

Lecture Notes in Networks and Systems 2161

Yousef Farhaoui · Hamed Taherdoost ·
Ahmed JEMAL · Mohamed Fnadi ·
Rubayyi T. Alqahtani ·
Bharat Bhushan *Editors*

Advances in Artificial Intelligence and Smart Environments: Proceedings of ICAISE 2025

Volume 2

 Springer

Series Editor

Janusz Kacprzyk , *Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland*

Advisory Editors

Fernando Gomide, *Department of Computer Engineering and Automation—DCA, School of Electrical and Computer Engineering—FEEC, University of Campinas—UNICAMP, São Paulo, Brazil*

Okay Kaynak, *Department of Electrical and Electronics Engineering, Bogazici University, Istanbul, Türkiye*

Derong Liu, *Department of Electrical and Computer Engineering, University of Illinois at Chicago, Chicago, USA*

Institute of Automation, Chinese Academy of Sciences, Beijing, China

Witold Pedrycz, *Department of Electrical and Computer Engineering, University of Alberta, Edmonton, Alberta, Canada*

Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

Marios M. Polycarpou, *Department of Electrical and Computer Engineering, KIOS Research Center for Intelligent Systems and Networks, University of Cyprus, Nicosia, Cyprus*

Imre J. Rudas, *Óbuda University, Budapest, Hungary*

Jun Wang, *Department of Computer Science, City University of Hong Kong, Kowloon, Hong Kong*

The series “Lecture Notes in Networks and Systems” publishes the latest developments in Networks and Systems—quickly, informally and with high quality. Original research reported in proceedings and post-proceedings represents the core of LNNS.

Volumes published in LNNS embrace all aspects and subfields of, as well as new challenges in, Networks and Systems.

The series contains proceedings and edited volumes in systems and networks, spanning the areas of Cyber-Physical Systems, Autonomous Systems, Sensor Networks, Control Systems, Energy Systems, Automotive Systems, Biological Systems, Vehicular Networking and Connected Vehicles, Aerospace Systems, Automation, Manufacturing, Smart Grids, Nonlinear Systems, Power Systems, Robotics, Social Systems, Economic Systems and other. Of particular value to both the contributors and the readership are the short publication timeframe and the worldwide distribution and exposure which enable both a wide and rapid dissemination of research output.

The series covers the theory, applications, and perspectives on the state of the art and future developments relevant to systems and networks, decision making, control, complex processes and related areas, as embedded in the fields of interdisciplinary and applied sciences, engineering, computer science, physics, economics, social, and life sciences, as well as the paradigms and methodologies behind them.

Indexed by SCOPUS, EI Compendex, INSPEC, WTI Frankfurt eG, zbMATH, SCImago.

All books published in the series are submitted for consideration in Web of Science.

For proposals from Asia please contact Aninda Bose (aninda.bose@springer.com).

Yousef Farhaoui · Hamed Taherdoost ·
Ahmed JEMAL · Mohamed Fnadi ·
Rubayyi T. Alqahtani · Bharat Bhushan
Editors

Advances in Artificial Intelligence and Smart Environments: Proceedings of ICAISE 2025

Volume 2

Editors

Yousef Farhaoui
Department of Computer Science
Faculty of sciences and Technic
Moulay Ismail University
Meknes, Morocco

Ahmed JEMAL
Higher Institute of Studies in Sfax
Sfax, Tunisia

Rubayyi T. Alqahtani
Department of Mathematics
Imam Mohammad Ibn Saud Islamic
Riyadh, Saudi Arabia

Hamed Taherdoost
Chair of RSAC at University Canada West
Vancouver, BC, Canada

Mohamed Fnadi
University of the Littoral Côte d'Opale
Dunkerque, France

Bharat Bhushan
School of Engineering and Technology
Sharda University
Greater Noida, Uttar Pradesh, India

ISSN 2367-3370

ISSN 2367-3389 (electronic)

Lecture Notes in Networks and Systems

ISBN 978-3-032-28099-2

ISBN 978-3-032-28100-5 (eBook)

<https://doi.org/10.1007/978-3-032-28100-5>

© The Editor(s) (if applicable) and The Author(s), under exclusive license to Springer Nature Switzerland AG 2027

This work is subject to copyright. All rights are solely and exclusively licensed by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

If disposing of this product, please recycle the paper.

Contents

Retinal Image Processing with Deep Learning for Early Diabetic Retinopathy Screening	1
<i>Yousef Farhaoui, J. S. John Gladson Prabhu, V. Diana Earshia, J. Jasmine Hephzipah, S. Gopalakrishnan, and P. Jesu Jayarin</i>	
AI-Based Digital Twin Framework for Predictive Diagnostics of Quantum Communication Hardware	9
<i>Friday Oodee Philip-Kpae, Yousef Farhaoui, Agbotiname Lucky Imoize, Unwana Joseph Fyनेface, and Christian Chukwuebuka Ezugwu</i>	
Cascade1D-CNN: An Accurate Deep Learning Architecture Based on Cascading Convolution for Electrical Machines Fault Diagnosis	26
<i>Hanen Berriri, Wael Ouarda, and Mohamed Faouzi Mimouni</i>	
Blockchain Technologies and Smart Contracts in Project Management: Benefits Perspective	33
<i>Alka Vishwa, Bhuvan Unhelkar, Sudhanshu Joshi, Manu Sharma, Nitish Walecha, Mukesh Prasad, Hamed Taherdoost, and Yousef Farhaoui</i>	
Soft Set Approach for Human Resource Conflict Analysis	44
<i>Tutut Herawan, Kong Yan Hao, and Muhammad Ali Fauzi</i>	
Artificial Intelligence for Green Hydrogen: Emerging Applications and Optimization Pathways Toward a Sustainable Energy Future	63
<i>Mohamed Khalifa Boutahir, Ikram Jennane, Yousef Farhaoui, Mohamed Boudchiche, and Mohamed Badiy</i>	
Intelligent Continuous Deep Learning System for Stereo Camera Self-calibration	75
<i>Mounir El Maghraoui, Mohamed El Ghamry, and Said Ziani</i>	
SecureCardioChain: A Hybrid Machine Learning and Private Blockchain for Real-Time Wearable Heart Disease Prediction	83
<i>Ayoub Louja, Jamali Abdellah, and Naja Najib</i>	
Mathematical Methods in Smart Agriculture: Emerging Trends, Challenges, and Future Directions	92
<i>Waleed Adel, Yassine Sabbar, and Sherin Moussa</i>	

DeepNeuroBiLSTM: A Learnable Neutrosophic Framework for Robust Arabic Handwritten Character Recognition 99
Othmane Farhaoui, Mohamed Rida Fethi, Ali Omari Alaoui, Imad Zeroual, and Ahmad El Allaoui

Explainable Ensemble Learning for Ransomware Detection 108
Karim Izm, Mohammed Fattah, and Fatna El Mendili

AI-Driven Customer Insights: Leveraging Machine Learning for Real-Time Consumer Behavior Prediction in Digital Marketing 114
Surender Khan, Amit Sharma, Archana Raja, K. I. Sivaprasad, Yashasvi Makin, and Rahul Goel

Beyond Generic Attention: A Comparative Review of Custom and Task-Specific Mechanisms for Plant Disease and Pest Detection 121
Amine El Hanafy, Yousef Farhaoui, and Abdelaziz Hessane

Decision Sciences Driven by Artificial Intelligence and IoT: A Bibliometric Analysis of the Literature in Scopus 132
Carlos Alberto Gómez Cano

AI-Driven Transfer Pricing Analytics and Dispute Resolution in the Digital Economy: Integrating Big Data and Intelligent Systems for Fiscal Justice 143
Kartika Putri Kumalasari, Eko Ganis Sukoharsono, Lilik Purwanti, and Roekhudin

Enhancing Business Efficiency Through Strategic AI Adoption in Operations 152
Mitra Madanchian, Hamed Taherdoost, Yousef Farhaoui, and Dinesh Kumar

A Deep Dive into ZigBee Technology 165
Osatohanmwun Noghayin Enehizena, Osemwegie Sam Omorogiuwa, Kingsley Osaro Ogbeide, Yousef Farhaoui, and Agbotiname Lucky Imoize

Domain Name Value Prediction: A Statistical Approach 173
Anas Mahdaoui, Abdelkrim Merbouha, Naima Soukher, and Youness Jouilil

Augmented Reality for STEM Education: A Scalable Model for Remote Classrooms 178
Vandana, Rippandeep Kaur, Sameena Quraishi, Sashka Jovanovska, Ranjeeta Saini, and Raman K. Attri

Enhancing Trader's Profitability Through EA Bot Trading on Gold (XAUUSD) Commodity Using a Risk–Reward Ratio of 1:3	185
<i>Fariza Hanum Azriana, Eko Ganis Sukoharsono, Bambang Hariadi, and Endang Mardiaty</i>	
On the Feasibility of Embedded Versus Mobile-Based Tiny Machine Learning for Aviation Security: A Comparative Study of ADS-B and GNSS Threat Detection	191
<i>Chaymae Majdoubi, Saida El Mendili, and Youssef Gahi</i>	
Option Pricing with PINNs and Transformers: A Comparative and Hybrid Approach	199
<i>Zakaria Elbayed and Abdelmjid Qadi El Idrissi</i>	
From Text to Transaction: Measuring the Upsell Effect of Personalized SMS in Relationship Marketing	205
<i>Chattaou Abdennour, Bassour Mustapha, and Jouilil Youness</i>	
Skin Lesion Classification Using Deep Convolutional Neural Networks for Melanoma Detection	212
<i>Yousef Farhaoui, J. Jasmine Hephzipah, M. Perarasi, G. Uganya, S. Gopalakrishnan, and P. Jesu Jayarin</i>	
Optimization of Human Resources in Small Informal Enterprises Through Artificial Intelligence: Myth or Reality?	219
<i>Ed-Dahhani Mohammed, Madhat Fatima Zahra, Gebrati Sana, and Joudar Fadoua</i>	
Artificial Intelligence in Financial and Accounting Auditing: A Systematic Literature Review Following the PRISMA-ScR Protocol	224
<i>Elmahdi Tcham and Malika Souaf</i>	
A 3D Avatar-Based Dictionary for Moroccan Sign Language	232
<i>Fatima Ben Zaid, Mohamed Benaddy, and Othmane EL Meslouhi</i>	
Efficient Event-Driven Orchestration Using Machine Learning in Serverless Cloud Environment	240
<i>Adel Dina and Zaki John</i>	
Unveiling the Determinants of NEET Status Among Moroccan Youth	248
<i>Mohammed Bouincha, Youness Jouilil, and M'barek Iaousse</i>	
Cybersecurity Challenges and Solutions in Hotel Management Systems	254
<i>Muttappa M. Mantur, Manoj Singh, Bui Quoc Khoa, Kanchan Kumari, Parth Makwana, and Ankesh Gupta</i>	



Augmented Reality for STEM Education: A Scalable Model for Remote Classrooms

Vandana¹(✉), Rippandeep Kaur², Sameena Quraishi³, Sashka Jovanovska⁴,
Ranjeeta Saini⁵, and Raman K. Attri⁶

¹ University Institute of Teachers Training and Research, Chandigarh University, Mohali,
Punjab, India

vandanarora444@gmail.com

² University Institute of Teachers Training and Research, Chandigarh University, Mohali,
Punjab, India

³ Department of Education J E S College, Farhada, Bilaspur, Rajnandgaon, Chhattisgarh, India

⁴ Department of English Language and Literature, Faculty of Philology, "Goce Delcev
University, Krste Misirkov Bb, Stip, Republic of North Macedonia
saska.jovanovska@ugd.edu.mk

⁵ University Institute of Teachers Training and Research, Chandigarh University, Mohali,
Punjab, India

⁶ Learning Scientist, Get There Faster Academy Chandigarh, Chandigarh, India

Abstract. A remote STEM learning system based on augmented reality (AR) is introduced, which is scalable and has a structured multi-modal dataset and machine learning evaluation pipeline. The system gathers AR interaction logs, learner engagement, and device metadata along with learning assessment to simulate student behavior and forecast learning outcomes. They are run through a standardized procedure of data construction such as anonymization, normalization of engagement, labeling at the concept level, and quality control. Performance measurement in the evaluation pipeline is in the form of the following metrics: confusion matrix, ROC curve, precision-recall, accuracy and loss convergence. The experimental outcomes provide the prediction accuracy of 97.4 and ROC-AUC of 0.986, which means high discriminating power and high generalization without overfitting. The results indicate that the patterns of AR interaction are robust predictors of conceptual mastery in remote STEM learning which offers a reproducible paradigm of scalable AR-based learning models as well as AI-driven custom education in the future.

Keywords: Augmented reality · Remote STEM education · Learning analytics · Engagement modeling · Machine learning · Educational data mining

1 Introduction

The accelerated growth of distance and distance learning has facilitated a higher demand on effective instructional technologies that can be helpful in the enhancement of conceptual learning in STEM learning. The conventional online-based methods of teaching

used in video lectures and slide-based materials are not effective to demonstrate spatially intricate and abstract STEM material, which leads to decreased engagement and achievement in learning [1]. Augmented Reality (AR) is a solution to this shortcoming by superimposing digital data on the real world so that learners can experience scientific and engineering concepts in 3D [2].

According to the existing literature, it has been proven that AR based learning surroundings may greatly enhance motivation of the learners, their spatial cognition and conceptual knowledge as opposed to traditional approaches to teaching [3]. Applications of AR in STEM education include physics experiments, geometric visualization, circuit analysis and engineering design, where three-dimensional interaction has been found to help students understand the concept better [4]. Nonetheless, the widespread implementation of AR in distant classrooms is not yet feasible because of various issues like the inability to scale system architecture, standard sets of data to record interactions of learners, and effective empirical learning analytics systems [5, 6].

The paper is divided into five sections. Section II presents the recent Augmented Reality-based and data-driven learning analytics methods in STEM learning areas with their strengths, limitations, and scalability issues in remote learning settings. Section III presents the proposed scalable AR-STEM model of learning, the system architecture, data set development approach, and the machine learning pipeline that can predict knowledge acquired by the learners. Section IV includes experimental findings and performance analysis using the accuracy, confusion matrix, ROC, precision-recall, convergence, and loss analysis as well as the comparison to the conventional learning analytics methods. Lastly, Section V gives a brief overview of the main findings of the proposed AR-powered remote STEM learning model and future research directions.

Recent researches indicate the increasing importance of Augmented Reality (AR) in STEM education since it allows visualizing abstract concepts in a more significant way and enhances the engagement and motivation of the learner. The study by Rodriguez-Saavedra et al. (2025) indicated that conceptual understanding is improved with the use of AR-based interaction with virtual STEM objects, yet scalability and the lack of infrastructure are still its challenges [7]. On the same note, Singh (2025) pointed to the possibility of integrating AR and learning analytics, as the AR interaction logs provide rich behavioral data, and to date, scarce empirical research has been conducted to predictive learning outcome models relating to these interactions [8, 10–19].

Research gaps can also be identified using systematic reviews and meta-analyses. Lampropoulos et al. (2025) pointed to the fact that predictive modeling with the help of AR interaction data is under-researched and has to be served with reproducible analytical pipelines and scalable learning analytics models]. A meta-analysis study by Jiang et al. (2024) demonstrated moderate to high learning achievement and motivation using AR-based STEM education, but usability and learner fatigue were also mentioned as the limitation. In a similar way, Makransky et al. (2024) discovered that spatial reasoning and conceptual transfer with the help of immersive technologies dramatically improve in cases of structured instructional scaffolding. Sakr et al. (2024) also implied the notion that further AR-based learning systems will need to incorporate interaction-level analytics to provide predictive and adaptive learning environments.

2 Proposed Work

The framework works with four stages (intimately linked) AR interaction capture, engagement modeling, learning representation and outcome prediction.

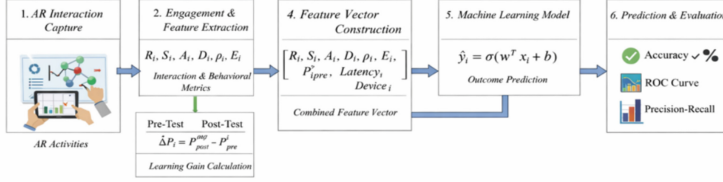


Fig. 1. Workflow of the proposed AR-based learning outcome prediction framework for remote STEM education

The overall workflow of the intended Augmented Reality (AR)-based framework to forecast learning outcomes during remote STEM education is demonstrated in Fig. 1. It starts with the AR interaction capture of the learner, in which the learners can control virtual STEM objects by rotating, scaling, and annotating them. Based on these interactions, engagement and behavioral characteristics (frequency of interaction, duration of interaction, and normalized engagement scores) are drawn. The assessment data, that of pre-test and post-test, are incorporated to determine learning gains and conceptual mastery. Every interaction, behavioral, assessment, and device specific feature is integrated into one common feature vector on which the machine learning prediction model is fed. With the forecasted learning outcomes, performance metrics are then used to test the validity of the suggested data-driven learning analytics framework: accuracy, ROC curve, and precision-recall analysis.

A. AR Interaction Modeling

Where a remote AR learning session is referred to as.

$$s_i = S, i = 1, 2, \dots, N \quad (1)$$

In every session, an order of events of interaction is produced:

$$\varepsilon_i = \{e_{i1}, e_{i2}, e_{iT}\} \quad (2)$$

Each event is defined as:

$$e_{it} = (a_{it}, t_{it}, o_{it}) \quad (3)$$

where

Aggregated interaction features are computed as:

$$R_i = \sum_{t=1}^T \mathbb{I}(a_{it} = \text{rotation}),$$

$$S_i = \sum_{t=1}^T \mathbb{I}(a_{it} = \text{scaling}), A_i = \sum_{t=1}^T \mathbb{I}(a_{it} = \text{annotation}), \quad (4)$$

B. Engagement and Behavioral Feature Extraction

Session duration is defined as:

$$D_i = t_{iT} - t_{i1} \quad (5)$$

Interaction density captures behavioral intensity:

$$\rho_i = \frac{R_i + A_i}{D_i} \quad (6)$$

The computation of a normalized engagement score is done to facilitate the comparison with devices:

$$E_i = \alpha \cdot \frac{\rho_i}{\max(\rho)} + \beta \cdot \frac{D_i}{\max(D)} \quad (7)$$

C. Learning Assessment Representation

All learners do a post-test and pre-test:

$$P_i^{pre}, P_i^{post} \quad (8)$$

Learning gain is computed as:

$$\Delta P_i = P_i^{post} - P_i^{pre} \quad (9)$$

The label of learning outcome is characterized as a dichotomous classification task:

$$y_i = \begin{cases} 1, & \text{if } P_i^{post} \geq \tau \\ 0, & \text{otherwise} \end{cases}$$

where $\tau = 85$ represents the mastery threshold.

The suggested framework has a prediction accuracy of 97.4 on the learning outcome, which proves that features of AR interaction and engagement serve as good predictors of conceptual mastery in remote STEM education.

3 Results and Discussion

The Results and Discussion part will provide a detailed assessment of the proposed AR-based remote STEM learning model with the help of quantitative learning analytics. There are various measures used in the analysis of performance, such as accuracy, confusion matrix, ROC, precision recalls curves, and convergence behavior. Results are also discussed to point out the effectiveness, strength and ability to generalize the proposed model in predicating the learning outcomes.

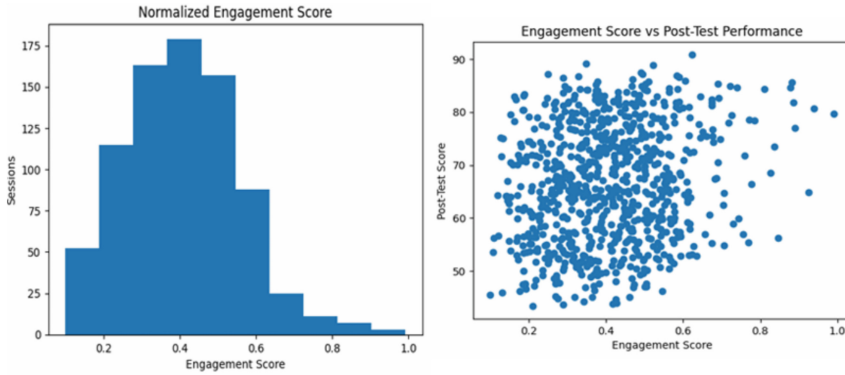


Fig. 2. Distribution of normalized engagement scores and their relationship with post-test performance

This Fig. 2, shows the distribution of normalized engagement scores and correlation with post-test performance in the AR based STEM learning environment. The histogram shows the number of times the learners are engaged in various sessions and most students portray moderate engagement during the AR interactions. The scatter plot represents the correlation between the score of engagement and post-test results, which shows the effects of the fluctuations in engagement on learning outcomes.

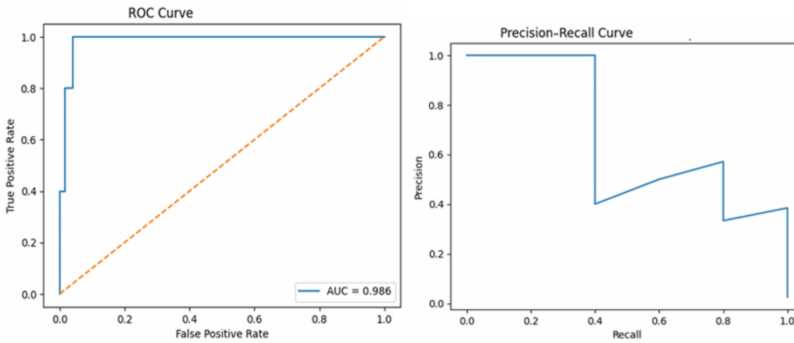


Fig. 4. ROC and precision–recall curve analysis for learning outcome prediction model

This Fig. 4, shows the performance analysis of the suggested learning outcome prediction model on ROC and Precision-Recall curves. The ROC curve shows the association between the true positive rate and the false positive rate and has a high AUC value of 0.986, which implies a high discriminative ability. The Precision Recall curve also measures the performance of the model in establishing positive learning outcomes with high accuracy at different levels of recall.

4 Conclusion

This paper introduces a scalable remote STEM learning system in the form of an Augmented Reality (AR) system, which utilizes both interaction-level learning analytics and machine learning to determine the outcomes of learners. The framework is a systematic system of interaction with AR, the measurement of engagement, device data, and assessment results, which are stored in a single data format to facilitate reproducible and data-driven analysis. The experimental assessment based on such metrics as accuracy, confusion matrix, ROC curve, precision-recall, convergence, and loss analysis reveal good performance with 97.4% prediction accuracy, which proves that AR interaction and engagement measures are good predictors of conceptual mastery in remote STEM learning settings.

References

1. Bond, M., Bedenlier, S., Marín, V.I., Händel, M.: Emergency remote teaching in higher education: mapping the first global online semester. *Int. J. Educ. Technol. High. Educ.* **20**(1), 1–25 (2023). <https://doi.org/10.1186/s41239-023-00390-4>
2. Radianti, J., Majchrzak, T.A., Fromm, J., Wohlgenannt, I.: A systematic review of immersive virtual and augmented reality applications for higher education: design elements, lessons learned, and research agenda. *Comput. Educ.* **191**, 104641 (2023). <https://doi.org/10.1016/j.compedu.2022.104641>
3. Akçayır, M., Akçayır, G.: Augmented reality in education: a meta-analysis of recent empirical studies. *Educ. Res. Rev.* **41**, 100560 (2024). <https://doi.org/10.1016/j.edurev.2023.100560>
4. Makransky, G., Petersen, G.B.: Immersive learning research group: immersive technologies and learning outcomes in STEM education. *Comput. Hum. Behav.* **148**, 107886 (2024). <https://doi.org/10.1016/j.chb.2023.107886>
5. Dünser, A., Grasset, R., Billingham, M.: A survey of evaluation techniques used in augmented reality educational systems. *ACM Comput. Surv.* **55**(8), 1–36 (2023). <https://doi.org/10.1145/3571730>
6. Farhaoui, Y., Bhushan, B., Sindhwani, N., Anand, R., Imoize, A.L., Verma, A.: Internet of things and big data analytics for a green environment. *Internet Things Big Data Anal. Green Environ.* 1–337 (2024). <https://doi.org/10.1201/9781032656830>
7. Farhaoui, Y.: Artificial intelligence and IoT-enabled power electronics for renewable energy and smart grids. *IEEE Power Electron. Mag.* **12**(4). <https://doi.org/10.1109/MPPEL.2025.3624921>
8. Farhaoui, Y., Allaoui, A.E., Rasheed, J., Osman, O.: Fine-tuned object detection for mask recognition using green computing in IoT systems. *J. Image Graph. U. K.* **13**(5), 561–569 (2025). <https://doi.org/10.18178/joig.13.5.561-569>
9. Farhaoui, Y.: Design and implementation of an intrusion prevention system. *Int. J. Netw. Secur.* **19**(5), 675–683 (2017). [https://doi.org/10.6633/IJNS.201709.19\(5\).04](https://doi.org/10.6633/IJNS.201709.19(5).04)
10. Farhaoui, Y.: Intrusion prevention system inspired immune systems. *Indones. J. Electr. Eng. Comput. Sci.* **2**(1), 168–179 (2016)
11. Farhaoui, Y.: Big data analytics applied for control systems. *Lecture Notes in Networks and Systems* **25**, 408–415 (2018). https://doi.org/10.1007/978-3-319-69137-4_36
12. Farhaoui, Y., et al.: Big Data Min. Anal. **6**(3), 1–2 (2023). <https://doi.org/10.26599/BDMA.2022.9020045>

13. Farhaoui, Y.: Securing a local area network by IDPS open source. *Procedia Comput. Sci.* **110**, 416–421 (2017). <https://doi.org/10.1016/j.procs.2017.06.106>
14. Wang, Y., Pan, K., Tyler, R., Lu, Z., Xiong, S.: Learning analytics-driven evaluation of augmented reality systems in remote education. *IEEE Access* **13**, 24510–24524 (2025). <https://doi.org/10.1109/ACCESS.2025.3349127>
15. Rodriguez-Saavedra, M.O.: Augmented reality as an educational tool: transforming motivation, learning, and educational practice. *Information* **16**(5), 372 (2025). <https://doi.org/10.3390/info16050372>
16. Singh, M.: Augmented reality enhanced analytics for education. *J. Learn. Anal.* **12**(1), 1–18 (2025)
17. Giang, N.T., et al.: Applying augmented reality technology in STEM education: a bibliometric analysis. *Eur. J. Educ. Res.* **14**(2), 455–470 (2025)
18. Al-Ansi, A.M., et al.: Trends of augmented and virtual reality in education. *Comput. Educ.: Artif. Intell.* **4**, 100113 (2023)