Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

Mapping the Research Landscape of Artificial Intelligence Innovation for Dropout Prevention and Learning Opportunity Loss Mitigation Policy

Iik Nurulpaik*, Ahmad Satibi, Encep Supriatna, Oki Suprianto
Universitas Pendidikan Indonesia.
*****Corresponding Author. Email: iik.nurulpaik@upi.edu

Abstract: This study aims to map the research landscape of Explainable Artificial Intelligence (XAI) for dropout prevention and learning loss mitigation. The study employed bibliometric science mapping to identify publication trends, conceptual structures, and emerging research directions. A Scopus search using the query TITLE-ABS-KEY("Explainable Artificial Intelligence" OR "Explainable AI") AND TITLE-ABS-KEY(Dropout OR "Learning Loss Mitigation") initially returned 207 records. No restrictions on language, document type, or publication year were applied during the retrieval process. Seven records with missing author metadata were excluded, leaving 200 documents published between 2020 and 2026 for analysis using Biblioshiny and VOSviewer. The results revealed rapid publication growth, with an annual growth rate of 57.04%, peaking in 2025 with 99 publications. Dominant themes included deep learning, explainable AI, learning systems, machine learning, dropout prediction, SHAP, LIME, interpretability, and uncertainty, while three broad conceptual clusters centered on deep learning, explainable artificial intelligence, and contrastive learning. Learning loss mitigation did not form a stable research cluster, indicating that the field has progressed more rapidly in explaining dropout prediction than in establishing connections between XAI and longitudinal learning decline. Theoretically, this study identifies a research agenda that integrates learning loss indicators with explainability, uncertainty, and fairness. Practically, it suggests that education policymakers should prioritize human-supervised early-warning systems whose explanations can be translated into timely and actionable interventions.

Article History
Received: 07-06-2026
Revised: 14-07-2026
Accepted: 30-08-2026
Published: 20-09-2026

Key Words:
Artificial Intelligence; Bibliometric Analysis; Dropout Prevention; Explainable Artificial Intelligence; Learning Loss Mitigation.

How to Cite: Nurulpaik, I., Satibi, A., Supriatna, E., & Suprianto, O. (2026). Mapping the Research Landscape of Artificial Intelligence Innovation for Dropout Prevention and Learning Opportunity Loss Mitigation Policy. *Jurnal Kependidikan : Jurnal Hasil Penelitian Dan Kajian Kepustakaan Di Bidang Pendidikan, Pengajaran, Dan Pembelajaran*, *12*(3), 1379-1389. https://doi.org/10.33394/jk.v12i3.21069

https://doi.org/10.33394/jk.v12i3.21069

Introduction

School dropout and learning loss are closely linked policy concerns because both undermine educational equity, student progression, and long-term human-capital development. Dropout risk reflects academic performance, attendance, socioeconomic conditions, engagement, family support, and school attachment, with evidence also showing heterogeneity across gender and financial circumstances (Bayrakceken et al., 2025; Košir et al., 2025; Biswas & Bhattacharya, 2025; Roman et al., 2022). Post-pandemic disruption further intensified concern about interrupted learning, uneven recovery, and disengagement (Harmey & Moss, 2023; Gicheva et al., 2025; Togo et al., 2025). These problems create a need for predictive Artificial Intelligence (AI) that can identify risk early from heterogeneous educational data and support timely intervention (Sajja et al., 2025). Yet conventional high-performing AI models can be difficult to interpret and may reproduce bias when sensitive or unevenly represented student attributes influence predictions (Cheniti-Belcadhi et al., 2025; Tariq et al., 2025).

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

Explainable Artificial Intelligence (XAI) addresses these limitations by making model reasoning, influential features, and prediction logic more understandable to human users (Minh et al., 2022; Dwivedi et al., 2023). In education, this matters because AI outputs may affect decisions about academic support, counseling, retention, and resource allocation. Global and local explanation methods can make student-performance predictions more interpretable, but the use of sensitive attributes also creates a need to examine why particular variables influence risk estimates and whether those influences are educationally defensible (Adnan et al., 2022; Deho et al., 2023). Accordingly, XAI shifts attention from predictive accuracy alone toward transparency, fairness, accountability, and actionable explanations that teachers and policymakers can scrutinize before intervention (Nagy & Molontay, 2024). Human-machine collaboration is especially relevant at the school level because risk scores should inform professional judgment rather than replace it (Bulut et al., 2024).

The rapid growth of AI in education has also produced a fragmented evidence base. Existing bibliometric studies have mapped AI in computational thinking, broad educational applications, STEM classrooms, and sustainable education (Al Husaeni et al., 2025; Chen et al., 2023; Fu et al., 2025; Tsakeni et al., 2025; Abulibdeh, 2025), but they do not specifically show how XAI, dropout prevention, and learning loss are connected within the same knowledge structure. This gap is important because dropout prediction is increasingly explainable, whereas learning loss is usually examined as a separate pedagogical or post-disruption problem rather than as an input to transparent early-warning systems.

Accordingly, this study maps the research landscape of XAI in relation to school dropout prevention and learning loss mitigation. The novelty of this study lies in integrating three streams that have largely developed separately and in identifying where their conceptual links remain weak. The analysis focuses on publication growth, dominant keywords, co-occurrence structure, thematic evolution, and future directions, with the broader objective of informing XAI-based early-warning systems that are not only predictive but also interpretable, fair, and usable for educational intervention.

Research Method

This study employed bibliometric science mapping to identify publication trends, conceptual structures, and emerging research directions. Scopus was used because it provides standardized bibliographic metadata across disciplines and supports reproducible bibliometric analysis (Singh et al., 2021). Data were retrieved with the query TITLE-ABS-KEY("Explainable Artificial Intelligence" OR "Explainable AI") AND TITLE-ABS-KEY(Dropout OR "Learning Loss Mitigation"). The search was not restricted by year so that the temporal range would emerge from the indexed records; the resulting publications spanned 2020-2026.

The initial retrieval produced 207 documents. No language or document-type filter was imposed at the search stage. Metadata were then checked for author, affiliation, source, year, keyword, abstract, and citation completeness. Seven records with empty author metadata were excluded because they could not be used reliably in author and collaboration analyses, yielding a final dataset of 200 documents. This broad-recall strategy was retained to avoid prematurely excluding relevant XAI work, but it also allowed a small amount of cross-domain keyword noise, which is addressed in the interpretation of the results.

VOSviewer was used for author-keyword co-occurrence mapping. Keywords were required to occur at least five times (n >= 5); full counting was applied, link strengths were normalized using Association Strength, and clusters were generated with the VOS clustering

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

procedure at the default resolution setting (1.00). These parameters were selected to retain recurring concepts while limiting isolated low-frequency terms.

Biblioshiny was used for descriptive statistics, trend topics, thematic mapping, and thematic evolution (Lim et al., 2024). The Thematic Map used authors' keywords (DE), up to 250 terms, a minimum cluster frequency of 5, no stemming, Louvain community detection, label size 0.3, three labels per cluster, and label repulsion enabled. Thematic evolution used the same keyword field and minimum frequency across four time slices (2020-2022, 2023, 2024-2025, and 2026). Results were interpreted substantively rather than treating every automatically generated term as an educational theme.

Table 1. Summary of the final document of the analyzed search results

Indicator	Value
Timespan	2020–2026
Sources	162
Documents	200
Annual Growth Rate	57.04%
Authors	780
Author’s Keywords (DE)	660
Average citations per doc	4.475

Results and Discussion

1) Publication Development Trends

Publication output accelerated sharply after 2023. The dataset contained 3 documents in 2020, 8 in 2022, 10 in 2023, 35 in 2024, and 99 in 2025; the 45 records indexed for 2026 should be read as a partial-year count. The annual growth rate of 57.04% indicates that explainability has rapidly moved into the mainstream of AI-based academic-risk research. Substantively, this growth reflects a transition from asking whether a model can identify at-risk students to asking whether schools can understand and responsibly act on the model's prediction.

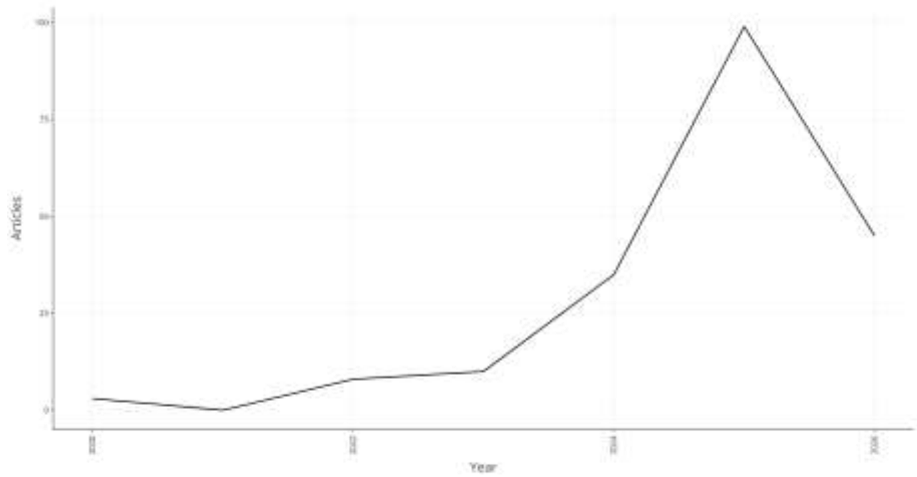

Figure 1. Annual Scientific Production in the XAI research landscape, school dropout, and learning loss

This shift is consistent with the chronological development of explainable academic-risk research. Early studies demonstrated interpretable deep-learning approaches for dropout prediction and called for student-performance models whose decisions could be inspected (Baranyi et al., 2020; Chitti et al., 2020). Subsequent work extended interpretability to MOOC dropout and personalized intervention (Khan et al., 2023; Nagy & Molontay, 2024),

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

while recent studies apply XAI to dropout risk in different institutional and national settings (Mustofa et al., 2025; Albugami et al., 2026; Barboza et al., 2026). The main implication of the publication trend is therefore not simply quantitative growth, but a stronger expectation that academic-risk models must support transparent educational decisions.

The policy significance of this transition is that explainability is increasingly being connected with actionability. Studies that combine human and machine insights, explainable prediction of academic performance, and predictive models for identifying at-risk students show a movement toward decision support rather than stand-alone classification (Bulut et al., 2024; Paul et al., 2025; Salmon & Elyjoy, 2025). At the same time, the literature warns that explanation quality cannot be separated from predictive performance; educational systems need a defensible balance between accuracy and interpretability so that interventions remain both technically credible and understandable to users (Zanellati et al., 2024).

2) Network Trends and Analysis by Theme

Keyword analysis was dominated by deep learning (92 occurrences), explainable AI (80), learning systems (73), explainable artificial intelligence (58), and machine learning (54). These frequencies show that the field remains computationally driven but increasingly connects predictive modeling with interpretability and learning-system applications. The co-occurrence map organizes this landscape into three broad communities centered on deep learning, explainable AI/learning systems, and explainable artificial intelligence with decision-making and uncertainty.

The educationally most relevant community links explainable AI with students, forecasting, dropout prediction, interpretability, SHAP, LIME, educational data mining, predictive analytics, and risk assessment. This pattern indicates that XAI is becoming a bridge between student-risk classification and intervention design: schools need not only a probability of dropout, but also understandable information about the academic and non-academic factors driving that probability (Nagy & Molontay, 2024; Mustofa et al., 2025; Paul et al., 2025; Salmon & Elyjoy, 2025).

The remaining clusters add two complementary concerns. Deep-learning terms emphasize the need to explain complex models that are otherwise difficult for educational users to inspect, while decision-making, uncertainty, and robustness terms shift attention toward the reliability of explanations used for intervention. Explainable pipelines and global/local explanations are increasingly used to make dropout predictions more actionable and to reduce the risk that a technically strong model becomes an opaque decision rule (Adnan et al., 2022; Bettahi et al., 2025; Camargos & Silveira, 2025; Tiukhova et al., 2024). This concern is reinforced by research showing that sensitive attributes require explicit justification in learning analytics and that performance-explainability trade-offs should be evaluated rather than assumed away (Deho et al., 2023; Zanellati et al., 2024).

Together, these clusters suggest that the field is moving from prediction-centered AI toward decision-support systems in which predictive performance, interpretability, and accountability are treated as interdependent requirements.

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

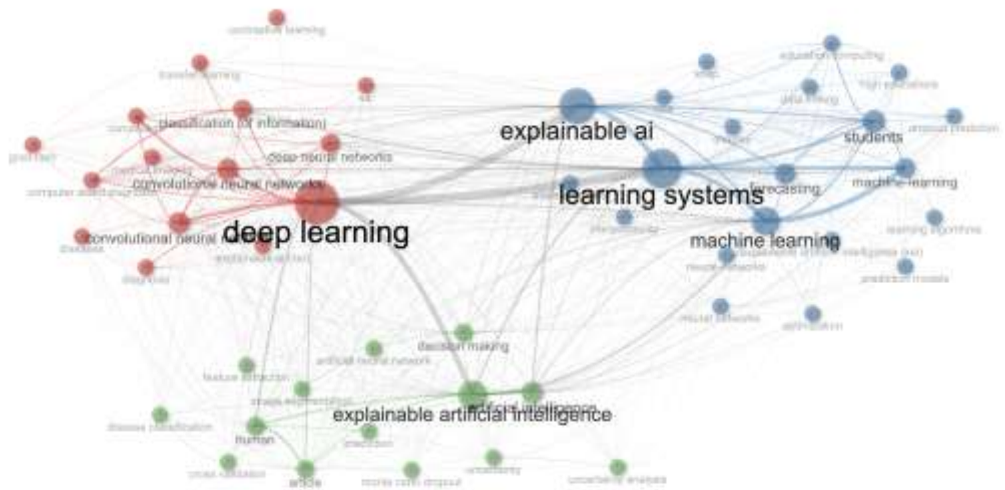

Figure 2. Co-Occurrence Network Visualization by Keywords in the XAI research landscape, school dropout, and learning loss

Trend-topic analysis (Table 2) reinforces this transition. Contrastive learning, adversarial machine learning, and decision support systems were concentrated around 2024; deep learning, explainable AI, and learning systems became dominant in 2025; and statistical tests and uncertainty quantification shifted toward 2026. The progression indicates movement from model development toward validation, reliability, and decision support rather than a simple replacement of one algorithm by another.

Two peripheral terms require caution. The keyword "female" in Table 2 and "remote sensing" in the 2026 thematic evolution are not interpreted as core educational themes. The former is plausibly linked to records examining gender heterogeneity in dropout and post-pandemic academic recovery, where female is used as a demographic descriptor or analytic subgroup (Biswas & Bhattacharya, 2025; Gicheva et al., 2025). By contrast, "remote sensing" is not substantively aligned with the educational focus. Both terms entered because the Scopus query deliberately used the broad term "dropout" without subject-area, language, or document-type restrictions. In multidisciplinary indexing, "dropout" can describe demographic attrition or technical/modeling processes beyond student dropout, allowing low-frequency cross-domain terms to enter the network. Their appearance therefore illustrates residual retrieval noise and the recall-precision trade-off of the broad search strategy; it also supports the need for domain validation in future bibliometric searches. Within the education-focused terms, uncertainty quantification is especially important because a school intervention should depend not only on a risk score but also on how confident and stable that prediction is. Recent explainable and hybrid dropout models similarly emphasize interpretable risk factors and model reliability rather than accuracy alone (Waseem et al., 2026; Tiukhova et al., 2024).

Table 2. Topic trends in the XAI research landscape, school dropout, and learning loss

Term	Frequency	Year (Q1)	Year (Median)	Year (Q3)
contrastive learning	10	2024	2024	2025
adversarial machine learning	9	2024	2024	2025
decision support systems	7	2024	2024	2025
deep learning	92	2025	2025	2025
explainable ai	80	2024	2025	2025
learning systems	73	2025	2025	2026
statistical tests	12	2025	2026	2026
female	10	2025	2026	2026

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

uncertainty quantification	8	2025	2026	2026

3) Evolution of Research Themes

Figure 3 shows a clear thematic evolution. In 2020-2022, artificial intelligence, deep learning, forecasting, and XAI reflected an early emphasis on prediction and initial interpretability, consistent with interpretable dropout modeling in higher education (Baranyi et al., 2020). In 2023, learning systems, students, and machine learning became more explicit, indicating closer alignment with educational data and explainable MOOC prediction (Khan et al., 2023). During 2024-2025, explainable AI and decision-making moved toward the center of the field, consistent with research that treats explanations as a basis for intervention rather than as a purely technical add-on (Melo et al., 2022; Nagy & Molontay, 2024). By 2026, uncertainty, statistical testing, and model-validation terms became more visible, indicating increased concern with whether explanations and predictions are dependable enough for institutional use (Tiukhova et al., 2024).

The presence of "remote sensing" in the final time slice should be read as the same cross-domain retrieval effect noted for "female" rather than as evidence that remote sensing has become an educational research priority. Because automated thematic evolution inherits the vocabulary of the full dataset, a small number of peripheral multidisciplinary records can generate visually noticeable labels. Retaining and explicitly qualifying these terms is preferable to silently deleting them after analysis, but it is also a methodological limitation of the broad search strategy.

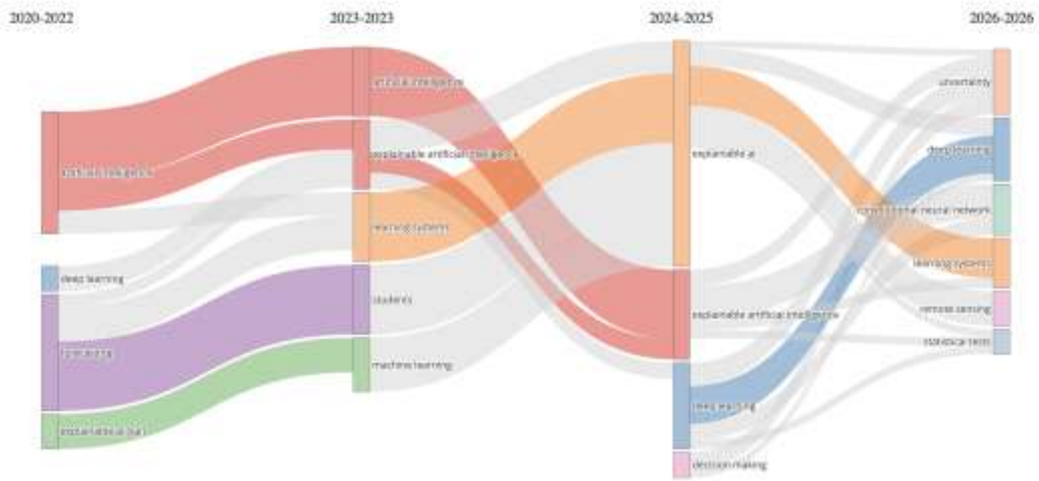

Figure 3. Thematic Evolution in the XAI research landscape, school dropout, and learning loss

4) Opportunities and Directions for Future Research

The research landscape points to a practical next step: XAI-based early-warning systems should connect risk prediction with local and global explanations, uncertainty estimates, fairness checks, and intervention options. SHAP, LIME, counterfactual explanations, and feature importance can make risk signals interpretable, while stability analysis and subgroup evaluation can reduce the chance that schools act on fragile or biased predictions (Adnan et al., 2022; Mustofa et al., 2025; Camargos & Silveira, 2025; Tiukhova et al., 2024). Fairness assessment should explicitly examine sensitive attributes rather than merely removing them from the model, because exclusion does not necessarily eliminate indirect bias (Deho et al., 2023). Recent school and university dropout studies also show that explainability is becoming central to operational prediction systems across contexts (Albugami et al., 2026; Barboza et al., 2026). Privacy-preserving approaches such as

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

federated learning are relevant when models are developed across institutions that cannot centralize sensitive student records (Lamsiyah et al., 2025).

A critical gap is the weak integration of learning loss with XAI. This is not only a matter of limited scholarly attention. Dropout is comparatively easy to operationalize as a discrete outcome (enrolled versus withdrawn) and is often available in administrative or learning-management-system data. Learning loss, by contrast, is a longitudinal and partly counterfactual construct: it requires an expected learning trajectory or prior baseline, repeated measures, curriculum-sensitive indicators, and careful distinction between temporary performance fluctuation and persistent loss (Page et al., 2021; Harmey & Moss, 2023). Post-pandemic evidence also shows that learning disruption and recovery are heterogeneous rather than uniform across learners and contexts (Gicheva et al., 2025; Togo et al., 2025). In addition, early learning difficulty may appear through intermediate signals such as confusion, low engagement, or poor conceptual understanding rather than a single administrative endpoint; explainable detection of learner confusion illustrates how such proximal indicators can be modeled, but these signals are rarely integrated into a common learning-loss construct (Alsuhaimi & Almatrafi, 2024). These data are less standardized across schools and are frequently fragmented across assessment, attendance, engagement, and contextual systems. Moreover, much XAI research explains the output of predictive classifiers, whereas learning loss requires interpretation of developmental change and, ideally, evidence about which intervention can alter that trajectory. This mismatch between readily labeled dropout outcomes and complex longitudinal learning-loss constructs helps explain why the two literatures have rarely converged.

Future studies should therefore model dropout risk and learning decline as related but distinct outcomes. Longitudinal multi-school datasets could combine achievement growth, attendance, engagement, and contextual variables; explanations should be tested for stability across time and student groups; and counterfactual or actionable explanations should be evaluated by whether educators can translate them into feasible support. Existing work on collaborative high-school dropout identification and explainable academic-performance prediction suggests that human interpretation should be incorporated into the evaluation loop rather than treated as a post-processing step (Bulut et al., 2024; Paul et al., 2025). The research goal should move beyond explaining why a model predicts risk toward determining whether an explanation improves intervention quality, equity, and student outcomes. This agenda would connect the predictive strengths of XAI with the pedagogical purpose of preventing both disengagement and cumulative learning decline.

A useful design principle emerging from this literature is to separate three layers of an educational early-warning system: prediction, explanation, and intervention. Prediction estimates who may be at risk; explanation identifies which variables and patterns are responsible for that estimate; intervention translates the explanation into an educational response that can be reviewed by teachers, counselors, and school leaders. Conflating these layers can produce technically explainable systems that are still educationally unhelpful. Conversely, a human-supervised architecture can combine transparent risk models, professional judgment, and documented support actions, which is consistent with the growing emphasis on collaborative and accountable educational AI (Bulut et al., 2024; Nagy & Molontay, 2024; Zanellati et al., 2024).

The separation between dropout prediction and learning-loss mitigation also reflects differences in data infrastructure and evaluation logic. Dropout studies can usually be trained against a clearly recorded administrative outcome, whereas learning loss requires repeated evidence of change relative to an expected trajectory. Schools often store grades, attendance,

Vol. 12, No. 3 : September 2026
E-ISSN: 2442-7667
pp. 1379-1389
Email: jklppm@undikma.ac.id

engagement, assessment results, and counseling records in different systems, making it difficult to construct a unified longitudinal label. Even when predictive performance is strong, an explanation of a dropout score does not automatically reveal whether the student is experiencing persistent learning loss, temporary disengagement, or a contextual disruption. This distinction matters because the appropriate response differs across these conditions. A transparent educational early-warning system should therefore represent risk as a set of related indicators rather than a single binary label, and should make visible the evidence used to distinguish academic decline from other sources of withdrawal risk. Research on explainable dropout prediction, student-performance interpretation, and model stability provides useful components for this architecture, but the bibliometric map shows that these components have not yet been consolidated into a shared learning-loss framework (Adnan et al., 2022; Paul et al., 2025; Tiukhova et al., 2024).

The findings also imply that explainability needs to be evaluated at the level of educational use, not only at the level of the algorithm. Local explanations are valuable when a teacher needs to understand why one student has been flagged, whereas global explanations help school leaders examine whether the model systematically relies on a small set of variables across the student population. Counterfactual explanations can further indicate which changeable conditions might reduce predicted risk, but they become educationally meaningful only when the suggested changes are feasible, ethically acceptable, and within the school's capacity to support. Similarly, fairness cannot be established merely by reporting overall accuracy: performance and explanation stability should be examined across relevant student groups, particularly when demographic or socioeconomic variables are associated with unequal dropout patterns (Biswas & Bhattacharya, 2025; Deho et al., 2023). The literature therefore supports a governance-oriented view of XAI in which prediction thresholds, explanation methods, uncertainty, subgroup performance, and the resulting intervention are documented together. This approach can reduce the risk that an early-warning system becomes an automated labeling mechanism and instead position it as a transparent decision-support process that combines computational evidence with professional judgment (Bulut et al., 2024; Camargos & Silveira, 2025; Zanellati et al., 2024).

Conclusion

This bibliometric study shows that XAI research related to dropout has expanded rapidly and is increasingly organized around interpretability, learning systems, uncertainty, and accountable decision support. The strongest evidence base concerns explaining dropout and academic-risk prediction, whereas learning loss mitigation remains weakly integrated. This imbalance is theoretically important because learning loss is a longitudinal educational process rather than a simple classification label, and practically important because early intervention may be more effective when gradual learning decline is detected before withdrawal becomes imminent. The study therefore reframes the next stage of XAI in education as the integration of prediction, explanation, uncertainty, fairness, and learning-growth indicators within human-supervised intervention systems. The broad Scopus query increased recall but introduced a small amount of cross-domain terminology; this limitation should be addressed in future work through education-domain filtering and manual relevance checks.

Recommendation

For school policymakers, XAI-based early-warning systems should be adopted only with human oversight, clear data-governance rules, periodic fairness and calibration audits, and explanations that lead to specific support actions rather than automatic labeling (Bulut et al., 2024; Deho et al., 2023). Dashboards should combine dropout risk with indicators of learning progress, attendance, and engagement, display prediction uncertainty, and document the interventions taken. For future researchers, priorities include longitudinal and multi-school validation, explicit operationalization of learning loss, comparison of local, global, and counterfactual explanation methods, subgroup fairness analysis, privacy-preserving modeling, and prospective evaluation of whether XAI-informed interventions improve retention and learning outcomes. Bibliometric studies should also refine search strategies with education-related subject filters and manual screening so that multidisciplinary uses of the term "dropout" do not distort thematic interpretation.

References

Abulibdeh, A. (2025). A systematic and bibliometric review of artificial intelligence in sustainable education: Current trends and future research directions. Sustainable Futures, 10, 101033.

Adnan, M., Uddin, M. I., Khan, E., Alharithi, F. S., Amin, S., & Alzahrani, A. A. (2022). Earliest possible global and local interpretation of students' performance in virtual learning environment by leveraging explainable AI. IEEE Access. https://doi.org/10.1109/ACCESS.2022.3227072

Al Husaeni, D. F., Widiaty, I., Mulyanti, B., Abdullah, A. G., Riza, L. S., Suherman, A., & Al Husaeni, D. N. (2025). Trends and impacts of artificial intelligence application in the development of computational thinking skills. Informatics in Education, 24(2), 261–298. https://doi.org/10.15388/infedu.2025.14

Albugami, S., Wali, A., & Almagrabi, H. (2026). Predicting student dropout in Saudi universities using machine learning and explainable AI. PeerJ Computer Science. https://doi.org/10.7717/peerj-cs.3490

Alsuhaimi, R., & Almatrafi, O. (2024). Identifying learners' confusion in a MOOC forum across domains using explainable deep transfer learning. Information, 15(11), 681. https://doi.org/10.3390/info15110681

Baranyi, M., Nagy, M., & Molontay, R. (2020). Interpretable deep learning for university dropout prediction. Proceedings of the 21st Annual Conference on Information Technology Education. https://doi.org/10.1145/3368308.3415382

Barboza, A., Huamani, J., Santisteban, J., Maculan, N., & Mauricio, D. (2026). Prediction and explainability of school dropout in Peru using machine learning and explainable artificial intelligence. IEEE Access. https://doi.org/10.1109/ACCESS.2026.3675564

Bayrakceken, E., Çinici, M., & Alkan, Ö. (2025). School dropout among children aged 5–17 in Türkiye and related factors: A logistic regression analysis. BMC Pediatrics, 25, Article 661. https://doi.org/10.1186/s12887-025-06034-4

Bettahi, A., Belouadha, F.-Z., & Harroud, H. (2025). A modular and explainable machine learning pipeline for student dropout prediction in higher education. Algorithms, 18(10), 662. https://doi.org/10.3390/a18100662

Biswas, S., & Bhattacharya, K. (2025). Gender heterogeneity in secondary school dropout due to financial shocks: Evidence from India. International Journal of Educational Development, 119, Article 103452. https://doi.org/10.1016/j.ijedudev.2025.103452

Bulut, O., Wongvorachan, T., He, S., & Lee, S. (2024). Enhancing high-school dropout identification: A collaborative approach integrating human and machine insights. Discover Education. https://doi.org/10.1007/s44217-024-00209-4

Camargos, R. C., & Silveira, I. F. (2025). Mitigating cognitive biases in predicting student dropout: Global and local explainability with Explainable Boosting Machine. Journal of Universal Computer Science. https://doi.org/10.3897/jucs.131773

Chen, H. E., Sun, D., Hsu, T. C., Yang, Y., & Sun, J. (2023). Visualising trends in computational thinking research from 2012 to 2021: A bibliometric analysis. Thinking Skills and Creativity, 47, Article 101224.

Cheniti-Belcadhi, L., Hadyaoui, A., & Mitwally, M. A. A. (2025). Ontology-based adaptive assessment in digital education: Inclusive, transparent, and fair AI for assessment. In [Book/proceedings title not provided] (pp. 203–238). https://doi.org/10.4018/979-8-3373-2130-1.ch007

Chitti, M., Chitti, P., & Jayabalan, M. (2020). Need for interpretable student performance prediction. Proceedings of the International Conference on Developments in eSystems Engineering. https://doi.org/10.1109/DeSE51703.2020.9450735

Deho, O. B., Joksimovic, S., Li, J., Zhan, C., Liu, J., & Liu, L. (2023). Should learning analytics models include sensitive attributes? Explaining the why. IEEE Transactions on Learning Technologies. https://doi.org/10.1109/TLT.2022.3226474

Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., ... & Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. ACM computing surveys, 55(9), 1-33.

Fu, Y., Weng, Z., & Wang, J. (2025). Examining AI use in educational contexts: A scoping meta-review and bibliometric analysis. International journal of artificial intelligence in education, 35(3), 1388-1444.

Gicheva, D., Edmunds, J., Eilam, N., Hutchins, B., & Arshavsky, N. (2025). Gender differences in college students’ academic performance during and after the COVID-19 pandemic: Is females’ recovery lagging behind? Economics Letters, 255, Article 112491. https://doi.org/10.1016/j.econlet.2025.112491

Harmey, S., & Moss, G. (2023). Learning disruption or learning loss: Using evidence from unplanned closures to inform returning to school after COVID-19. Educational Review, 75(4), 637-656.

Khan, L. H., Haque, M. A., Ibrahim, E. A., Mostakim, M., & Hossain, M. I. (2023). Interpretable MOOC dropout prediction using different ensemble methods and XAI. ICAAIC 2023. https://doi.org/10.1109/ICAAIC56838.2023.10140724

Košir, S., Aslan, M., & Lakshminarayanan, R. (2025). Adolescent dropout and school attachment: The moderating effects of gender. International Journal of Educational Development, 117, Article 103356. https://doi.org/10.1016/j.ijedudev.2025.103356

Lamsiyah, S., Nourbakhsh, A., El-Amrany, S., & Schommer, C. (2025). Privacy-preserving federated learning for student dropout prediction: Enhancing model transparency with explainable AI. Lecture Notes in Computer Science. https://doi.org/10.1007/978-3-031-98465-5_41

Lim, W. M., Kumar, S., & Donthu, N. (2024). How to combine and clean bibliometric data and use bibliometric tools synergistically: Guidelines using metaverse research. Journal of Business Research, 182, Article 114760.

Melo, E., Silva, I., Costa, D. G., Viegas, C. M. D., & Barros, T. M. (2022). On the use of eXplainable artificial intelligence to evaluate school dropout. Education Sciences. https://doi.org/10.3390/educsci12120845

Minh, D., Wang, H. X., Li, Y. F., & Nguyen, T. N. (2022). Explainable artificial intelligence: a comprehensive review. Artificial Intelligence Review, 55(5), 3503-3568.

Mustofa, S., Emon, Y. R., Mamun, S. B., Akhy, S. A., & Ahad, M. T. (2025). A novel AI-driven model for student dropout risk analysis with explainable AI insights.

Computers and Education: Artificial Intelligence. https://doi.org/10.1016/j.caeai.2024.100352

Nagy, M., & Molontay, R. (2024). Interpretable dropout prediction: Towards XAI-based personalized intervention. International Journal of Artificial Intelligence in Education. https://doi.org/10.1007/s40593-023-00331-8

Page, E., Leonard-Kane, R., Kashefpakdel, E., Riggall, A., & Guerriero, S. (2021). Learning Loss, Learning Gains and Wellbeing: A Rapid Evidence Assessment. Education development trust.

Paul, R., Sarker, S., El Aouifi, H., Hussain, S., Baruah, A. K., & Gaftandzhieva, S. (2025). Analyzing dropout of students and an explainable prediction of academic performance utilizing artificial intelligence techniques. Frontiers in Education. https://doi.org/10.3389/feduc.2025.1698505

Roman, N. V., Davidse, P. E., Human-Hendricks, A., Butler-Kruger, L., & Sonn, I. K. (2022). School dropout: Intentions, Motivations and self-efficacy of a sample of South Africa youth. Youth, 2(2), 126-137.

Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2025). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. Technology, knowledge and learning, 1-31.

Salmon, O. O., & Elyjoy, M. M. (2025). Towards Integration of AI Driven Predictive Model in identifying At-Risk Students in Online Learning Platforms. African Journal of Computing, Data Science and Informatics (AJCDSI), 1(1), 87-109.

Singh, V. K., Singh, P., Karmakar, M., Leta, J., & Mayr, P. (2021). The journal coverage of Web of Science, Scopus and Dimensions: A comparative analysis. Scientometrics, 126(6), 5113-5142.

Tariq, R., Orozco-del-Castillo, M. G., Zamir, M. T., Ramirez-Montoya, M. S., & Wilberforce, T. (2025). Explainable artificial intelligence for predictive modeling of student stress in higher education. Scientific Reports, 15, Article 38375. https://doi.org/10.1038/s41598-025-22171-3

Tiukhova, E., Vemuri, P., Flores, N. L., Islind, A. S., Óskarsdóttir, M., Poelmans, S., Baesens, B., & Snoeck, M. (2024). Explainable learning analytics: Assessing the stability of student success prediction models by means of explainable AI. Decision Support Systems. https://doi.org/10.1016/j.dss.2024.114229

Togo, E., Mwase-Vuma, T. W., Thakwalakwa, C., Millar, E., Markiewicz, M., Kadzamira, E., Kayange, J. J., Mkombe, D., & Fehringer, J. (2025). The thought that I could continue with school got lost: A qualitative exploration of the impact of COVID-19 on the education and sexual and reproductive health of Malawi youth. Reproductive Health, 22, Article 33. https://doi.org/10.1186/s12978-025-01972-9

Tsakeni, M., Nwafor, S. C., Mosia, M., & Egara, F. O. (2025). Mapping the scaffolding of metacognition and learning by AI tools in STEM classrooms: A bibliometric–systematic review approach (2005–2025). Journal of Intelligence, 13(11), 148.

Waseem, M., Abidin, S., Alam, M., Husain, M. S., Khan, M. Z., & Ashraf, Z. (2026). VertiDaX: An explainable hybrid deep learning model for dropout prediction with vertical integration. PeerJ Computer Science. https://doi.org/10.7717/peerj-cs.3718

Zanellati, A., Zingaro, S. P., & Gabbrielli, M. (2024). Balancing performance and explainability in academic dropout prediction. IEEE Transactions on Learning Technologies. https://doi.org/10.1109/TLT.2024.3425959