and interpretive processes that give predictive data meaning in school settings. Methodologically, the research advances the field by using a qualitative multiple case study approach that integrates interviews, document analysis, and observational data. This triangulation provides a more holistic understanding of the practical realities, barriers, and affordances associated with predictive tools in diverse school contexts. This study is limited by its focus on a relatively small number of case study schools, which may constrain the generalizability of findings to other educational settings or countries. It does not include student perspectives or quantitative measures of learning impact, which would provide a more comprehensive view of how predictive analytics influences educational experiences and outcomes. Future research should explore longitudinal effects of predictive system adoption, the ethical implications of student data use, and the impact of predictive interventions on learner agency and equity. Expanding inquiry to include diverse stakeholder voices-particularly students-will be crucial for shaping predictive systems that are not only effective, but also just and inclusive.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing; Conceptualization; Data curation; In-vestigation.

Author 2: Data curation; Investigation; Formal analysis; Methodology; Writing - original draft.

Author 3: Supervision; Validation; Other contribution; Resources; Visuali-zation; Writing - original draft.

REFERENCES

Alhwaiti, Y., Khan, M., Asim, M., Siddiqi, M. H., Ishaq, M., & Alruwaili, M. (2025). Leveraging YOLO deep learning models to enhance plant disease identification. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-92143-0

Bonney-King, J., Fischer, J., & Miller-Cushon, E. (2025). Effects of reward type and previous social experience on cognitive testing outcomes of weaned dairy calves. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-91843-x

Borycka, K., Młyńczak, M., Rosoł, M., Korzeniewski, K., Iwanowski, P., Heřman, H., Janku, P., Uchman-Musielak, M., Dosedla, E., Diaz, E. G., Sudoł-Szopińska, I., Mik, M., Ratto, C., & Spinelli, A. (2025). Detection of obstetric anal sphincter injuries using machine learning-assisted impedance spectroscopy: a prospective, comparative, multicentre clinical study. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-92392-z

Chandel, P., & Lim, F. V. (2025). Generative AI and Literacy Development in the Language Classroom: A Systematic Review of Literature. *Ubiquitous Learning*, *18*(2), 31–49. https://doi.org/10.18848/1835-9795/CGP/v18i02/31-49

Chandra, S. S., Kumar, R., Arjunasamy, A., Galagali, S., Tantri, A., & Naganna, S. R. (2025). Predicting the compressive strength of polymer-infused bricks: A machine learning approach with SHAP interpretability. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-89606-9

DeFeo, D. J., Gerken, S., Tran, T. C., Khodyakov, D., & Fink, A. (2025). General education biology labs: a Delphi study of student learning outcomes. *Discover Education*, *4*(1). https://doi.org/10.1007/s44217-025-00428-3

Dell, T., Voigt, M. B., Isaak, A., Boehner, A., Pieper, C., Mesropyan, N., Kupczyk, P., Luetkens, J., & Kuetting, D. (2025). Impact of robotic assistance on the learning curve in endovascular interventions: exploring the role of operator experience with the CorPath GRX system. *CVIR Endovascular*, *8*(1). https://doi.org/10.1186/s42155-025-00529-y

Dorathi Jayaseeli, J. D., Briskilal, J., Fancy, C., Vaitheeshwaran, V., Patibandla, R. S. M. L., Syed, K., & Swain, A. K. (2025). An intelligent framework for skin cancer detection and classification using fusion of Squeeze-Excitation-DenseNet with Metaheuristic-driven ensemble deep learning models. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-92293-1

Ganiyu, I. O., Plotka, G., Seuwou, P., & Ige-Olaobaju, A. (2025). Examining the use of LEGO Serious Play to enhance postgraduate research capacity. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-024-03930-5

Ghavami Hosein Pour, B., Karimian, Z., & Hatami Niya, N. (2025). A narrative review of advancing medical education through technology: the role of smart glasses in situated learning. *BMC Medical Education*, *25*(1). https://doi.org/10.1186/s12909-025-06949-7

Giesler, L. P., O'Brien, W. T., Bain, J., Spitz, G., Jaehne, E. J., van den Buuse, M., Shultz, S. R., Mychasiuk, R., & McDonald, S. J. (2025). Investigating the role of the brain-derived neurotrophic factor Val66Met polymorphism in repetitive mild traumatic brain injury outcomes in rats. *Behavioral and Brain Functions* , *21*(1). https://doi.org/10.1186/s12993-025-00270-5

Grosso, F. (2025). Integrating psychological and mental health perspectives in disease management: improving patient well-being. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-025-04359-0

Houston, N., Manrique, F., Mo, S., Ruoqian, W., Wenjing, J., & Yuting, L. (2025). Designing an effective educational toy: incorporating design-thinking in the design classroom. *Discover Education*, *4*(1). https://doi.org/10.1007/s44217-025-00402-z

Jiang, D., Wang, S., Xiao, Y., Zhi, P., Zheng, E., Lyu, Z., & Guo, Q. (2025). Risk factors and prediction model of metabolic disorders in adult patients with pituitary stalk interruption syndrome. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-91461-7

Karume, A. K., Sugut, J., Sankei, P., Kimathi, P. M., Guleid, A., Kimonge, D., Ebert, E., Wanjiku, G., Myers, J. G., & Beck, A. (2025). Improvement in clinician confidence in and knowledge of Diabetic Ketoacidosis management following a case-based curriculum in Kenya. *BMC Medical Education*, *25*(1). https://doi.org/10.1186/s12909-025-06898-1

Kidayi, P. L., Dausen, E. J., Ndile, M., Sixsmith, J., Mawona, Z. M., Berntsen, K., Manangwa, S. E., Smit, J. M., Rogathi, J., & de Zeeuw, J. (2025). Development of a training programme to improve health literacy and respectful compassionate care competencies among undergraduate student nurses: a quantitative study. *BMC Medical Education*, *25*(1). https://doi.org/10.1186/s12909-025-06894-5

Linardon, J. (2025). Navigating the Future of Psychiatry: A Review of Research on Opportunities, Applications, and Challenges of Artificial Intelligence. *Current Treatment Options in Psychiatry*, *12*(1). https://doi.org/10.1007/s40501-025-00344-1

Ljungblad, L. W., Murphy, D., & Fonkalsrud, H. E. (2025). A mixed reality for midwifery students:

a qualitative study of the technology's perceived appropriateness in the classroom. *BMC Medical Education*, *25*(1). https://doi.org/10.1186/s12909-025-06919-z

Mancilla, S., Wences, G., Hernández-López, E., & Cohen, I. (2025). Sub-spatial prediction of votes integrating socioeconomic, educational, and age strata with machine learning and topological data analysis. *Journal of Big Data*, *12*(1). https://doi.org/10.1186/s40537-025-01112-x

Muthmainnah, M., Cardoso, L., Marzuki, A. G., & Al Yakin, A. (2025). A new innovative metaverse ecosystem: VR-based human interaction enhances EFL learners' transferable skills. *Discover Sustainability*, *6*(1). https://doi.org/10.1007/s43621-025-00913-7

Ominyi, J., Nwedu, A., Agom, D., & Eze, U. (2025). Leading evidence-based practice: nurse managers' strategies for knowledge utilisation in acute care settings. *BMC Nursing*, *24*(1). https://doi.org/10.1186/s12912-025-02912-5

Palladino, P., Trotta, E., Bonvino, A., Carlucci, L., & Cottini, M. (2025). How do you feel during English class? Emotions and metacognition in primary school children learning English as a second language. *Metacognition and Learning*, *20*(1). https://doi.org/10.1007/s11409-025-09414-4

Patwary, M. N., & Sajib, M. N. F. (2025). Exploring Tertiary Students' Perceptions of Using Smartphones to Enhance EFL Writing: Pedagogical Implications. *International Journal of Technology, Knowledge and Society*, *21*(2), 51–72. https://doi.org/10.18848/1832-3669/CGP/v21i02/51-72

Qader, M. A., Hosseini, L., Abolhasanpour, N., Oghbaei, F., Maghsoumi-Norouzabad, L., Salehi-Pourmehr, H., Fattahi, F., & Sadeh, R. N. (2025). A systematic review of the therapeutic potential of nicotinamide adenine dinucleotide precursors for cognitive diseases in preclinical rodent models. *BMC Neuroscience*, *26*(1). https://doi.org/10.1186/s12868-025-00937-9

Rubio-López, A., García-Carmona, R., Zarandieta-Román, L., Rubio-Navas, A., González-Pinto, Á., & Cardinal-Fernández, P. (2025). Analysis of stress responses in medical students during simulated pericardiocentesis training using virtual reality and 3D-printed mannequin. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-92221-3

Seiler, J., Wetscher, M., Harttgen, K., Utzinger, J., & Umlauf, N. (2025). High-resolution spatial prediction of anemia risk among children aged 6 to 59 months in low- and middle-income countries. *Communications Medicine*, *5*(1). https://doi.org/10.1038/s43856-025-00765-2

Sirocchi, C., Urschler, M., & Pfeifer, B. (2025). Feature graphs for interpretable unsupervised tree ensembles: centrality, interaction, and application in disease subtyping. *BioData Mining*, *18*(1). https://doi.org/10.1186/s13040-025-00430-3

Sueda, T., Yasui, M., Nishimura, J., Kagawa, Y., Kitakaze, M., Mori, R., Matsuda, C., Ushimaru, Y., Sugase, T., Mukai, Y., Komatsu, H., Yanagimoto, Y., Kanemura, T., Yamamoto, K., Wada, H., Goto, K., Miyata, H., & Ohue, M. (2025). Learning curve analysis for prophylactic bilateral robot-assisted lateral lymph node dissection for lower rectal cancer: a retrospective study. *Techniques in Coloproctology*, *29*(1). https://doi.org/10.1007/s10151-025-03119-1

Yenew, C., Bayeh, G. M., Gebeyehu, A. A., Enawgaw, A. S., Asmare, Z. A., Ejigu, A. G., Tsega, T. D., Temesgen, A., Anteneh, R. M., Yigzaw, Z. A., Yirdaw, G., Tsega, S. S., Ahmed, A. F., & Yeshiwas, A. G. (2025). Scoping review on assessing climate-sensitive health risks. *BMC Public Health*, *25*(1). https://doi.org/10.1186/s12889-025-22148-x

Zhang, Z., Zhao, Y., Ma, Y.-J., Chen, C.-Q., Li, Z.-Y., Wang, Y.-K., Zhang, S.-J., Li, H.-M., Li, Y., Tian, Y., & Tian, H. (2025). Prediction of STAS in lung adenocarcinoma with nodules ≤ 2 cm using machine learning: a multicenter retrospective study. *BMC Cancer*, *25*(1). https://doi.org/10.1186/s12885-025-13783-z