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A Progressive Visualisation-Based Learning Framework for Moroccan Pupils and Students: From Data Exploration to Interactive Instruction and Complex Data

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ABSTRACT

Moroccan pupils and students face a double challenge: national and international assessments show low proficiency in mathematics, reading, and science, whereas mobile connectivity is almost universal. This article proposes a learning framework that uses visualisation to connect these

two facts. The framework, called Explore–Interact–Extend (EIE), moves learners from open exploration of local data, through teacher-designed interactive visualisations, to complex multivariate, temporal, and projected data with explicit safeguards against misreading. We ground the design in published indicators, namely the 2025 cycle of the Programme for International Student Assessment (PISA), the 2023 cycle of the Trends in International Mathematics and

Science Study (TIMSS), national digital-access statistics, and the scale of the pioneer-school programme, and in 33 scholarly sources published between 2023 and 2026. A comparison with seven existing approaches shows that none of the works reviewed here combines open exploration, guided interaction, safeguards for complex data, offline use, and right-to-left support in one design. We describe a mobile-first, offline-capable, trilingual platform architecture and a cluster-randomised evaluation plan of about nine classes per arm. The framework has not yet been tested with learners; its value lies in a set of testable design rules for Moroccan classrooms and teacher-training centres.

Key words: complex data, data literacy, interactive visualisation, Moroccan education.

1. Introduction

Morocco is reforming its school system at a large scale. The pioneer-school programme grew from 626 pilot schools in 2023–2024 to 4,626 schools in 2025–2026, about 54% of public primary schools and more than two million pupils [1]. The learning results remain low. In the 2025 cycle of the Programme for International Student Assessment (PISA), 87% of Moroccan 15-year-olds scored below baseline proficiency in reading, 84% in mathematics, and 77% in science, whereas the average across the Organisation for Economic Co-operation and Development (OECD) was 25.7% in science [2], [3]. In the 2023 Trends in International Mathematics and Science Study (TIMSS), Morocco ranked 56th of 58 countries in grade 4 mathematics and second to last of 44 countries in both grade 8 subjects [4].

Mobile access is widespread. In January 2025, 92.2% of the population used the internet and mobile connections equalled 143% of the population [5]. Most learners therefore carry a device that can display, filter, and compare data. What is missing is a teaching design that turns this device into a tool for reasoning about data.

Visualisation is a natural candidate for such a design. The cognitive theory of multimedia learning explains why: learners process verbal and visual material in separate channels of limited capacity and must actively select, organise, and integrate what they see [6]. Visualisation is not automatically beneficial, however. Visualisation literacy varies widely and is measured inconsistently [7], interactive designs can help or overload learners [8], and projections of complex data invite false readings [9].

Existing work treats exploration, interactive teaching, and complex data separately, and it rarely addresses the Moroccan

classroom. The Moroccan studies we found examine the adoption of e-learning and mobile learning [10], [11], perceptions of learning analytics and generative artificial intelligence (GenAI) [12], [13], and one conceptual analytics model for pioneer colleges [14]. To our knowledge, none of these works proposes a sequence of visualisation-based learning activities for pupils and students. This article addresses three research questions.

RQ1. Which learning problems of Moroccan pupils and students can visualisation-based instruction address, given published indicators?

RQ2. How should exploration, interaction, and complex-data work be sequenced and supported in Morocco?

RQ3. How does the proposed design compare with existing approaches, and how should it be evaluated?

We make five contributions: a data-grounded description of the Moroccan context (Section 3), the EIE framework with design rules (Section 4), a platform architecture adapted to Moroccan constraints (Section 4), a comparison with seven existing approaches (Section 5), and an evaluation protocol (Section 6). Section 2 reviews related work, and Sections 7 and 8 discuss and conclude.

Scope and method

This is a conceptual article built on secondary data. We searched for recent sources (2023–2026) on visualisation literacy, interactive teaching, dashboards, complex data, and digital learning in Morocco. We opened each source and checked its bibliographic data against the publisher or repository page. Peer-reviewed papers, book chapters, and two preprints form the scholarly base. Official or press reports supply the national indicators and are marked as such in the reference list. The search was targeted, not systematic, and we collected no primary data.

2. Related work

2.1. Cognitive foundations and literacy

Mayer’s review of four decades of the cognitive theory of multimedia learning lists 15 evidence-based design principles grouped under three goals: reducing extraneous processing, managing essential processing, and fostering generative processing [6]. These goals frame our choices about interaction and guidance. Visualisation literacy, the ability to read and interpret visually represented data, is less settled. A systematic review of 43 reports found heterogeneous terms, definitions, and measures, and only 19 reports used

questionnaires, mostly with bar, line, and pie charts [7]. Twenty-one educators and researchers listed 19 challenges and 43 research questions for visualisation education [15]. In school-level (K-12) STEM education, a review of 83 studies found that authentic problem solving and real-world data were effective strategies for statistical and data literacy [16], whereas a review of 42 studies on teachers reported knowledge gaps among both pre-service and in-service teachers [17].

2.2. Interactive teaching

Interaction helps when it lets learners hide what is irrelevant. In a within-subject study with 160 participants (80 data scientists and 80 non-experts), filtering, encoding, and connecting performed best among seven interaction techniques, and expertise changed confidence but not accuracy [8]. Interactive simulations show consistent benefits in science classrooms: 100 third-grade pupils who used PhET simulations for two months outscored a textbook group [18], and a review of 14 studies reports gains in achievement and conceptual understanding, whereas higher-order skills and motivation are less studied [19]. A network meta-analysis of 53 studies ranked augmented reality first overall among four interactive formats [20]. Computational notebooks are also used to teach data analysis: female graduate students in a social network analysis course showed stronger conceptual understanding and greater enjoyment [21].

2.3. Dashboards and learning analytics

An umbrella review of 22 systematic reviews identified gaps in inclusiveness, unresolved questions of privacy and data ownership, and limited translation of predictive analytics into interventions [22]. A review of 39 studies of student-facing dashboards found that most still rely on activity data from learning management systems (LMS) and on descriptive analytics, and it argued for diagnostic and prescriptive support [23]. In primary and secondary schools, a scoping review reports moderate-to-clear learning improvements from visual learning analytics but calls for more systematic research [24]. Teachers can take part in design: a pilot study involved 4, 3, and 14 teachers in its three design steps [25], and 25 primary teachers co-designed dashboards through iterative cycles [26].

Literacy shapes use. Teachers with lower visualisation literacy produced shallower dashboard interpretations, and excessive guidance reduced interpretation depth [27]. In a study of 23 teachers, data storytelling reduced cognitive load, especially for those with lower literacy [28]. Students are not always aware of dashboards: in a survey of 1,020 university students, only 16.2% knew of available dashboards [29].

2.4. Generative artificial intelligence

GenAI adds a new layer. In a case study of 59 participants from non-computational fields, combining a visualisation-generation tool with a large language model enhanced the learning of advanced data-analytics skills, although users still needed technical knowledge to configure the interface [30]. A randomised trial with 117 higher-education students found that proactive GenAI agents improved comprehension of visual learning analytics more than passive agents, and the benefits persisted [31]. In a five-week study with 30 students, an agent that elicited reflection improved the calibration of self-assessment [32]. Moroccan university students, however, report cautious and non-stabilised uses of GenAI, mainly for information retrieval and writing, and they worry about its cognitive effects [13].

2.5. Complex data

Complex data raise the risk of false patterns. A review of 136 papers, together with interviews of practitioners and experts, concluded that the misuse of t-distributed stochastic neighbour embedding (t-SNE) and uniform manifold approximation and projection (UMAP), for example reading distances between clusters as meaningful, stems mainly from limited literacy about dimensionality reduction [9]. For temporal data, quality metrics and uncertainty highlighting help readers see which parts of a projection are reliable [33].

2.6. Language, script, and digital learning in Morocco

Language and script shape visualisation design. An analysis of 128 visualisations from Arabic news outlets found that designers placed the vertical axis on the right for categorical data in 81% of cases but were inconsistent for numerical data, and no unified guidelines exist for right-to-left (RTL) scripts [34]. In Moroccan secondary schools, science subjects are taught in French, and students from disadvantaged rural and public schools with weaker French hold more negative views of this arrangement, whereas translanguaging can help [35].

Studies of digital learning in Morocco report positive expectations and practical barriers. A survey compared students' and teachers' perceptions of e-learning and m-learning [10]. In a comparison of 588 university students, 243 of them Moroccan, performance expectancy, effort expectancy, and social influence drove mobile-learning adoption [11]. A phenomenological study of ten undergraduates at Mohammed V University describes both enhancing and challenging experiences, including technical barriers and motivation problems [36]. Moroccan students show awareness of and interest in learning analytics but worry

about data privacy [12]. Among teacher trainers, digital-competence gaps concentrate in content creation and troubleshooting [37]. A conceptual model for pioneer colleges turns student digital traces from trilingual platforms into simple indicators on a teacher dashboard, but it has not yet been tested [14]. For delivery, progressive web applications (PWAs) combine advantages of web and native applications in developing contexts [38].

2.7. Synthesis

These strands leave three gaps: no sequence links exploration, interaction, and complex data; few designs serve Arabic and French learners in one system; and few designs suit the connectivity and teacher-support conditions described in Section 3.

3. The Moroccan context in numbers

3.1. Learning outcomes

Figure 1 compares Moroccan mean scores in PISA 2025 with the OECD averages. Morocco scored 355 in mathematics, 321 in reading, and 358 in science, against OECD averages of 463, 461, and 482 [2]. The reported changes since 2022 are -10 , -18 , and -7 points, and the science change is not statistically significant [2], [3]. The 2022 values in Figure 1 are derived by subtracting these changes from the 2025 scores. We express the distance from the OECD average as a relative gap:

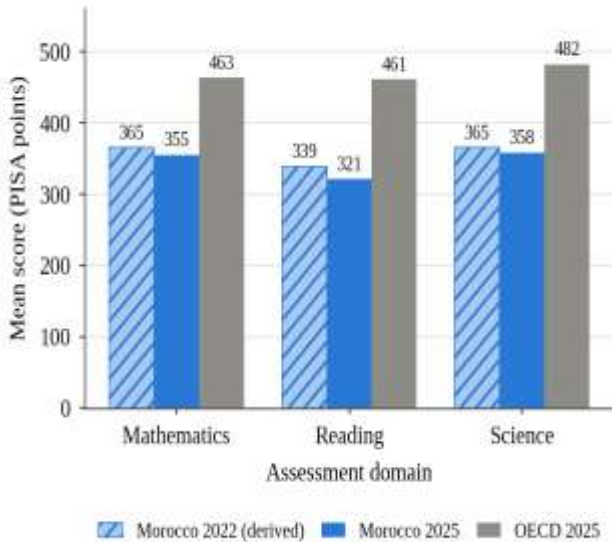


Figure 1: Mean scores of Moroccan 15-year-olds in PISA 2025 and 2022 (2022 values derived from the reported changes) with OECD averages for 2025. Data from [2], [3].

$$G_d = 100 \times \frac{S_{OECD,d} - S_{MA,d}}{S_{OECD,d}} \quad (1)$$

where $S_{OECD,d}$ and $S_{MA,d}$ are the OECD and Moroccan mean scores in domain d . The gap is 23.3% in mathematics, 30.4% in reading, and 25.7% in science. Reading has both the largest gap and the largest fall, which is relevant here because reading a chart draws on language and number skills alike.

Figure 2 shows the share of students below baseline proficiency, Level 2. In science, only 0.1% of Moroccan students reached Levels 5 and 6 [2], and the assessment covered 6,978 students in 179 institutions [3].

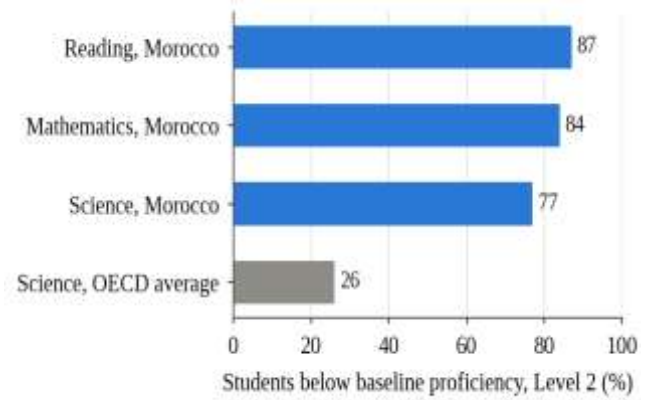


Figure 2: Share of students below baseline proficiency (Level 2) in PISA 2025, rounded to whole percentages. Data from [2], [3].

Grade-level results from TIMSS 2023 point the same way. Grade 4 pupils scored 393 in mathematics and 390 in science, both ranking 56th of 58 countries, and grade 8 students scored 327 in science, second to last of 44 countries [4]. Because the TIMSS scale centrepoin is 500 [39], the grade 8 science mean lies 173 points below it. Press reports describe a fall of 67 points in this result since 2019 [4].

3.2. Digital access

Figure 3 shows digital access in January 2025. Morocco had 35.3 million internet users (92.2% of 38.3 million inhabitants), 54.9 million cellular mobile connections (143%), and 21.3 million social media user identities (55.5%) [5]. Connections can exceed 100% because one person may hold several. Mobile access is therefore widespread, which supports a mobile-first design. These figures describe population-level access, not the quality of connections or the devices available to pupils in rural schools, which we treat as an open question.

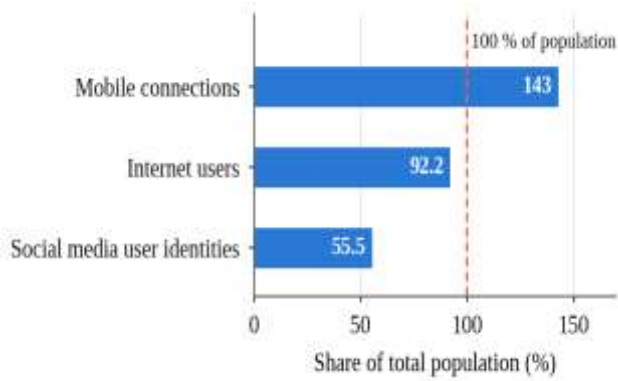


Figure 3: Digital access in Morocco, January 2025, as a share of the total population. Data from [5].

3.3. Scale of the school and university systems

Figure 4 shows the growth of the pioneer-school programme: 626 primary schools in the 2023–2024 pilot, 786 middle schools (about 678,000 students) in the 2024–2025 pilot, and 4,626 primary schools in 2025–2026, with more than two million pupils and about 75,000 teachers [1]. The World Bank reports that pioneer-school students outperform 82% of their peers in comparable schools after one year [1]. In higher education, more than 1.25 million students were enrolled in 2024–2025, about 1.1 million of them in public institutions [40].

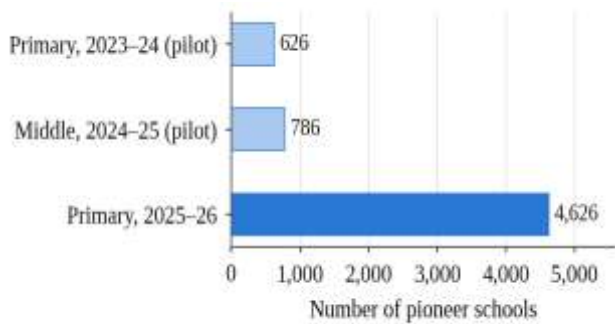


Figure 4: Number of pioneer schools by programme phase. Data from [1].

3.4. Design requirements

Table 1 turns these indicators into ten design requirements, R1 to R10, that guide the framework in Section 4.

Table 1: Indicators and the design requirements they imply.

Indicator	Design requirement
77–87% below baseline in PISA 2025 [2], [3]	R1: Start from concrete local data and short, question-led tasks.
Gap to OECD of 23.3–30.4% (1)	R2: Train chart and table reading in every subject, not only in mathematics.
TIMSS grade 8 science mean of 327 [4]	R3: Tie interactive activities to science and mathematics content.
92.2% internet use, 143% mobile connections [5]	R4: Design for mobile screens first.
4,626 pioneer schools, about 75,000 teachers [1]	R5: Deliver through teacher-adaptable templates that scale.
Science taught in French [35], RTL conventions unsettled [34]	R6: Provide Arabic (RTL), French, and English interfaces.
Teacher digital and data-literacy gaps [17], [37]	R7: Add storytelling and fading guidance for teachers [27], [28].
Privacy concerns among students [12]	R8: Apply privacy by design and opt-in analytics.
More than 1.25 million university students [40]	R9: Extend Stage 3 to university and teacher-training levels.
Connection quality not covered by access statistics [5]	R10: Work offline and synchronise when connected [38].

4. The proposed solution: the EIE framework

4.1. Overview

The EIE framework (Figure 5) sequences three stages. Stage 1 gives learners control: they pose questions and build simple charts from local data. Stage 2 gives control to the teacher’s design: learners work with a few purposeful interactions and predict before they see a result. Stage 3 raises data complexity, and safeguards replace unsupported reading of complex views. An arrow returns from Stage 3 to Stage 1 because findings in complex data create new questions that learners then investigate themselves.

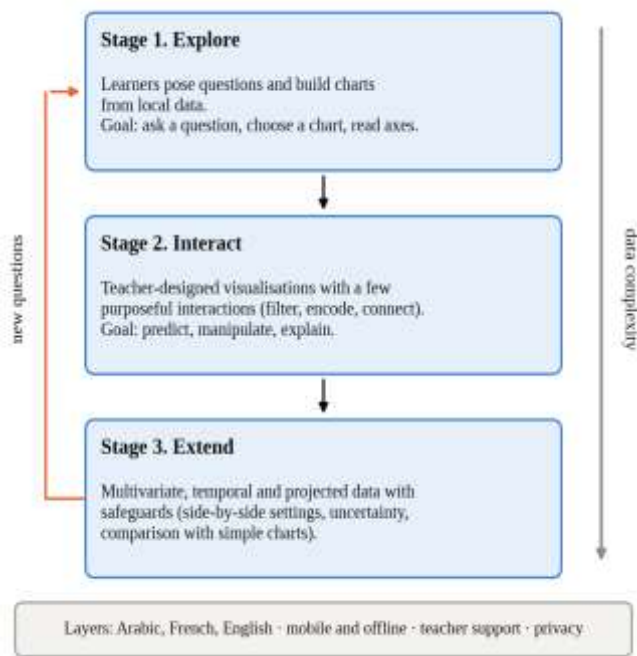


Figure 5: The Explore–Interact–Extend (EIE) framework.

Four principles run through all stages. First, use local and authentic data [16]. Second, limit interaction to what supports the task and hides the irrelevant [8]. Third, give modest guidance and fade it [27]. Fourth, check every complex view against a simple one [9].

4.2. Stage 1: Explore

In Stage 1, pupils and students explore data before any formal instruction. Tasks are short and framed by questions, for example: how long do classmates travel to school, and how does study time vary across the class? Learners choose a chart type, read the axes aloud, and write one sentence on what the chart shows and one on what it does not show. Datasets come from the class itself, from open Moroccan data portals such as that of the national planning authority (Haut-Commissariat au Plan, HCP), and from the indicators in Section 3. This stage addresses the motivation and goal-setting themes that visualisation educators identify [15], and it practises the axis-reading skills whose measurement remains inconsistent [7].

4.3. Stage 2: Interact

In Stage 2, the teacher selects or adapts an interactive template. Each template offers at most three interactions, chosen from filtering, encoding, and connecting, because these performed best in a controlled comparison [8]. Before each interaction, learners write a prediction; the view then reveals the result, and learners explain any difference. The prediction step is our proposal and is not yet tested. Guidance

is modest at the start and fades over successive activities, since excessive guidance reduced the depth of teachers’ interpretations [27]. Teachers with lower visualisation literacy receive templates with a short data story attached, which reduced cognitive load in a study of 23 teachers [28]. Where a science concept exists in simulation form, the template links to it, because simulations improved learning in classroom studies [18], [19].

4.4. Stage 3: Extend

In Stage 3, learners meet data that cannot be read from a single chart: several variables, time series, or two-dimensional projections. Three safeguards apply. *Side-by-side settings*: any projection is shown at several parameter settings, and learners note which patterns persist. *Uncertainty display*: unreliable regions of a projection are marked [33]. *Simple-view check*: each complex view is paired with a plain chart of the same data. These safeguards address the literacy gap behind the misuse of t-SNE and UMAP [9]. For university students and trainee teachers, Stage 3 also uses learning traces, such as engagement and persistence indicators, following the indicator set proposed for pioneer colleges [14], and it includes a discussion of privacy [12].

4.5. Activities for pupils and for students

Table 2 shows how the stages differ between lower- and upper-secondary pupils and university students or trainee teachers. The same three stages apply, but the datasets, the level of design responsibility, and the complexity differ.

Table 2: Stage activities for pupils and for students, with the rule that governs each stage.

Stage	Lower- and upper-secondary pupils	University students and trainee teachers	Safeguard or rule
1. Explore	Class survey (travel time, study time); public indicators of schooling; one-sentence notes on what a chart shows and does not show	Open data from national portals; questions written by the students; comparison of two indicators	Local data; question first, chart second
2. Interact	Interactive chart of PISA and TIMSS scores with a subject filter; predict, then reveal	Design an interactive view; write the prediction prompts for a class	At most three interactions; guidance fades
3. Extend	Small multiples by subject and year, compared with a simple chart (upper secondary only)	Projection of multivariate data at several settings; learning-trace indicators; privacy discussion	Side-by-side settings; uncertainty display; simple-view check

4.6. Platform architecture

Figure 6 shows the proposed architecture. The learner device runs a PWA, which can store datasets and activities for offline use and so meets requirements R4 and R10 [38]. The interface is available in Arabic with RTL layout, French, and English, following the trilingual setup reported for pioneer colleges [14] and the axis conventions documented for Arabic content [34]. A translanguaging option shows labels in two languages at once, in line with evidence on translanguaging [35]. The teacher console holds the template editor, the guidance settings, and a class overview with simple colour-coded alerts, following co-design results for teacher dashboards [25], [26].

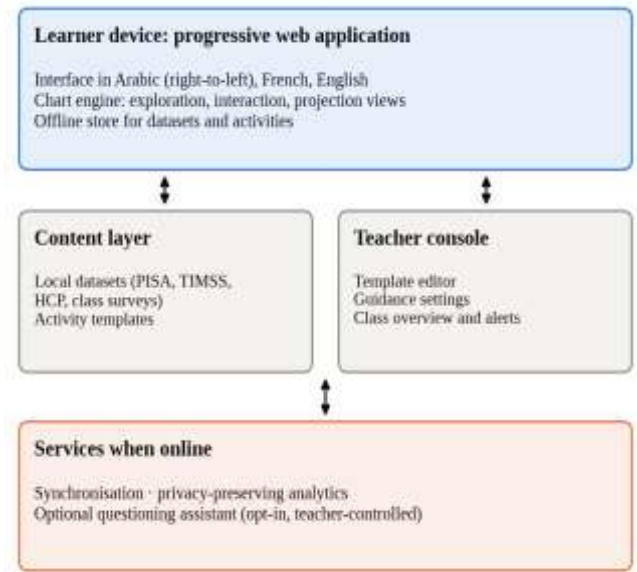


Figure 6: Proposed platform architecture.

When a connection is available, services synchronise data and run privacy-preserving analytics. An optional questioning assistant asks learners to explain a chart rather than giving the answer, because an eliciting agent improved reflection [32] and proactive agents improved comprehension [31]. The assistant is opt-in and teacher-controlled because Moroccan students are cautious about GenAI [13].

4.7. Illustrative walkthrough

Consider a lower-secondary science class that uses the data in Figure 1. In Stage 1, pupils read the nine bars and the axis and write what the chart shows and does not show. In Stage 2, the teacher hides the OECD bars and asks pupils to predict whether the relative gap is larger in reading or in mathematics; the values then appear, and the answer, 30.4% against 23.3%, follows from (1). In Stage 3, trainee teachers in a regional education and training centre (CRMEF) compare the PISA changes with the TIMSS results and the connectivity indicators, and discuss why country-level indicators alone cannot show causes. This walkthrough is an illustration, not an experiment.

5. Comparison with existing solutions

5.1. Evidence base

Table 3 summarises twelve studies that represent the approaches we compare, with their designs, sample sizes, and main reported results. All figures are as reported by the cited authors.

Table 3: Evidence base for existing approaches and components.

Ref.	Approach	Design and sample	Main reported result
[8]	Interactive visualisation	Within-subject study, 160 participants (80 data scientists, 80 non-experts), seven techniques	Filter, Encode, and Connect performed best; hiding irrelevant information raised accuracy and lowered load
[18]	Simulations	Experiment, 100 grade 3 pupils, PhET versus textbook, two months	Higher scores and better explanations with simulations
[19]	Simulations	Systematic review, 14 studies (2020–2026)	Consistent gains in achievement and conceptual understanding; higher-order and affective outcomes less studied
[20]	Interactive environments	Network meta-analysis, 53 primary studies	Augmented reality ranked most effective overall; mixed reality had the largest effect sizes
[21]	Notebooks	Graduate course, female students; document analysis and questionnaire	Stronger conceptual understanding and more engagement
[30]	GenAI visualisation	Case study, 59 participants (43 undergraduates, 16 professionals)	Visualisation tool with a language model enhanced learning of advanced skills; technical knowledge still needed
[31]	GenAI agents for dashboards	Randomised trial, 117 higher-education students	Proactive agents improved comprehension; benefits persisted

[32]	Interactive dashboard with agent	30 students, five weeks, three conditions	Eliciting agent increased reflection and improved calibration
[28]	Storytelling dashboards	23 teachers, pupil dilation as load measure	Storytelling reduced cognitive load, especially for lower literacy
[27]	Guidance on dashboards	Think-aloud study with teachers of varied literacy	Lower literacy gave shallower interpretation; excessive guidance hindered
[26]	Co-designed dashboards	Design-based research, 25 primary teachers	High satisfaction with text clarity; navigation needed improvement
[14]	Pioneer-college analytics model	Design-based research; conceptual model, not tested	Five-module model with trilingual data and teacher dashboard

5.2. Comparison on seven criteria

Table 4 compares the seven existing approaches, A1 to A7, with EIE (A8) on seven criteria: open exploration by learners (C1), structured interaction with fading guidance (C2), safeguards for complex data (C3), teacher support and analytics (C4), offline or low-bandwidth use (C5), Arabic RTL and multilingual support (C6), and local data and curriculum alignment (C7). A criterion scores 2 points if fully addressed, 1 if partly addressed, and 0 if not reported in the cited studies. The maximum is 14. Ratings for A1 to A7 reflect what the cited studies report, and a tool may offer more than its studies describe. Ratings for EIE are design intent and have not been tested.

Table 4: Comparison of existing approaches (A1–A7) and the proposed framework (A8) on seven criteria.

Approach	C1	C2	C3	C4	C5	C6	C7	Score
A1 Static charts and infographics (baseline)	○	○	○	○	●	●	●	4
A2 Interactive simulations [18]–[20]	●	●	○	○	○	○	○	3
A3 Notebook coding [21]	●	●	●	○	○	○	○	4
A4 GenAI-assisted visualisation [30]	●	●	●	○	○	○	○	4
A5 Learning analytics dashboards [22]–[24]	○	○	●	●	○	○	○	3
A6 AI-augmented dashboards [28], [31], [32]	○	●	●	●	○	○	○	4
A7 Pioneer-college analytics model [14]	○	○	●	●	○	●	●	7
A8 EIE (proposed)*	●	●	●	●	●	●	●	14

● fully addressed (2 points); ● partly addressed (1); ○ not reported in the cited studies (0). C1: open exploration; C2: structured interaction with fading guidance; C3: safeguards for complex data; C4: teacher support and analytics; C5: offline or low-bandwidth use; C6: Arabic RTL and multilingual support; C7: local data and curriculum alignment. *Design intent, not yet evaluated.

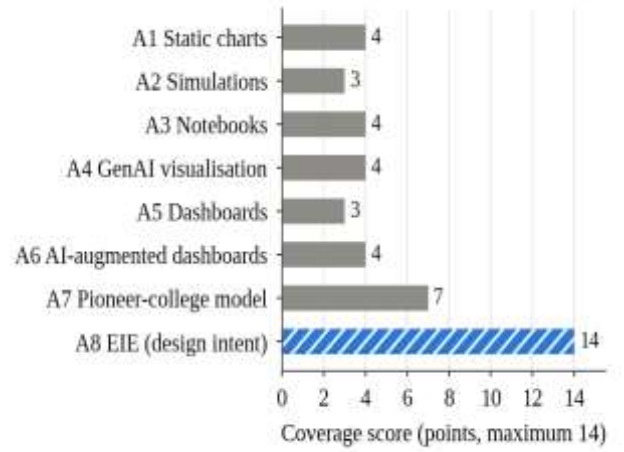


Figure 7: Coverage score of each approach on the seven criteria of Table 4. The hatched bar for EIE shows design intent, not measured performance.

5.3. Reading the comparison

The existing approaches score between 3 and 7 points. The pioneer-college model scores highest among them because it covers teacher analytics, trilingual data, and local data [14], but it does not teach learners to explore data or to read complex views. Simulations and notebooks have the strongest classroom evidence for learning [18], [19], [21], and EIE should reuse them as components of Stage 2 rather than replace them. GenAI tools broaden access to visualisation but need technical knowledge [30].

EIE scores 14 by design, which shows what it aims to cover, not what it achieves. Its weaknesses are plain: it has no classroom evidence yet, it costs more to develop and to train teachers for than a single tool, and it depends on teachers' digital competence [37]. The comparison therefore supports a research programme, not a claim of superiority.

6. Evaluation plan

6.1. Design and sample size

We propose a cluster-randomised trial with two arms: EIE and conventional instruction with static charts. Classes are the clusters. Participants are lower-secondary pupils in pioneer middle schools and cohorts of trainee teachers in regional centres. Language of instruction and school setting (urban or rural) are recorded because they shape learners' views of French-medium science teaching [35]. For a standardised effect of $d = 0.5$, a two-sided significance level of 0.05, and power of 0.80, an individually randomised trial needs 63 participants per arm. Clustering inflates this number by the design effect:

$$\text{DEFF} = 1 + (m - 1)\rho \quad (2)$$

where m is the class size and ρ is the intraclass correlation. With $m = 25$ and an assumed $\rho = 0.10$, the design effect is 3.4, which gives about 214 participants, or nine classes, per arm. The value of ρ is an assumption and should be replaced by an estimate from pilot data. The main learning outcome is the normalised gain:

$$g = \frac{\text{Post-Pre}}{100-\text{Pre}} \quad (3)$$

where Pre and Post are percentage scores on the same instrument before and after the intervention.

6.2. Hypotheses and measures

Table 5 lists five hypotheses and the measures that test them.

Table 5: Hypotheses, outcomes, and measures.

No.	Hypothesis	Measure
H1	EIE learners gain more in chart reading than controls	Normalised gain (3) on a translated, validated visualisation-literacy test; instrument choice informed by [7]
H2	Prediction-first tasks reduce misreadings of projections	Share of incorrect statements on cluster distances and sizes [9]
H3	Fading guidance gives deeper interpretation than constant guidance	Coded depth of think-aloud interpretations [27]
H4	EIE does not raise cognitive load	Self-reported load; pupil dilation in a subsample [28]
H5	Gains hold across language of instruction and school setting	Subgroup contrasts [35]

6.3. Ethics and privacy

Participants include minors, so parental consent, school approval, and data minimisation apply. Analytics are opt-in and aggregated, and learners see what is collected, because Moroccan students expect transparency and consent [12].

7. Discussion

The data in Section 3 show a large gap in basic proficiency alongside near-universal mobile access. EIE responds to both facts: it uses the device that learners already hold, and it starts from tasks that need little prior knowledge. For pupils, the early stages give practice in reading axes and in stating what a chart does not show. For university students and trainee teachers, Stage 3 develops the critical reading of complex outputs that they will meet in research, in learning analytics, and in AI tools. For the pioneer-school programme, templates and short data stories could let teachers use the approach without advanced digital skills, which matters given documented gaps among teacher trainers [37] and teachers [17].

Compared with related work, the contribution of EIE is integration rather than a new technique. It combines components that have individual evidence, namely interaction techniques [8], storytelling [28], agents [31], [32], and dimensionality-reduction literacy [9], inside one sequence, and it adapts them to Arabic and French use and to variable connectivity.

Limitations. First, the framework is untested with learners. Second, the national indicators are secondary: the TIMSS scores, the share of students below baseline in mathematics, and the enrolment figures come from press reports of official data, and the 2022 PISA values are derived by subtraction. Third, the review is targeted, so relevant studies may be missing. Fourth, the ratings in Table 4 are the author’s judgements and depend on what the cited studies report. Fifth, most cited experiments come from outside Morocco, and their effects may not transfer.

Equity. Rural learners and learners with weaker French could gain the most or be left behind. The subgroup analysis in H5 is planned for this reason.

8. Conclusion

This article proposed the EIE framework, in which Moroccan pupils and students explore local data, work with a few purposeful interactions, and then meet complex data with safeguards against misreading. The design rests on published indicators and on 33 scholarly sources from 2023 to 2026. The comparison shows that no reviewed approach covers exploration, guided interaction, complex-data safeguards, offline use, and RTL support together, and it also shows that EIE has no empirical evidence yet. Future work will build the prototype, estimate the intraclass correlation and effect sizes

in a pilot with cohorts from a regional centre, and then run the trial described in Section 6.

References

- [1] World Bank, “Morocco’s pioneer schools: Advancing improved student learning,” World Bank, Washington, DC, USA, May 21, 2026. [Online]. Available: <https://www.worldbank.org/en/news/feature/2026/05/21/morocco-s-pioneer-schools-advancing-improved-student-learning>
- [2] OECD, “Education GPS: Morocco – Student performance (PISA 2025),” OECD, Paris, France, Sep. 2026. [Online]. Available: <https://gpseducation.oecd.org/CountryProfile?primaryCountry=MAR&topic=PI>
- [3] “PISA 2025: Nearly three-quarters of Moroccan students fall below minimum proficiency levels,” *Yabiladi*, Sep. 9, 2026. [Online]. Available: <https://en.yabiladi.com/articles/details/202395/pisa-2025-nearly-three-quarters-moroccan.html>
- [4] “Moroccan students rank lowest globally in TIMSS 2023 math and science,” *Yabiladi*, Dec. 5, 2024. [Online]. Available: <https://en.yabiladi.com/articles/details/157141/moroccan-students-rank-lowest-globally.html>
- [5] DataReportal, “Digital 2025: Morocco,” 2025. [Online]. Available: <https://datareportal.com/reports/digital-2025-morocco>
- [6] R. E. Mayer, “The past, present, and future of the cognitive theory of multimedia learning,” *Educ. Psychol. Rev.*, vol. 36, no. 1, Art. no. 8, 2024, doi: 10.1007/s10648-023-09842-1.
- [7] S. Beschi, D. Falessi, S. Golia, and A. Locoro, “Characterizing data visualization literacy: A systematic literature review,” arXiv:2503.14468, 2025.
- [8] N. van Berkel *et al.*, “Impact of interaction technique in interactive data visualisations: A study on lookup, comparison, and relation-seeking tasks,” *Int. J. Hum.-Comput. Stud.*, vol. 192, Art. no. 103359, 2024, doi: 10.1016/j.ijhcs.2024.103359.
- [9] H. Jeon, J. Park, S. Shin, and J. Seo, “Stop misusing t-SNE and UMAP for visual analytics,” arXiv:2506.08725, 2025.
- [10] A. Dehbi, R. Dehbi, A. Bakhouyi, and M. Talea, “Survey analysis of students and teachers’ perceptions of e-learning and m-learning in Morocco,” *Int. J. Interact. Mob. Technol.*, vol. 17, no. 3, pp. 102–122, 2023, doi: 10.3991/ijim.v17i03.36325.
- [11] M. M. Elaish *et al.*, “A comparative study of students’ adoption and usage of mobile learning in developing countries: Tunisia, Morocco, and Libya,” *Educ. Technol. Res. Dev.*, vol. 74, no. 2, pp. 1187–1220, 2026, doi: 10.1007/s11423-026-10613-2.
- [12] S. Fadli and A. El Mediouni, “Digital transformation in higher education: Moroccan university students’ perceptions and expectations on learning analytics implementation for learning optimization,” in *Internationalization of Higher Education and Digital Transformation*, A. Adoui, Ed. Cham, Switzerland: Palgrave Macmillan, 2024, pp. 259–276, doi: 10.1007/978-3-031-76444-8_14.
- [13] Y. Niniss, A. Alla, and T. Azzimani, “Generative artificial intelligence in the context of the internationalization of higher education in Morocco: Perceptions of use and effect on student engagement,” in *Internationalization of Higher Education and Digital Transformation*, A. Adoui, Ed. Cham, Switzerland: Palgrave Macmillan, 2024, pp. 221–242, doi: 10.1007/978-3-031-76444-8_12.
- [14] L. Lamalif, M. Machkour, S. Faris, and K. Mansouri, “Analysis of learning in Moroccan secondary education: Computer model and data-driven pedagogy,” *Front. Educ.*, vol. 11, Art. no. 1890197, 2026, doi: 10.3389/feduc.2026.1890197.
- [15] B. Bach *et al.*, “Challenges and opportunities in data visualization education: A call to action,” *IEEE Trans. Vis. Comput. Graphics*, 2023, doi: 10.1109/TVCG.2023.3327378.
- [16] A. Friedrich *et al.*, “What shapes statistical and data literacy research in K-12 STEM education? A systematic review of metrics and instructional strategies,” *Int. J. STEM Educ.*, vol. 11, Art. no. 58, 2024, doi: 10.1186/s40594-024-00517-z.
- [17] S. Schreiter *et al.*, “Teaching for statistical and data literacy in K-12 STEM education: A systematic review on teacher variables, teacher education, and impacts on classroom practice,” *ZDM Math. Educ.*, vol. 56, no. 1, pp. 31–45, 2024, doi: 10.1007/s11858-023-01531-1.

- [18] H. Diab, W. Daher, B. Rayan, N. Issa, and A. Rayan, "Transforming science education in elementary schools: The power of PhET simulations in enhancing student learning," *Multimodal Technol. Interact.*, vol. 8, no. 11, Art. no. 105, 2024, doi: 10.3390/mti8110105.
- [19] S. A. Ningrum *et al.*, "Effectiveness of PhET simulations on learning outcomes in science and chemistry education: A systematic review," *Multimodal Technol. Interact.*, vol. 10, no. 7, Art. no. 69, 2026, doi: 10.3390/mti10070069.
- [20] A. Koç and S. Kanadlı, "Effect of interactive learning environments on learning outcomes in science education: A network meta-analysis," *J. Sci. Educ. Technol.*, vol. 34, no. 4, pp. 681–703, 2025, doi: 10.1007/s10956-025-10202-7.
- [21] G. Amoudi and D. Tbaishat, "Interactive notebooks for achieving learning outcomes in a graduate course: A pedagogical approach," *Educ. Inf. Technol.*, vol. 28, no. 12, pp. 16669–16704, 2023, doi: 10.1007/s10639-023-11854-x.
- [22] I. Masiello *et al.*, "A current overview of the use of learning analytics dashboards," *Educ. Sci.*, vol. 14, no. 1, Art. no. 82, 2024, doi: 10.3390/educsci14010082.
- [23] L. Paulsen and E. Lindsay, "Learning analytics dashboards are increasingly becoming about learning and not just analytics—A systematic review," *Educ. Inf. Technol.*, vol. 29, no. 11, pp. 14279–14308, 2024, doi: 10.1007/s10639-023-12401-4.
- [24] Z. Mohseni, I. Masiello, R. M. Martins, and S. Nordmark, "Visual learning analytics for educational interventions in primary and secondary schools: A scoping review," *J. Learn. Anal.*, vol. 11, no. 2, pp. 91–111, 2024, doi: 10.18608/jla.2024.8309.
- [25] Z. Mohseni, I. Masiello, and R. M. Martins, "Co-developing an easy-to-use learning analytics dashboard for teachers in primary/secondary education: A human-centered design approach," *Educ. Sci.*, vol. 13, no. 12, Art. no. 1190, 2023, doi: 10.3390/educsci13121190.
- [26] Z. Mohseni and I. Masiello, "Co-designing, developing, and implementing multiple learning analytics dashboards for data-driven decision-making in education: A design-based research approach," *Educ. Technol. Res. Dev.*, vol. 74, no. 2, pp. 517–548, 2026, doi: 10.1007/s11423-025-10577-9.
- [27] S. Pozdniakov *et al.*, "Investigating the effect of visualization literacy and guidance on teachers' dashboard interpretation," *J. Learn. Anal.*, vol. 12, no. 1, pp. 367–390, 2025, doi: 10.18608/jla.2024.8471.
- [28] Y. Liu, S. Pozdniakov, and R. Martinez-Maldonado, "The effects of visualisation literacy and data storytelling dashboards on teachers' cognitive load," *Australas. J. Educ. Technol.*, vol. 40, no. 1, pp. 78–93, 2024, doi: 10.14742/ajet.8988.
- [29] E. Cano García and M.-d.-M. Suárez, "Student awareness and preferences for learning analytics dashboards: Misalignments with self-regulation of learning," *Technol. Knowl. Learn.*, vol. 31, no. 3, pp. 1341–1360, 2026, doi: 10.1007/s10758-026-09969-4.
- [30] J. Valverde-Rebaza, A. González, O. Navarro-Hinojosa, and J. Noguez, "Advanced large language models and visualization tools for data analytics learning," *Front. Educ.*, vol. 9, Art. no. 1418006, 2024, doi: 10.3389/feduc.2024.1418006.
- [31] L. Yan *et al.*, "The effects of generative AI agents and scaffolding on enhancing students' comprehension of visual learning analytics," *Comput. Educ.*, vol. 234, Art. no. 105322, 2025, doi: 10.1016/j.compedu.2025.105322.
- [32] L. Graf, P. Bassner, M. Anzinger, F. Dietrich, S. Krusche, and O. Poquet, "Interactive learning dashboards: Rethinking learning visualisations as engagement tools," *Educ. Inf. Technol.*, pp. 1–27, 2026, doi: 10.1007/s10639-026-14082-1.
- [33] T. Munz-Körner and D. Weiskopf, "Exploring visual quality of multidimensional time series projections," *Vis. Informatics*, vol. 8, no. 2, pp. 27–42, 2024, doi: 10.1016/j.visinf.2024.04.004.
- [34] M. Alebri, N. Rakotondravony, and L. Harrison, "Design patterns in right-to-left visualizations: The case of Arabic content," in *Proc. IEEE Vis. Conf. (VIS), Short Papers*, 2024.
- [35] S. Ben Hammou, M. Saissi, and A. Tritha, "L2-French-medium instruction (FMI) in Moroccan secondary education: Benefits, challenges, and the role of translanguaging," *SN Soc. Sci.*, vol. 5, Art. no. 83, 2025, doi: 10.1007/s43545-025-01121-w.
- [36] I. Ould-Bouya, A. Azhar, and Y. Baahmad, "Digital transformation in Moroccan higher education:

Challenges and opportunities at Mohammed V University in Rabat,” *Int. J. Lang. Lit. Stud.*, vol. 8, no. 5, pp. 294–304, 2026, doi: 10.36892/ijlls.v8i5.2582.

- [37] A. Benaoui, A. El Youssefi, and Y. Farhaoui, “Enhancing digital competencies among teacher trainers in Morocco: A cluster analysis approach,” in *Innovative Approaches and Applications for Sustainable Development (I2ASD 2025)*, E. A. Abdellaoui Alaoui, M. Merras, and A. Nayyar, Eds. Cham, Switzerland: Springer, 2026, pp. 611–614, doi: 10.1007/978-3-031-97825-8_122.
- [38] C. Cuenca-Enrique *et al.*, “Progressive web apps: An optimal solution for rural communities in developing countries?” in *Information Systems and Technologies (WorldCIST 2023)*, A. Rocha, H. Adeli, G. Dzemyda, F. Moreira, and V. Colla, Eds. Cham, Switzerland: Springer, 2024, pp. 356–365, doi: 10.1007/978-3-031-45648-0_35.
- [39] TIMSS & PIRLS International Study Center, “TIMSS 2023 international results: Average achievement (Grade 8),” Boston College, Chestnut Hill, MA, USA, 2024. [Online]. Available: <https://timss2023.org/results/grade-8-math-achievement/>
- [40] “More students enrolling in Moroccan universities, private schools on the rise,” *Hespress English*, Oct. 30, 2025. [Online]. Available: <https://en.hespress.com/124404-more-students-enrolling-in-moroccan-universities-private-schools-on-the-rise.html>