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Artificial intelligence-driven educational technology innovation and sustainable digital transformation: Patent-based evidence on global technological inequality

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Artificial intelligence-driven educational technology innovation and sustainable digital transformation: Patent-based evidence on global technological inequality

Abstract: Equitable digital education is central to Sustainable Development Goal 4 (SDG 4). Yet as digital systems shape how education is delivered, assessed and governed, a deeper divide is emerging between countries that can merely adopt educational technologies and those that can develop, adapt and govern them. This study examines the global distribution of technology-shaping capacity in education using 274,825 educational-technology patent records filed from 2006 to 2025. We combine four-period spatial mapping, concentration measures, 16 technology themes, annual trajectories, and LightGBM-SHAP interpretation of high-value patents from 2013 to 2023. Geographic participation expanded after 2011, yet inventive activity remained strongly concentrated: the leading country accounted for 63.48-77.62% of records across the three mature periods, while the five leading countries consistently exceeded 90%. Innovation shifted from stand-alone teaching tools toward virtual reality, artificial intelligence, adaptive learning, platform-based services and data-intensive systems. Geographic, technological and temporal variables contributed 33.33%, 27.03% and 25.78%, respectively, to the prediction of high-value patents, and high-value inventions were concentrated in a limited set of country-theme pathways. These patterns reveal a capability divide overlooked by connectivity indicators. Education systems may gain access to advanced tools without gaining the capacity to adapt them to local languages and curricula, audit algorithms, govern data or develop alternatives. By revealing where technology-shaping capacity and high-value innovation are concentrated, this study can help policymakers identify priorities for capability building, technology transfer and governance support to advance more inclusive and sustainable digital transformation toward SDG 4.

Keywords: SDG 4; sustainable digital transformation; educational technology upgrading; global educational equity; technology-shaping capability; patent analysis

1. Introduction

Education is explicitly recognized in the United Nations 2030 Agenda through Sustainable Development Goal 4 (SDG 4), which calls for inclusive and equitable quality education and lifelong learning opportunities for all (United Nations General Assembly, 2015). As course materials, teaching activities and learning support become increasingly digital, connectivity is becoming an important condition for educational participation. The 2026 Global Education Monitoring Report again places access and equity at the center of the global education agenda, while the Transforming Education Summit +4 links inclusive digital transformation to progress toward SDG 4 and greater resilience in education systems (Global Education Monitoring Report Team, 2026; UNESCO, 2026). Yet this transition remains deeply unequal. In 2025, approximately 94% of people in high-income countries used the internet, compared with only 23% in low-income countries (International Telecommunication Union, 2025). The connectivity divide therefore remains a direct barrier to equitable progress toward SDG 4.

Unequal access, however, captures only the most visible part of digital inequality. Differences in skills, quality of use, institutional capacity and realized benefits also shape who can participate meaningfully in digital transformation (Lythreatis et al., 2022; Meng et al., 2024; Timotheou et al., 2023). This distinction becomes increasingly important as educational technology moves from stand-alone devices and online platforms toward artificial intelligence (AI), learning analytics, immersive media, adaptive tutoring and data-driven services (Holmes

and Tuomi, 2022; Molenaar, 2022; Ouyang and Jiao, 2021). These systems require algorithms, data, engineering expertise, language resources, curriculum alignment, continuous maintenance and independent evaluation. The ability to purchase a technology and the ability to understand, modify and govern it are therefore no longer equivalent.

This emerging technology-shaping capability divide has direct sustainability implications. Educational technologies embed choices about supported languages, assessment practices, data collection, accessibility and pedagogical defaults. Countries that cannot develop, adapt or audit these systems may remain dependent on external providers even after schools become connected (Chiu et al., 2023; Kasneci et al., 2023; Khosravi et al., 2022; Nguyen et al., 2023). Such dependence can narrow educational autonomy, weaken public control over learner data and concentrate influence over future learning infrastructures (Miao and Holmes, 2023; OECD, 2023; Regan and Jesse, 2019). Social sustainability also intersects with environmental sustainability because advanced digital systems depend on data centers, devices and material supply chains whose energy, water and electronic-waste burdens are unevenly distributed.

Research on educational technology has mainly examined adoption, learning effects, teacher acceptance and ethical governance, whereas innovation studies have focused on patent volume, technological trajectories and value. The connection between these literatures remains underdeveloped. Patent data provide a systematic means of tracing where formal inventive activity occurs, how technological composition changes and through which geographical and technological pathways high-value intellectual property is formed (Arts et al., 2021; Higham et al., 2021; Hu et al., 2023).

This study analyzes 274,825 educational-technology patent records filed worldwide from 2006 to 2025 and explores three interrelated issues: whether broader geographic participation has reduced concentration in formal inventive capacity; whether educational technology is shifting toward more knowledge-, data- and platform-intensive systems; and whether high-value patents are widely distributed across countries and themes or concentrated in a limited set of pathways. To examine these issues, we combine four-period spatial mapping, concentration indices, technology-theme analysis, annual trajectories and LightGBM-SHAP interpretation within a unified analytical framework. By linking geographic concentration, technological upgrading and high-value patent formation, this study provides a new basis for understanding educational inequality not only as unequal access to technology, but also as unequal capacity to shape it.

2. Materials and methods

2.1 Research framework

This study develops a patent-based framework for examining sustainable digital transformation in education through three connected dimensions: spatial concentration, technological upgrading and high-value patent formation (Fig. 1). Patent records were retrieved and cleaned using IPC codes related to educational technologies and educational information systems. Standardized bibliographic, country, classification, applicant, family, citation and text fields were then used to connect the geography of inventive activity with technological trajectories and observable value signals (Arts et al., 2021; Higham et al., 2021).

The first part examines whether wider participation is accompanied by a dispersal of inventive power. The second part identifies 16 technology themes and evaluates their semantic structure and temporal evolution. The

third part defines high-value patents using legal, family, international-protection and citation indicators and applies LightGBM-SHAP to interpret temporal, geographical, technological, applicant-related, collaboration and text variables. Country-theme-value flows provide an integrated view of the pathways through which technological value is formed. The sustainability interpretation focuses on technology-shaping capacity: the ability to create, adapt, evaluate and govern educational technologies rather than merely procure them.

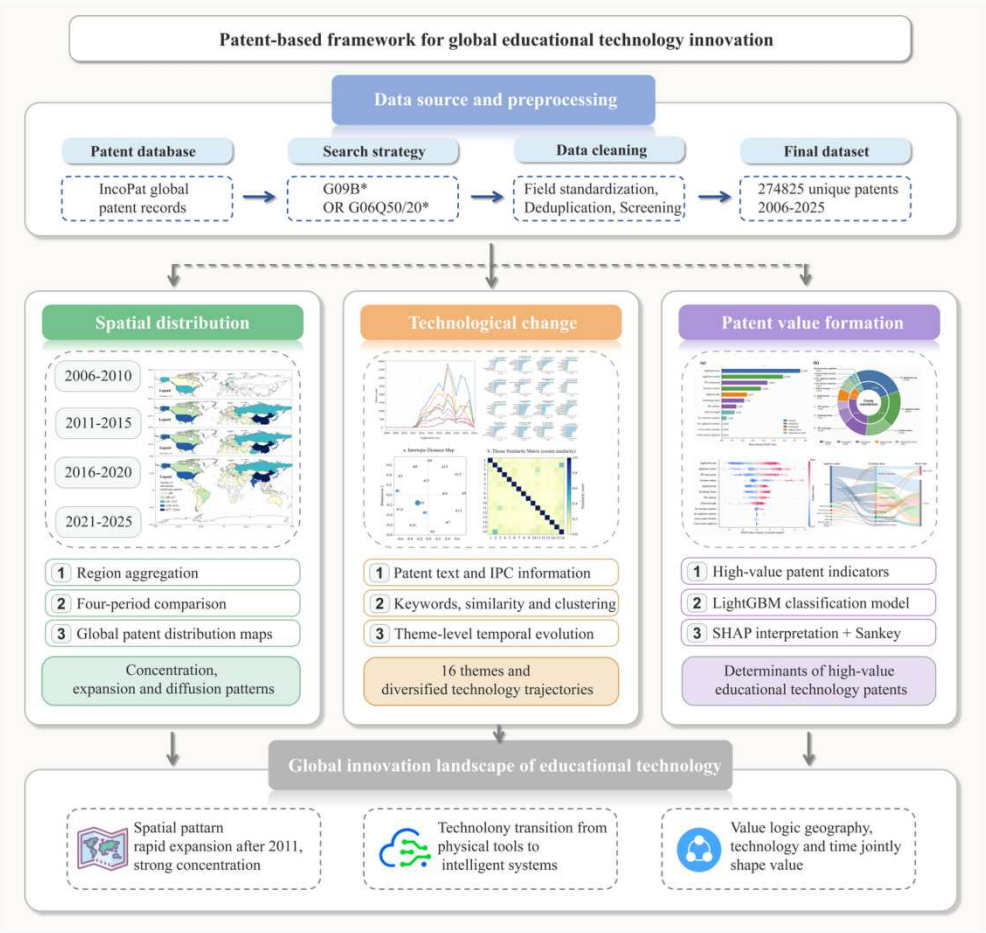


Fig. 1. Patent-based framework linking spatial concentration, technological upgrading and high-value formation to an SDG 4 technology-shaping capability divide.

2.2 Data sources

The patent data were obtained from the incoPat global patent database, which integrates records from major patent offices and provides standardized information on bibliographic data, applicants, inventors, application dates, patent families, legal status, citations and technical classifications. Educational technology patents were retrieved using IPC=(G09B* OR G06Q50/20*). G09B covers technologies for education, instruction and demonstration, while G06Q50/20 covers information and communication technologies applied to education. After field standardization, screening and duplicate removal, 274,825 unique records were retained. Cross-country interpretation follows established patent-statistics guidance and recognizes differences in filing incentives, market structures and patent institutions (World Intellectual Property Organization, 2024; European Patent Office, 2025).

The retained fields included title, application date, applicant and inventor country, patent type, legal status, Patent Cooperation Treaty status, family information, forward citations, IPC subclass and main group, applicant

type and patent text. Spatial and thematic analyses used the full 2006-2025 period, divided into 2006-2010, 2011-2015, 2016-2020 and 2021-2025. The first interval was retained as a visual baseline but excluded from mature-period concentration comparisons because of sparse coverage. The machine-learning analysis used patents filed from 2013 to 2023 to reduce instability from the earliest records and publication lag in the newest records. Patent indicators were not merged with educational access or learning-outcome data and are interpreted only as structural evidence of formal inventive and technology-shaping capacity.

2.3 Methods

2.3.1 Spatial participation and concentration

Records were aggregated by applicant country and application period. Applicant-country aggregation characterizes the location of formal patent ownership, although patent-office practices, filing incentives and family definitions affect cross-country comparisons (Arts et al., 2021; Higham et al., 2021). Let i denote a patent, c a country or territory and t a time period. The number of educational-technology patents in country c during period t was calculated as:

$$P_{c,t}=\sum_{i=1}^{N} I(C_i=c)\cdot I(Y_i\in t) \quad (1)$$

where $P_{c,t}$ is the number of educational technology patents in country or region c during period t, C_i is the applicant country or region of patent i, Y_i is the application year of patent i, and I() is an indicator function that equals 1 if the condition is satisfied and 0 otherwise.

The patent share of country or region c during period t was calculated as:

$$S_{c,t}=\frac{P_{c,t}}{\sum_{c=1}^{C} P_{c,t}}\times 100\% \quad (2)$$

where S_ct is the share of country c in global educational-technology patenting during period t. For each mature period, we additionally calculated the number of countries or territories with at least one observed record, the share of the leading country, the combined share of the five leading countries and the Herfindahl-Hirschman index (HHI), defined as the sum of squared national patent shares. These measures distinguish geographic participation from the concentration of inventive power.

2.3.2 Technology-theme identification and evolution

Technology themes were identified from patent text and technical classification information. The workflow combined text cleaning, class-based term frequency-inverse document frequency (c-TF-IDF), intertopic distance, cosine similarity, hierarchical clustering and expert interpretation, following text-based patent analytics and the BERTopic procedure (Arts et al., 2021; Grootendorst, 2022). Sixteen themes were retained. Let k denote a technology theme. The number of patents assigned to theme k during period t was calculated as:

$$N_{k,t}=\sum_{i=1}^{N} I(T_i=k)\cdot I(Y_i\in t) \quad (3)$$

where $N_{k,t}$ is the number of patents in theme k during period t, and T_i is the technological theme assigned to patent i.

The relative share of theme k during period t was calculated as:

$$R_{k,t}=\frac{N_{k,t}}{\sum_{k=1}^{K} N_{k,t}}\times 100\% \quad (4)$$

where $R_{k,t}$ represents the proportion of theme k among all educational technology patents during period t. The change in the relative share of theme k between two adjacent periods was calculated as:

$$\Delta R_{k,t}=R_{k,t}-R_{k,t-1} \quad (5)$$

where $\Delta R_{k,t}$ indicates the expansion or decline of theme k over time.

2.3.3 High-value patent definition

Patent value is not directly observable. We therefore constructed a binary high-value label from complementary indicators of legal, technological and strategic value: invention-patent grant status, PCT filing, multinational family coverage, forward citations and family forward citations. These indicators are widely used to capture patent quality, international protection and economic significance (Hall et al., 2005; Harhoff et al., 1999; Higham et al., 2021; Hu et al., 2023). The high-value indicator was defined as:

$$H_i=\begin{cases}1, & \textit{if patent i satifies the strict high-value criterion}\\ 0, & \textit{otherwise}\end{cases} \quad (6)$$

where H_i represents the high-value status of patent i. The strict high-value criterion required an invention patent to be granted, filed through the Patent Cooperation Treaty, protected in a multinational patent family and supported by both patent-level and family-level forward-citation signals. The composite rule was expressed as:

$$Q_i=f(G_i,PCT_i,F_i,C_i,FC_i) \quad (7)$$

where G_i represents invention grant status, PCT_i indicates whether patent i has a PCT application, F_i represents multi-country family coverage, C_i represents forward citations, and FC_i represents family-level forward citations. The final high-value patent variable H_i was used as the dependent variable in the machine-learning model.

2.3.4 High-value modelling and interpretation

LightGBM was fitted as a binary classifier because it accommodates large samples, nonlinear relationships, interactions and mixed predictor types (Ke et al., 2017). Predictors represented five groups: temporal; geographical; technological; applicant-related; and collaboration and text. Publication authority was excluded from the robust model to reduce direct patent-office effects. Let X_i denote the feature vector for patent i. The prediction function was expressed as:

$$\hat{y}_i=F(X_i)=\sum_{m=1}^{M} f_m(X_i),\quad f_m\in\mathcal{F} \quad (8)$$

where $\hat{y}_i$ is the model output, f_m is the m-th decision tree, M is the total number of trees, and F denotes the space of regression trees.

For the binary classification task, the predicted probability that patent i belongs to the high-value class was calculated as:

$$\hat{p}_i = \frac{1}{1+exp(-\hat{y}_i)} \quad (9)$$

where $\hat{p}_i$ is the predicted probability of patent i being classified as high-value. The objective function of the model was defined as:

$$\mathcal{L} = \sum_{i=1}^{N} l(H_i, \hat{p}_i) + \sum_{m=1}^{M} \Omega(f_m) \quad (10)$$

where $l(H_i, \hat{p}_i)$ is the binary classification loss function, and $\Omega(f_m)$ is the regularization term used to control model complexity.

2.3.5 SHAP interpretation and model evaluation

SHAP values were used to characterize patent-level contributions and global mean absolute importance (Lundberg and Lee, 2017). Individual predictors were also aggregated into the five conceptual groups. SHAP values are conditional model explanations and are interpreted as predictive associations rather than causal effects. The SHAP value of feature j for patent i was defined as:

$$\phi_{ij} = \sum_{S \subseteq M \setminus \{j\}} \frac{|S|!(M-|S|-1)!}{M!} \left[f_{S \cup \{j\}}(X_i) - f_S(X_i) \right] \quad (11)$$

where ϕ_{ij} is the SHAP value of feature j for patent i, M is the full set of features, S is a subset of features excluding feature j, and $f_{S \cup \{j\}}(X_i) - f_S(X_i)$ represents the marginal contribution of feature j.

The global importance of feature j was measured by the mean absolute SHAP value:

$$I_j = \frac{1}{N} \sum_{i=1}^{N} \left| \phi_{ij} \right| \quad (12)$$

where I_j represents the overall importance of feature j. To compare the relative contribution of different variable groups, the group-level SHAP contribution was calculated as:

$$GC_g = \frac{\sum_{j \in g} I_j}{\sum_{j=1}^{M} I_j} \times 100\% \quad (13)$$

where GC_g is the contribution percentage of variable group g, and $j \in g$ indicates that feature j belongs to group g.

Model performance was evaluated using receiver operating characteristic area under the curve (ROC-AUC) and average precision. Average precision was emphasized because it is more informative when the positive class is relatively uncommon (Saito and Rehmsmeier, 2015). The receiver operating characteristic curve was constructed using the true-positive and false-positive rates:

$$TPR = \frac{TP}{TP+FN} \quad (14)$$

$$FPR = \frac{FP}{FP+TN} \quad (15)$$

where TP, FP, TN, and FN represent true positives, false positives, true negatives, and false negatives, respectively. ROC-AUC measures the overall discriminative ability of the model.

Average precision was calculated as:

$$AP=\sum_n (R_n-R_{n-1})P_n \quad (16)$$

where P_n and R_n represent precision and recall at the n-th threshold. Average precision was used to evaluate model performance under class imbalance.

3. Results

3.1 Global participation expanded without dispersing inventive power

The geographic coverage of educational-technology patenting expanded markedly after 2011, but this expansion did not produce a comparable redistribution of inventive power (Fig. 2). Patent records were observed for 86 countries or territories in 2011-2015, 107 in 2016-2020 and 104 in 2021-2025. Formal inventive activity therefore spread beyond its initial centers, while the distribution of records remained highly hierarchical.

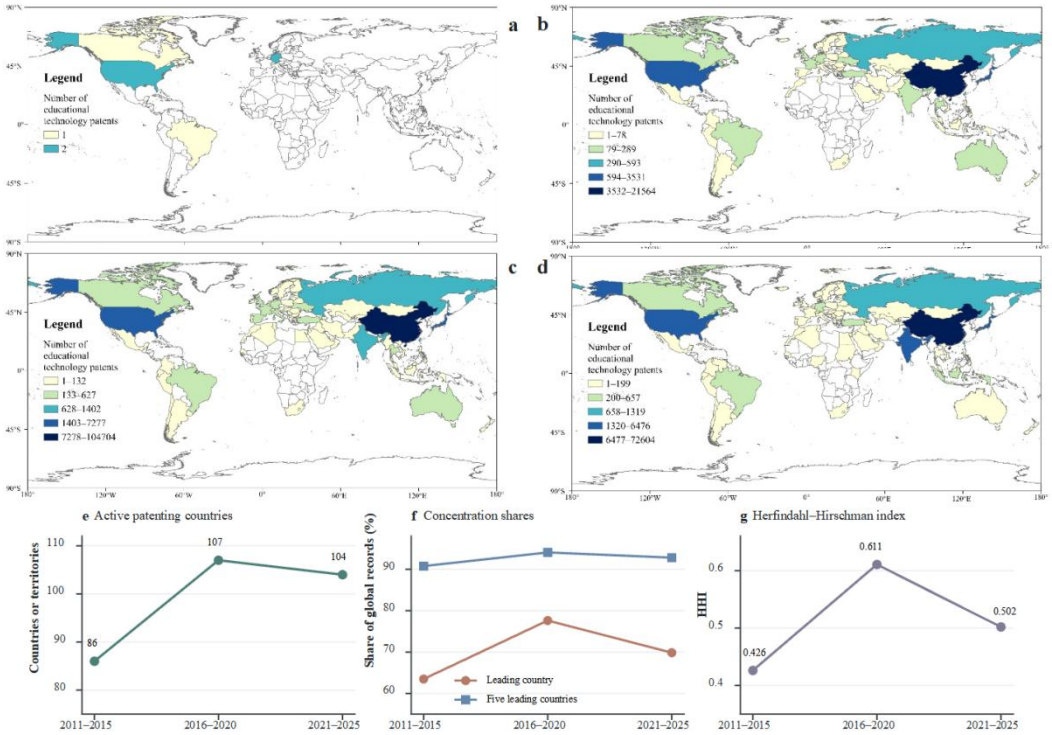


Fig. 2. Expansion and concentration of global educational-technology patenting, 2006–2025. (a–d) Spatial distributions of educational-technology patents across four periods (2006–2010, 2011–2015, 2016–2020, and 2021–2025). Maps use period-specific class breaks. (e) Number of countries or territories with observed educational-technology patent records across three five-year aggregation periods. (f) Shares of the leading country and the five leading countries calculated from aggregated patent records within each five-year period. (g) Herfindahl–Hirschman index (HHI) of national patent concentration calculated using country-level shares within each five-year period. Because educational-technology patenting was still at an early diffusion stage with limited international participation during 2006–2010, temporal analyses in (e–g) were conducted from 2011 onwards. Each point in (e–g) represents a statistical value aggregated over the corresponding five-year period rather than an individual year.

Broader participation did not produce balanced national shares. The leading country accounted for 63.48%, 77.62% and 69.85% of global records across the three mature periods, respectively; the corresponding shares of the

five leading countries were 90.78%, 94.07% and 92.82% (Fig. 2f). HHI values based on national shares were 0.426, 0.611 and 0.502 (Fig. 2g). Concentration peaked in 2016-2020 and subsequently declined, but remained far above an even distribution.

The national composition also changed. China became the largest source of patent records after 2011, while the United States, Japan and South Korea remained major secondary centers and India increased markedly in 2021-2025. Patent counts reflect market size, industrial structure, filing incentives and patent institutions and should not be equated with educational performance or technological quality. Nevertheless, a top-five share above 90% indicates that the countries able to set principal technological directions remain highly concentrated.

The coexistence of expansion and concentration is important for sustainable digital education. More countries appear in the patent landscape, but a narrow core continues to generate most formal inventions and high-value intellectual property. Countries outside this core may participate primarily as technology users or importers, limiting their ability to adapt systems to local languages, curricula, accessibility requirements and public data rules.

These results identify a technology-shaping capability divide rather than directly measuring educational inequality. They show where formal technological knowledge is accumulated and who is positioned to influence the infrastructure through which digital education is delivered. The distinction between wider use and concentrated technology-shaping capacity provides the basis for interpreting the thematic and patent-value results.

3.2 Technological upgrading changes the nature of the divide

Patent text and classification information reveal a broad transition from stand-alone teaching tools toward interconnected digital and intelligent learning systems (Fig. 3). Across 16 themes, innovation spans classroom equipment, assessment, language technologies, immersive environments, online platforms, AI-enabled learning, educational robots and specialized training systems. The thematic structure therefore captures both persistent physical technologies and emerging knowledge-, software- and data-intensive systems.

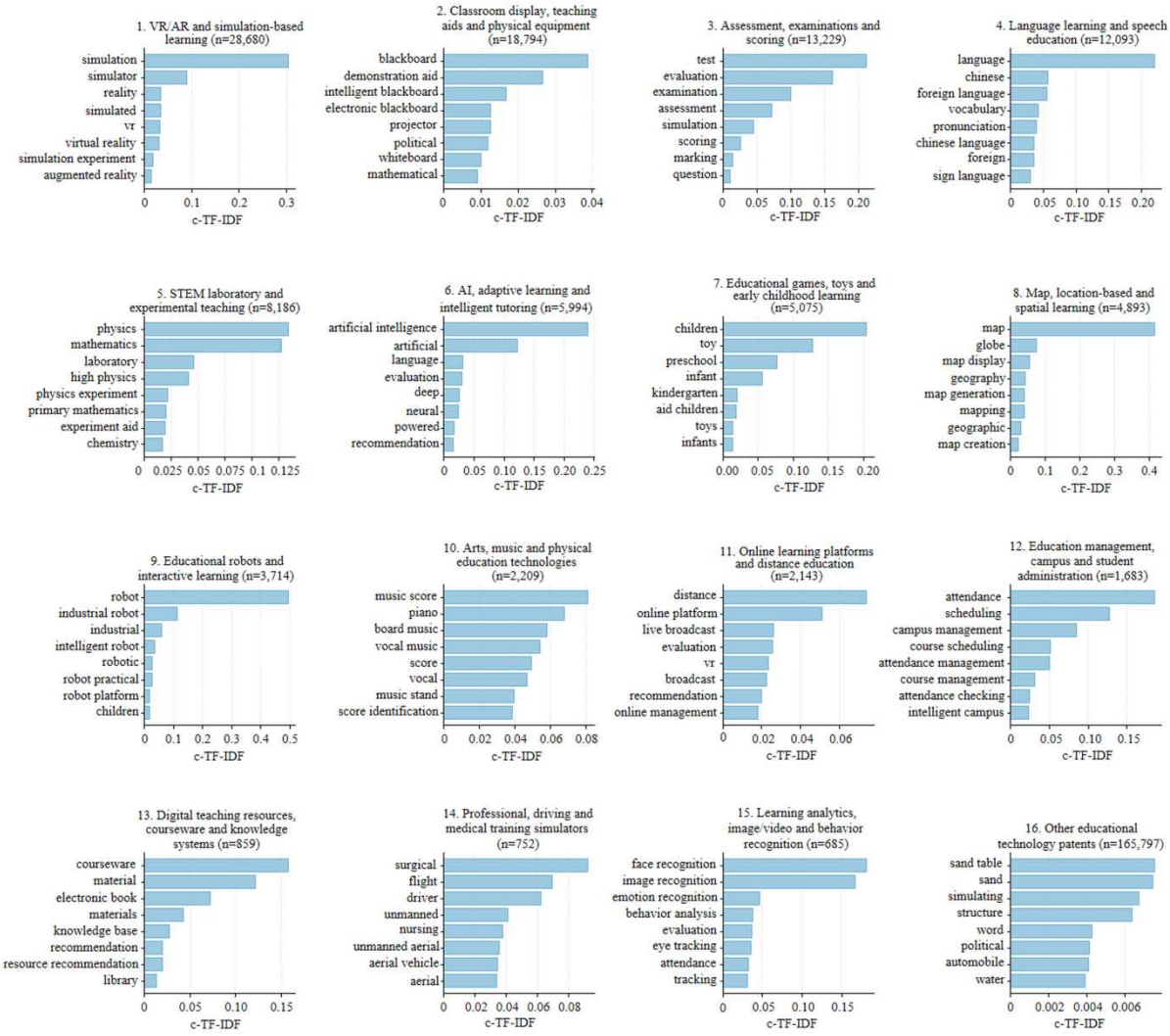


Fig. 3. Representative terms and sizes of 16 educational-technology themes. Bars report class-based TF-IDF weights; n denotes the number of patent records assigned to each theme.

Traditional teaching-support technologies remained substantial. Classroom display and physical equipment, STEM laboratory teaching, assessment and scoring, language learning and educational toys retained large patent volumes. Their persistence shows that digital transformation does not simply replace physical teaching tools; instead, software, data and connectivity are increasingly layered onto existing educational practices.

Emerging trajectories were more capability-intensive. VR/AR and simulation-based learning formed the largest identifiable theme, while AI, adaptive learning, intelligent tutoring, learning analytics and online platforms embedded algorithms, learner data and continuous software development into educational processes. These technologies require specialized expertise and institutional arrangements that are more difficult to acquire through one-off procurement.

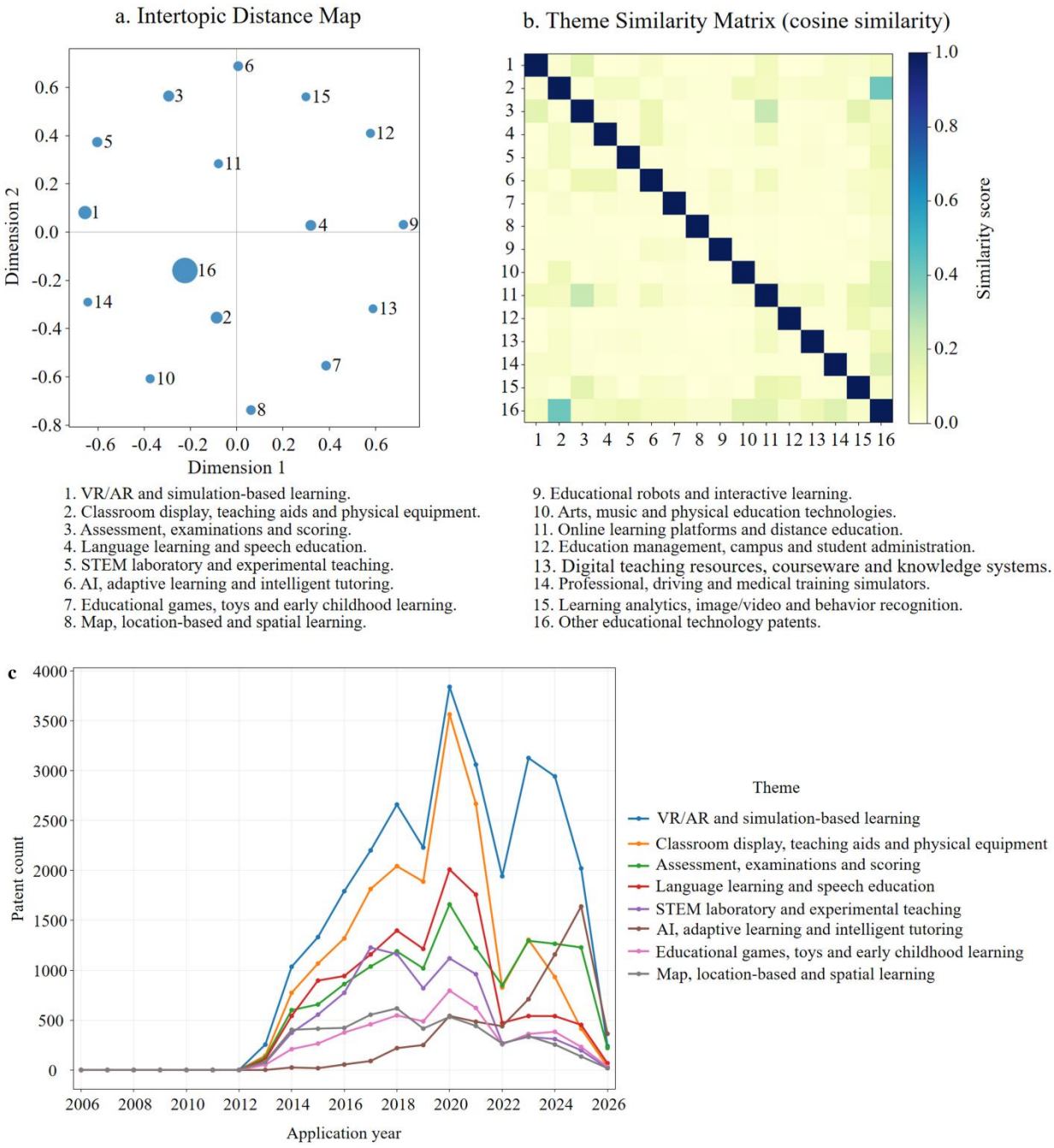


Fig. 4. Structure and evolution of educational-technology themes. (a) Intertopic distance, with bubble size indicating theme size. (b) Cosine-similarity matrix; numbers correspond to the themes in Fig. 3. (c) Annual patent counts for the eight leading themes. The final years may be affected by publication lag and incomplete coverage.

The intertopic-distance and similarity results show that educational technology is not converging on a single digital form (Fig. 4a,b). AI, learning analytics, online platforms, assessment and simulation share knowledge components, but their semantic boundaries remain distinguishable. Technological upgrading therefore occurs through the embedding of algorithms, data and immersive interaction across multiple educational settings rather than through the wholesale replacement of teaching tools by one AI category.

Annual trajectories reveal rapid expansion of VR/AR, simulation-based instruction and classroom equipment after 2014, with high levels around 2020; AI and adaptive learning accelerated later (Fig. 4c). The apparent decline in 2025 should be interpreted cautiously because publication lags and incomplete database coverage affect the final year. The broader movement toward systems requiring continuous data, software updates, language resources and

platform governance is nevertheless clear.

This transition changes the nature of the equity challenge. A country may be able to buy devices while lacking the research base, language resources or institutional infrastructure needed to modify, audit or replace the systems built around them. Universal connectivity remains indispensable, but the technological frontier is raising the capability threshold for meaningful participation in digital education.

Technology themes thus provide a structural indicator of where relevant knowledge is being accumulated. They do not show whether a technology improves learning, but they reveal whether the capabilities needed for local adaptation and governance are becoming broadly distributed. The results suggest that technological upgrading is adding a second divide in the capacity to shape digital education alongside the continuing divide in access.

3.3 High-value pathways expose a capability gap

High-value educational-technology patents were not evenly distributed across space or technological domains. The model examined whether observable value signals were associated with when innovation occurred, where applicants and inventors were located, which technological trajectories were pursued and what types of organizations patented them (Table 1; Fig. 5).

Table 1. Variables used in the machine-learning model

Variable group	Variables	Meaning in this study
Temporal factor	Application year	Time dimension used to capture changes in educational technology innovation across development stages.
Geographical factors	Applicant country Inventor country	Spatial origins of educational technology innovation from the applicant and inventor perspectives.
Technological factors	IPC main group IPC subclass Technology theme	Technical classification and thematic direction of educational technology patents.
Applicant-related factor	Applicant type	Organizational source of innovation, such as enterprise, university, research institute, or individual applicant.
Collaboration and textual factors	No. inventor countries No. applicant countries Cross-country inventor Cross-country applicant Title text length	International collaboration intensity and basic textual information of patent documents.

Application year was the most influential predictor, contributing 25.78% of total mean absolute SHAP importance. Applicant country contributed 20.30%, followed by IPC main group (14.81%), inventor country (13.03%), applicant type (8.27%) and technology theme (7.57%) (Fig. 5a). The grouped results show that geographical factors contributed 33.33%, technological factors 27.03% and the temporal factor 25.78%, whereas

applicant-related and collaboration-and-text factors contributed 8.27% and 5.59%, respectively (Fig. 5b).



Fig. 5. Predictive contributions associated with high-value educational-technology patents. (a) Mean absolute SHAP values and relative contributions of individual predictors. (b) Aggregated contributions of temporal, geographical, technological, applicant-related, and collaboration and text variables. (c) SHAP distribution across patent-level observations. SHAP values describe predictive associations and should not be interpreted causally.

The SHAP distribution confirms substantial heterogeneity among applicant countries, inventor countries, IPC groups and technology themes (Fig. 5c). More recent filing years were generally associated with positive contributions to the high-value classification, although this temporal pattern should not be interpreted as a causal effect. Because country, IPC and theme variables are categorical, their color gradients represent encoded categories rather than ordered continuous values.

Formal cross-country applicant and inventor indicators contributed relatively little. This does not imply that international knowledge exchange is unimportant; patent co-application and co-invention capture only a limited part of collaboration through multinational firms, licensing, open-source development, academic networks and platform diffusion. The results instead show that participation in formal international patent networks alone does not guarantee access to high-value technological pathways.

Country-theme-value flows further demonstrate the asymmetry (Fig. 6). China represented the largest source of patent records, while the United States, South Korea, India, Japan and other countries formed smaller secondary

pathways. High-value patents were concentrated within specific country-technology combinations, particularly those associated with immersive and simulation-based learning. Participation in patenting and control over frontier technological development are therefore not equivalent.

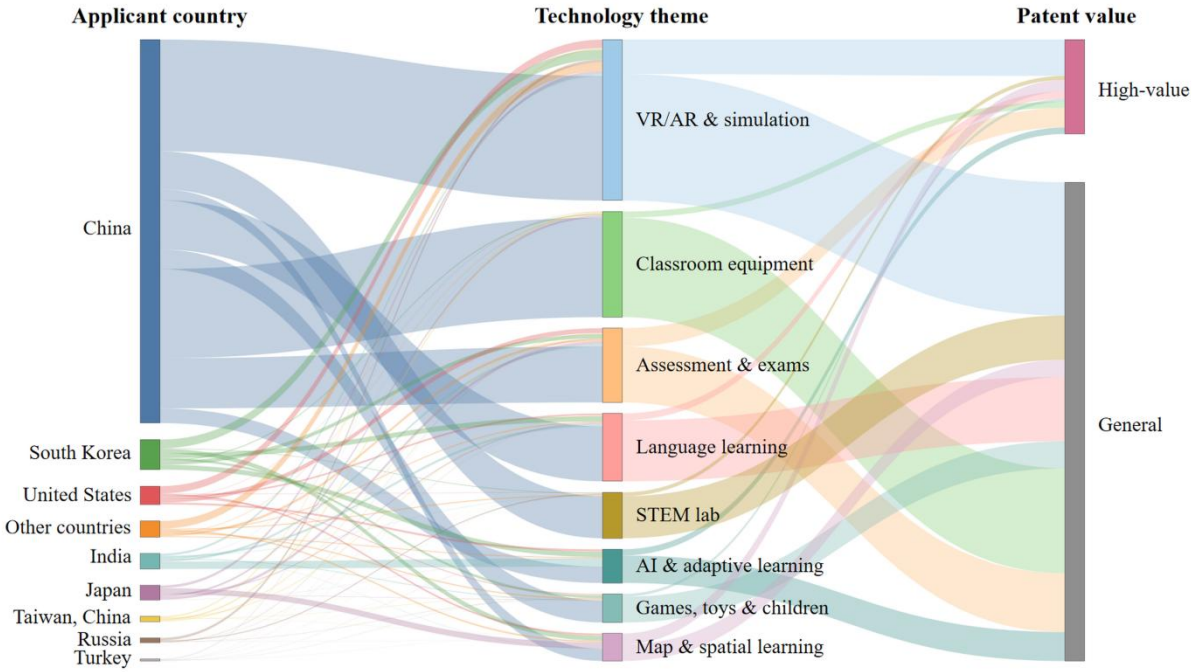


Fig. 6. Flows from applicant country to technology theme and patent-value category. Band width represents the relative number of records. High-value and other patents are classified using observable grant, PCT, multinational-family and citation indicators.

The concentration of value pathways has direct implications for sustainable digital transformation. Education systems can gain access to advanced products while remaining unable to inspect model behavior, negotiate standards, export data or develop alternatives. Where high-value knowledge is concentrated, supplier dependence and technological lock-in can persist even as the number of connected schools and digital users increases.

Taken together, the three parts of the analysis point in the same direction: geographic participation broadened without dispersing inventive power; technological upgrading increased knowledge and governance requirements; and high-value patents remained concentrated in limited country-theme pathways. Together, these findings identify a technology-shaping capability divide relevant to SDG 4.

4. Discussion

4.1 Technology-shaping capacity and sustainable digital education

The analysis connects two debates that are often treated separately. The first concerns whether learners and schools can access connectivity, devices and platforms. The second concerns who can create, adapt, evaluate and govern the technologies that increasingly organize educational activity. The first divide remains severe (Global Education Monitoring Report Team, 2026; International Telecommunication Union, 2025; Lythreatis et al., 2022). The second is visible in the coexistence of persistent geographic concentration, movement toward knowledge-intensive systems and unequal high-value pathways.

Immersive and AI-enabled learning depend on specialized design, interaction and institutional expertise that

cannot be acquired through hardware procurement alone (Hamilton et al., 2021; Makransky and Petersen, 2021; Petersen et al., 2022). Technology-shaping capacity therefore includes domestic research and development, engineering and pedagogical expertise for local adaptation, teacher trust and learner-instructor interaction, institutional capacity to evaluate algorithmic performance and bias, and public capacity to govern learner data, interoperability and procurement (Chan, 2023; Khosravi et al., 2022; Miao and Holmes, 2023; Nazaretsky et al., 2022; Nguyen et al., 2023; Selwyn, 2022; Seo et al., 2021). Weakness in these components does not prevent technology use, but it can lock education systems into technological trajectories and business models defined elsewhere.

The relationship between patent concentration and educational inequality is not mechanically causal. Concentration can generate risk through affordability, language coverage, curriculum alignment, data control, standard setting and supplier dependence, but it may also support scale economies and faster technological diffusion. Public procurement, open standards, competition policy, technology transfer and regional research cooperation can moderate these effects (Global Education Monitoring Report Team, 2023; OECD, 2023). The patent results identify the innovation structure through which such mechanisms may operate; they do not estimate learning effects.

Patent value and educational significance are also distinct. AI-supported education may produce substantial pedagogical value through software iteration, data accumulation and platform services even when individual patents show weaker value signals. Conversely, a legally valuable patent may have limited classroom impact. Sustainable digital education therefore requires evaluation across technological quality, educational usefulness, accessibility, governance and long-term maintainability rather than reliance on patent volume alone.

4.2 An SDG 4 framework for inclusive digital transformation

Universal access remains a non-negotiable foundation of SDG 4, but progress metrics should also examine whether education systems can maintain, modify and replace their digital infrastructure. Relevant indicators include domestic educational-technology R&D, open and interoperable interfaces, multilingual coverage, public code and models, algorithm-auditing capacity, data portability and procurement rules that prevent avoidable lock-in (Miao and Holmes, 2023; OECD, 2023; UNESCO, 2026). Counting devices or connected schools without these capabilities may overstate the sustainability of digital transformation.

International cooperation should prioritize capability formation alongside infrastructure. Practical routes include regional joint research centers, public digital-learning infrastructure, multilingual datasets, teacher-technologist co-design, domestic testing and certification, and technology transfer for low-resource languages and curricula. Such investment would shift development cooperation from short-term product provision toward long-term co-creation and would connect SDG 4 with the broader objective of reducing inequality among countries.

Platform providers and high-capability countries also carry responsibilities. Education systems need workable rights to export data, inspect model behavior, commission independent evaluation, access non-discriminatory interfaces and change suppliers (Nguyen et al., 2023; Regan and Jesse, 2019). These safeguards are especially important as adaptive learning and generative AI make educational services more continuous, personalized and data dependent (Chiu et al., 2023; Kasneci et al., 2023). Without them, global diffusion can expand the number of users

while deepening structural dependence.

This perspective reframes latecomer strategy. Countries do not need to compete across every technological field, but they do need the minimum capacity to evaluate imported systems and develop alternatives in locally important domains. Language technologies, vocational simulation, low-cost teacher-support tools, accessible assessment and public learning platforms offer plausible entry points. The aim is not technological self-sufficiency, but sufficient agency to negotiate, adapt and govern digital education.

4.3 Environmental sustainability, governance and evidence boundaries

Social sustainability cannot be separated from environmental sustainability. Advanced educational technologies depend on data centers, network infrastructure, devices and material supply chains, while rapid upgrade cycles can shift energy, water and electronic-waste burdens across countries (Baldé et al., 2024; Chugh, 2026; Freitag et al., 2021; Xiao et al., 2025). A credible sustainable-education strategy should therefore combine equitable technology-shaping capacity with energy-efficient infrastructure, repairable devices, responsible data-center procurement and lifecycle-aware replacement policies.

The present evidence does not quantify those environmental burdens. Patent records capture formal inventive activity and may underrepresent open-source development, service innovation, teaching practices and locally adapted solutions. Likewise, the high-value label reflects legal, family, international-protection and citation signals rather than educational effectiveness, market revenue or social value. These boundaries are important because an innovation system can be technologically dynamic without being educationally equitable or environmentally sustainable.

Future research should connect technological trajectories with national R&D capacity, school infrastructure, procurement systems, product deployment, energy and material footprints, and learning outcomes. Country-level panel analysis could test whether education systems with stronger research, engineering and governance capacity participate more successfully in frontier technologies and obtain more locally relevant benefits. Such integration would move from identifying a technology-shaping capability divide to evaluating the mechanisms through which it affects sustainable educational opportunity.

5. Conclusions

This study uses 274,825 educational-technology patent records to show that broader geographic participation has not eliminated concentration in formal inventive capacity. Patenting expanded after 2011, but the five leading countries consistently accounted for more than 90% of records. At the same time, innovation shifted toward AI, adaptive learning, immersive media and platform-based services that require continuous data, software, engineering and governance capabilities. Geographic, technological and temporal factors dominated high-value patent prediction, and high-value inventions were concentrated in a limited set of country-theme pathways.

These results extend the meaning of equity in digital education. Sustainable transformation requires more than connecting schools or distributing devices; it requires a broader distribution of the capacity to create, adapt, audit and govern the technologies through which education is delivered. Policy should combine universal access with interoperable public infrastructure, multilingual and locally relevant innovation, independent algorithm evaluation, data portability, lifecycle-aware procurement and long-term capability partnerships. Patent evidence cannot determine learning or environmental outcomes directly, but it reveals an innovation structure that should be

incorporated into assessments of progress toward SDG 4.

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