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Are African Teachers Ready for Artificial Intelligence? Decomposing Teacher Competencies and the Role of Initial and In-Service Training: Evidence from PASEC

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Abstract

Enthusiasm for artificial intelligence (AI) in African education is outpacing the conditions required for AI to improve teaching and learning. Because large-scale African datasets do not yet measure AI use, this study reframes the question and argues that teachers' professional competencies are the prerequisite for any successful AI integration: AI does not replace the teacher but transforms the teacher's role, and its benefits depend on teachers' content and pedagogical knowledge, qualifications and continuing training. Drawing on the PASEC2019 teacher assessment across 14 Francophone African education systems (19,141 teachers), the study measures teacher content and pedagogical (didactic) knowledge, decomposes their variance across teachers, schools and countries using three-level models on plausible values, quantifies the contribution of pre-service qualification and in-service training with design-based estimates using PASEC replicate weights, and builds a Teacher AI-Readiness Index (TARI) to rank the systems. Results show that about 39% of the variance in teacher competence lies between countries, indicating highly unequal AI-readiness foundations. Holding a professional teaching diploma (associated with gains of +15 to +27 points across dimensions) and receiving in-service training (+9 to +12 points) are the strongest and most robust correlates of competence, together with classroom electricity, whereas the sheer duration of initial training or the number of in-service domains adds nothing. The ranking reveals wide gaps, from Gabon, Senegal and Benin at the top to Chad, DR Congo and Madagascar at the bottom. These findings align with, and can help target, the teacher-centred priority reforms that many countries are pursuing through their GPE partnership compacts. The study concludes that credible AI-in-education strategies in Africa must first invest in teacher qualification and continuing training, a condition, not a mere precursor, of AI's effectiveness.

Keywords: *teacher competencies; AI readiness; teacher education; in-service training; PASEC; sub-Saharan Africa*

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1. Introduction

Artificial intelligence (AI) has moved to the centre of educational debate, and sub-Saharan Africa is no exception. Personalised learning paths, intelligent tutoring, automated feedback and always-available assistants promise much, and expectations run high. Yet these expectations are rising faster than education systems' capacity to benefit from them. A large body of evidence has long converged on a simple point: technology improves learning only when teachers can integrate it pedagogically (Miao et al., 2021; Holmes et al., 2019; UNESCO, 2024). AI does not replace the teacher; it transforms the teacher's role, shifting effort from routine tasks toward pedagogical judgement, contextualisation and support. Teacher competencies are therefore the true bottleneck and the true lever of AI integration.

This is especially acute in sub-Saharan Africa, where teaching quality remains the principal determinant, and the principal constraint, of learning (World Bank, 2018). The most rigorous evidence on teacher competencies in the region is sobering: many teachers imperfectly master the content they teach and, still more, how to teach it (Bold et al., 2017). Introducing AI tools into such a context without first securing the competencies that condition their useful application would risk bypassing teachers rather than augmenting them and widening, rather than narrowing, inequalities.

1.1 Teacher competencies and the AI shift

Recent syntheses of AI in education point to a redistribution of tasks rather than a replacement of the teacher: partial automation of marking, planning and monitoring, and personalisation of learning, but the retention indeed the intensification of the properly pedagogical role of contextualising, scaffolding and making sense of learning (Zawacki-Richter et al., 2019; Holmes et al., 2019; Selwyn, 2019). Far from lowering the demand for teacher competence, AI raises it: orchestrating intelligent tools, interpreting their outputs and connecting them to a pedagogical intention presupposes solid disciplinary and pedagogical knowledge. Institutional frameworks, foremost the AI competency framework for teachers (UNESCO, 2024), accordingly frame AI literacy as a competency to be built on pedagogical foundations, not as a substitute for them (Ng et al., 2021).

1.2 What builds teacher competence

Teacher quality is among the most robust school-level determinants of learning (Darling-Hammond, 2000; Hanushek & Rivkin, 2006). At its core lie two distinct but complementary forms of knowledge: content knowledge, mastering the subject and pedagogical content knowledge, knowing how to teach it which Shulman (1986)

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identified as the teacher's specific professional knowledge. These competencies are built through pre-service preparation (qualification, professional diploma, initial training) and continuing professional development, understood as investments in human capital (Becker, 1964) and in professional capital (Hargreaves & Fullan, 2012). The literature on effective professional development stresses sustained, content-focused, practice-oriented designs (Darling-Hammond et al., 2017), while cautioning that much professional development worldwide is fragmented and ineffective, so that the quantity of training does not guarantee the quality of professional learning (Popova et al., 2022; OECD, 2019). The distinction between the breadth and the depth of training will prove central to interpreting our results.

1.3 Theoretical framework: TPACK

The study is anchored in the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006), an extension of Shulman's (1986) pedagogical content knowledge. TPACK distinguishes content knowledge (CK), pedagogical content knowledge (PCK) and technological knowledge (TK). AI integration essentially adds a technological and AI-literacy layer (Ng et al., 2021; UNESCO, 2024) onto an existing base of CK and PCK: without a solid foundation, teachers cannot translate AI tools into effective instruction. PASEC2019 measures precisely this foundation teacher content and pedagogical knowledge, making it an ideal instrument for assessing the readiness base. From this framework we derive four propositions: (P1) teacher competencies vary substantially across systems, indicating unequal AI-readiness foundations; (P2) diploma-level pre-service preparation accounts for an important share of competency differences; (P3) in-service training is positively associated with competencies; and (P4) systems investing more in these dimensions display a stronger latent capacity to integrate AI.

1.4 The present study

Against this backdrop and given the absence of direct AI-use measures in large African datasets, this study diagnoses AI readiness through its foundations. Using the PASEC2019 teacher assessment, it asks three questions: how large are the differences in teacher content and pedagogical knowledge within and between schools and countries; to what extent do pre-service qualification and in-service training account for these differences; and how do the 14 systems compare on a composite index of teacher AI readiness? The contribution is threefold: a large-scale variance decomposition of teacher competencies; an estimate of the role of initial and continuing training using multilevel

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and design-based methods; and an original Teacher AI-Readiness Index that ranks systems and moves beyond descriptive performance reporting.

2. Methods

2.1 Data and sample

The data come from the PASEC2019 teacher assessment, administered in 14 Francophone African education systems to 19,141 teachers. The teacher tests yield plausible values for content knowledge in language and mathematics and for the corresponding pedagogical (didactic) knowledge (von Davier et al., 2009). The teacher questionnaire documents qualification, initial and in-service training, experience, status and the classroom environment. Data are analysed at the teacher level, nested within schools and countries.

2.2 Variables

Table 1 summarises the key variables; Appendix B details the exact coding and the item-specific treatment of non-response. Outcomes are the four competency scores (content and pedagogical, in language and mathematics). Predictors are grouped into pre-service (academic level, professional diploma, initial-training duration, practicum), in-service (participation, number of domains), digital environment (computer/tablet, classroom electricity) and controls.

Table 1:
Key variables and operationalisation

Construct	PASEC source	Operationalisation
Content knowledge (CK)	LECT_PV1–5; MATHS_PV1–5	Plausible values (language, mathematics)
Pedagogical content knowledge (PCK)	LECT_DIDA_PV1–5; MATHS_DIDA_PV1–5	Plausible values (language, mathematics)
Academic qualification	qm3	Ordinal level (1–12)
Professional diploma	qm4	1 = holds a diploma; 0 = none
Initial training	qm5; qm6	Duration (ordinal); practicum (months)
In-service training	qm7; qm9a–e	Received (2 years); number of domains (0–5)
Digital environment	qm26r; qm28	Computer/tablet; classroom electricity
Controls	qm1; qm2; qm10; qm13; qm19	Sex, age, experience, status, class organisation

***Source**: Authors, based on PASEC2019 data (2026).*

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2.3 Analytical strategy

Three complementary approaches are combined. First, three-level mixed models (teacher, school, country) are fitted to each competency score to estimate the share of variance lying between countries and between schools; this model-based step quantifies the inequality of foundations. Second, sequential models add blocks of predictors (pre-service, then in-service, then digital and controls) and track the reduction in variance attributable to each. Third, design-based coefficients are estimated on the plausible values with PASEC sampling and jackknife replicate weights, combined via Rubin's (1987) rules and robust to the complex sampling design (Raudenbush & Bryk, 2002). The variance decomposition rests on model-based inference; the coefficients rest on design-based inference.

2.4 Teacher AI-Readiness Index (TARI)

A composite Teacher AI-Readiness Index is built from six standardised components: qualification, initial training, in-service training, content knowledge, pedagogical knowledge and digital access. Components are standardised, aggregated with equal weights (a principal-component weighting serves as a robustness check) and rescaled to mean 50 and standard deviation 10. Individual scores are aggregated to the system level to rank the 14 countries, with jackknife confidence intervals.

3. Results

3.1 Teacher competencies are highly unequal across systems

The variance decomposition reveals striking inequalities (Table 2). For overall teacher competence, about 39% of the variance lies between countries, roughly 14% between schools within a country, and 47% between teachers within a school. Such concentration between countries confirmed for each of the four dimensions and highest for reading content knowledge (42%) means that a teacher's competence depends first on the system to which they belong. By the standards of international assessments this between-country share is large. Consistent with proposition P1, the foundations of AI readiness are therefore very unequally distributed across systems, raising the risk that AI, if deployed indiscriminately, would amplify existing gaps rather than close them.

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Table 2:
Variance decomposition of teacher competencies (share of variance, %)

Competency dimension	Between countries	Between schools	Between teachers
Overall competence	39.0%	14.3%	46.7%
Content — reading	42.2%	11.1%	46.7%
Pedagogical — reading	32.7%	16.2%	51.2%
Content — mathematics	30.2%	16.1%	53.7%
Pedagogical — mathematics	32.3%	19.6%	48.0%

***Source**: Authors, based on PASEC2019 data (2026). Three-level mixed models.*

3.2 Training accounts for part of the differences, especially between schools

The sequential models clarify the role of training (Table 3). Introducing the pre-service variables alone absorbs about 18% of the between-school variance; adding in-service training raises this to nearly 20%. The full model adding the digital environment and controls explains about 26% of the between-school variance, 12% of the between-teacher variance and 12.5% of the total variance, but only 9% of the between-country variance. This asymmetry is instructive: teacher training explains a substantial share of the differences between schools and between individuals, yet accounts only weakly for the gaps between systems, which reflect more structural factors (teacher labour markets, recruitment and qualification policies, financing).

Table 3:
Sequential models — variance explained (VE) of overall competence

Model	VE between countries	VE between schools	VE between teachers	VE total
M0 (empty)	---	---	---	---
M1 (+ initial training)	0.7%	18.2%	2.2%	3.9%
M2 (+ in-service training)	1.5%	19.6%	2.2%	4.4%
M3 (+ digital + controls)	8.6%	26.0%	11.7%	12.5%

***Source**: Authors, based on PASEC2019 data (2026). VE = reduction of variance relative to the empty model (M0).*

3.3 Certified qualification and in-service training are the strongest levers

The design-based regressions, run for each of the four competency dimensions, identify two dominant levers (Table 4). The professional diploma is the strongest correlate: holding a teaching diploma rather than none is associated with an advantage of nearly 15 points in reading content and up to 27 points in mathematics content ($p < 0.01$) sizeable gaps on the PASEC teacher scale. In-service training follows, with a systematic

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advantage of 9 to 12 points across all four dimensions ($p < 0.01$). Classroom electricity, an indicator of a better-resourced school environment, is also positive and significant. Academic level matters chiefly for pedagogical knowledge.

Two findings run against intuition and deserve attention. First, the sheer duration of initial training and the number of practicum months add nothing and are even negatively associated with pedagogical knowledge in reading. Second, the number of in-service domains is slightly negative: accumulating scattered domains does not build competence. Together, these results point to a clear conclusion, it is certified qualification and focused training (depth) that build competence, not the accumulation of duration or breadth. Access to a computer or tablet, finally, has no detectable effect, it's very low prevalence (under 3% of classrooms) making it non-discriminating.

Table 4:

Design-based effects on teacher competencies (coefficients, standard errors in parentheses)

Predictor	Reading (content)	Reading (pedagogy.)	Maths (content)	Maths (pedagogy.)
Academic level	0.4 (0.3)	1.0*** (0.4)	0.3 (0.3)	1.3*** (0.3)
Professional diploma	14.7*** (4.0)	19.3*** (5.1)	26.9*** (3.9)	24.6*** (4.6)
Initial training (duration)	-0.9 (0.9)	-2.3** (0.9)	-0.6 (1.0)	0.1 (1.0)
Practicum (months)	-0.3 (0.2)	-0.6*** (0.2)	-0.1 (0.2)	-0.3 (0.2)
In-service training	12.2*** (3.0)	11.5*** (3.6)	11.0*** (3.4)	8.9*** (3.4)
Number of domains	-1.8** (0.8)	-2.3** (0.9)	-0.9 (0.8)	-1.7** (0.9)
Computer/tablet	-0.2 (7.4)	-0.5 (7.7)	-5.1 (6.9)	6.8 (6.5)
Classroom electricity	12.8*** (2.7)	9.6*** (3.1)	9.7*** (2.9)	5.7* (3.1)

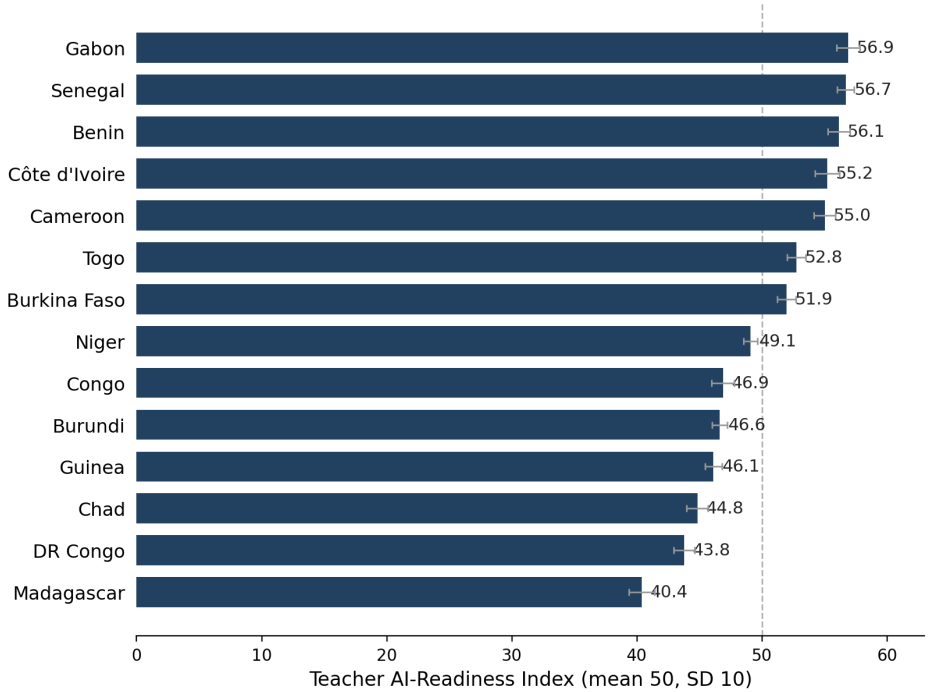
***Source**: Authors, based on PASEC2019 data (2026). Pooled model, international weight and country fixed effects; plausible values + jackknife replicate weights. *** p<0.01; ** p<0.05; * p<0.10.*

3.4 A contrasted ranking of systems

The AI-readiness index ranks the 14 systems (Figure 1; Appendix A). Gabon, Senegal and Benin lead, followed by Côte d'Ivoire and Cameroon, while Madagascar, DR Congo and Chad close the ranking. The gap between the extremes exceeds one and a half standard deviations of the index, confirming the magnitude of the differences in foundations. This ranking provides a comparative map, one that student-performance rankings alone do not offer of the systems where the teacher human-capital base is best and least prepared to host AI.

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Figure 1:
Ranking of the 14 systems on the Teacher AI-Readiness Index



***Source**: Authors, based on PASEC2019 data (2026). Index scaled to mean 50, SD 10; 95% confidence intervals.*

4. Discussion

The results carry a clear message for education policy: in Francophone Africa, readiness for AI is determined first by teachers' competences and by how systems build them. Four lines of interpretation follow.

4.1 Unequal foundations, and the equity risk of AI

That nearly 39% of the variance in teacher competence lies between countries extends the literature on the low and unequal competencies of teachers in Africa (Bold et al., 2017) and gives it new significance in the AI era: systems do not start from the same point, and a uniform diffusion of AI tools would risk widening gaps rather than closing them (Selwyn, 2019). Equity therefore requires differentiating strategies according to systems' readiness. Notably, the two systems at the foot of our ranking Chad and DR Congo are precisely those whose national reform agendas already single out teachers, a convergence we return to below.

4.2 Certified qualification and focused training, not accumulation

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The dominant weight of the professional diploma confirms that certification which bundles disciplinary and pedagogical preparation is the bedrock of competence, consistent with Shulman's (1986) framework and the teacher-quality literature (Darling-Hammond, 2000; Hanushek & Rivkin, 2006). The positive effect of in-service training points the same way, but our results specify its condition: the mere duration of initial training, the number of practicum months and the number of in-service domains add nothing and may weigh negatively. This apparent paradox echoes a well-established warning much training, worldwide, is fragmented and ineffective (Popova et al., 2022; OECD, 2019). Part of the counterintuitive pattern may also reflect endogeneity, as the least-prepared teachers are sometimes those most often sent to training. Either way, the implication is that depth certifying, content- and pedagogy-focused training builds competence, whereas breadth does not.

4.3 The digital environment and the sequencing of investments

The digital environment remains a binding constraint. Access to a computer or tablet is so rare that it has no measurable effect, and electricity itself a minority emerges as a marker of better-resourced schools. This reality argues for sequencing investments: building competencies and basic infrastructure first, before deploying AI tools that would otherwise remain inaccessible or bypass teachers (Holmes et al., 2019; UNESCO, 2024). In TPACK terms (Mishra & Koehler, 2006), the technological and AI-literacy layer must be built on a CK/PCK base that is actually present a base our data show to be uneven and, in several systems, fragile.

4.4 Convergence with the teacher-centred reform agenda

Our findings align closely with a policy momentum already under way. Under the GPE 2025 model, partner countries transform their systems by selecting a priority reform set out in a partnership compact (Global Partnership for Education, 2021, 2024b), and a striking number of these compacts place teachers and quality teaching at their heart (Global Partnership for Education, 2024a). The convergence is direct for the two systems our index ranks lowest. Chad's compact focuses on teachers' mastery of content and pedagogy through improved training, ongoing support from principals and advisors, and better teacher management, including recruitment, deployment and motivation; DR Congo's aims to make the teaching profession more attractive by strengthening recruitment, professional development and the teaching environment (Global Partnership for Education, 2024a). These priorities map almost one-to-one onto the levers our analysis identifies as decisive the professional diploma (certification), in-service training, and the school environment. The present evidence thus supports these reforms

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and offers an instrument the readiness index to target and monitor them, while cautioning that certification and focused, high-quality training, rather than sheer volume, are what will move competence.

Finally, the asymmetry of the sequential decomposition training explains differences between schools and teachers well, but between countries little suggests that narrowing cross-system gaps will require more than individual training: structural policies on teacher recruitment, qualification, status and financing, of the kind that teacher salaries dominating recurrent education spending make unavoidable (Global Partnership for Education, 2024b).

5. Conclusion

This article reverses the usual perspective on AI in African education: before asking whether teachers use AI, it establishes whether they possess the competencies that condition its useful use. Using the PASEC2019 teacher assessment across 14 systems, it shows that these competencies are highly unequally distributed about 39% of their variance lies between countries that the professional diploma and in-service training are their most robust levers whereas mere duration or accumulation of training adds nothing, and that the 14 systems fall into a sharply contrasted order of readiness, from Gabon and Senegal to Chad, DR Congo and Madagascar.

Five policy implications follow. First, prioritise certifying initial-teacher-education pathways, the diploma being the strongest lever. Second, reform in-service training toward depth over breadth sustained, subject- and pedagogy-focused provision and embed AI-literacy modules on that base (Darling-Hammond et al., 2017; UNESCO, 2024). Third, sequence AI investments: strengthen foundational competencies and basic infrastructure (electricity, connectivity) before deploying tools, so that technology augments rather than bypasses teachers. Fourth, target support to the least-ready systems, using the index to allocate resources; here the evidence reinforces the teacher-centred priority reforms that Chad, DR Congo and others are already pursuing through their GPE partnership compacts. Fifth, address between-country gaps through structural policies on recruitment, qualification and financing, which individual training alone cannot close.

The conclusion is unambiguous: AI-in-education strategies in Africa must first strengthen teachers' qualification and continuing training. AI will amplify good practice where competencies exist; where they are absent, no tool will substitute for them. Investing in teachers is not one precondition for AI among others it is the condition. Future research should document effective use of AI as it emerges, distinguish through longitudinal or experimental designs the effect of certification from that of training

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quality, and test which in-service modalities most raise teacher competence and, ultimately, AI readiness.

6. *References*:

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. Columbia University Press.

Bold, T., Filmer, D., Martin, G., Molina, E., Stacy, B., Rockmore, C., Svensson, J., &Wane, W. (2017). Enrollment without learning: Teacher effort, knowledge, and skill inprimary schools in Africa. *Journal of Economic Perspectives, 31*(4), 185–204. https://doi.org/10.1257/jep.31.4.185

PASEC. (2020). *PASEC2019 – Qualité des systèmes éducatifs en Afrique subsaharienne francophone*. Programme d'analyse des systèmes éducatifs de la CONFEMEN. https://archivespasec.confemen.org/wp-content/uploads/sites/2/2022/08/Rapport-international-evaluation-PASEC2019.pdf

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy evidence. *Education Policy Analysis Archives, 8*(1). https://doi.org/10.14507/epaa.v8n1.2000

Darling-Hammond, L., Hyler, M. E., & Gardner, M. (2017). *Effective teacher professional development*. Learning Policy Institute. https://learningpolicyinstitute.org/product/effective-teacher-professional-development-report

Global Partnership for Education. (n.d.). *Partnership compact guidelines*. https://www.globalpartnership.org/content/partnership-compact-guidelines

Global Partnership for Education. (2021). *GPE 2025 strategic plan*. https://www.globalpartnership.org/library/gpe-2025-strategic-plan

Global Partnership for Education. (2024a). *Teachers as architects of change in education policy dialogue* [Blog post]. https://www.globalpartnership.org/blog/teachers-architects-change-education-policy-dialogue

Global Partnership for Education. (2024b). *Results report 2024*. https://www.globalpartnership.org/content/results-report-2024

Hanushek, E. A., & Rivkin, S. G. (2006). Teacher quality. In E. A. Hanushek & F. Welch (Eds.), *Handbook of the economics of education* (Vol. 2, pp. 1051–1078). Elsevier. https://doi.org/10.1016/S1574-0692(06)02018-6

Hargreaves, A., & Fullan, M. (2012). *Professional capital: Transforming teaching in every school*. Teachers College Press.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). *AI and education: Guidance for policy-makers*. UNESCO.

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Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record, 108*(6), 1017–1054.https://doi.org/10.1111/j.1467-9620.2006.00684.x

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, 100041. https://doi.org/10.1016/j.caeai.2021.100041

OECD. (2019). *TALIS 2018 results (Volume I): Teachers and school leaders as lifelong learners*. OECD Publishing. https://doi.org/10.1787/1d0bc92a-en

Popova, A., Evans, D. K., Breeding, M. E., & Arancibia, V. (2022). Teacher professional development around the world: The gap between evidence and practice. *The World Bank Research Observer, 37*(1), 107–136. https://doi.org/10.1093/wbro/lkab006

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Sage.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. Wiley. https://doi.org/10.1002/9780470316696

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher, 15*(2), 4–14. https://doi.org/10.3102/0013189X015002004

UNESCO. (2024). *AI competency framework for teachers*. https://doi.org/10.54675/ZJTE2084

von Davier, M., Gonzalez, E., & Mislevy, R. J. (2009). What are plausible values and why are they useful? *IERI Monograph Series, 2*, 9–36.

World Bank. (2018). *World development report 2018: Learning to realize education's promise*. World Bank. https://doi.org/10.1596/978-1-4648-1096-1

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

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Appendix A. Teacher AI-Readiness Index ranking

Rank	Country	Index (TARI)	SE	95% CI
1	Gabon	56.9	0.47	[56.0; 57.8]
2	Senegal	56.7	0.34	[56.0; 57.4]
3	Benin	56.1	0.44	[55.3; 57.0]
4	Côte d'Ivoire	55.2	0.49	[54.3; 56.2]
5	Cameroon	55.0	0.44	[54.2; 55.9]
6	Togo	52.8	0.38	[52.0; 53.5]
7	Burkina Faso	51.9	0.39	[51.2; 52.7]
8	Niger	49.1	0.28	[48.5; 49.6]
9	Congo	46.9	0.46	[46.0; 47.8]
10	Burundi	46.6	0.31	[46.0; 47.2]
11	Guinea	46.1	0.35	[45.4; 46.8]
12	Chad	44.8	0.43	[44.0; 45.7]
13	DR Congo	43.8	0.43	[42.9; 44.6]
14	Madagascar	40.4	0.52	[39.4; 41.4]

***Source**: Authors, based on PASEC2019 data (2026). Weighted means (national weights) with jackknife standard errors.*

Appendix B. Variable coding and treatment of non-response

Variable	Item(s)	Coding
Content / pedagogical scores	LECT_PV*, MATHS_PV*, LECT_DIDA_PV*, MATHS_DIDA_PV*	Plausible values (mean of 5 PV for multilevel; 5 PV for design-based)
Academic level	qm3	Ordinal 1–12; NR 96/99 → missing
Professional diploma	qm4	1 = 2–8 (diploma); 0 = none; NR 9/10/96/99 → missing
Initial training	qm5; qm6	qm5 ordinal 1–6; qm6 months; NR 96/99 → missing
In-service training	qm7; qm9a–e	qm7 Yes=1; domain = (qm9x==1), 7 = n/a → 0; NR 6/9
Digital	qm26r; qm28	Yes=1 / No=2; NR 6/9 → missing
Controls	qm1; qm2; qm10; qm13; qm19	qm1 (1=homme, 2=femme) → femme=1 si qm1=2 ; âge (qm2) ; expérience (qm10) ; fonctionnaire=1 si qm13=1 ; multigrade/double-flux (qm19)

***Source** : Authors, based on PASEC2019 teacher questionnaire (2026). NR = non-response.*

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