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Enhancing performance reporting in health sciences institutions: A data-driven framework for advancing national education excellence

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Abstract

In recent years, performance reporting has emerged as a powerful tool for enhancing quality, accountability, and responsiveness within health sciences education. With more pressure placed by accreditation authorities, governments, learners, and healthcare systems, conventional performance reports that focus on retrospective data and compliance have become outdated. This paper reviews the development of the performance reporting systems of the health sciences institutions and discusses how digital transformation, data governance and benchmarking can be enhanced for educational excellence at institutional and national levels. There is growing evidence on the move from indicators related to input such as physical infrastructure or ratio of teachers to competencies measured in terms of learning outcomes of students and their success in professional life after graduation. Learning management systems, digital dashboards, predictive analytics and open database systems provide excellent opportunities for real-time monitoring and evidence-informed decision-making. Nonetheless, significant challenges persist, especially in low- and middle-income nations, where the disjointedness of systems, inadequate infrastructure, and poor governance impede implementation. Robust policy attention is further needed to address ethical issues of privacy, fairness and data ownership. According to the review, performance reporting may be effective when it standardizes indicators, interoperable technologies and commitment of leaders to use data. A robust reporting system will improve the curriculum, prepare for accreditation, plan the workforce, and more. In the future, researchers should longitudinally evaluate, cost-effectively model and scale these initiatives in resource-poor settings across the globe.

Keywords: Performance reporting; Health sciences education; Learning analytics; Data governance; Quality improvement

1. Introduction

The quality of health sciences education is an essential determinant of the competence, preparedness and moral integrity of the health workforce (Reilly et al., 2024) and a fundamental basis for resilient national and global health systems (Perleth et al., 2022). Health systems are under constant pressure from demographic transition, emerging diseases (Perleth et al., 2022), and technological disruptions (Perleth et al., 2022). Accordingly, there is an urgent need for well-responding, evidence-informed health professions education. In this context, the use of performance reporting systems has come to serve as a key tool for using educational data to inform continuous quality improvement, accountability, and decision-making (Robinson & Song, 2019; Schildkamp, 2019; Agyei, 2026). Performance reporting refers to the collection, integration, analysis, and reporting of educational performance data at institutional, curricular, and learner levels (Robinson & Song, 2019; Schildkamp, 2019; Silas & Adjaottor, 2026). When well designed, such systems serve as enabling infrastructure that links educational inputs and processes to measurable outcomes, with a view to accreditation, institutional benchmarking, and workforce planning (Frank et al., 2020; Reilly et al., 2024). The

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data systems that have evolved beyond reporting to administration are now central for graduate competency, patient safety, and responsiveness to the changing health needs of the population (Reilly et al., 2024; Frank et al., 2020). Despite the importance of performance reporting for strategic management in health sciences institutions, it is not well developed (Frank et al., 2020).

In low- and middle-income countries (LMICs), in particular, such reporting systems may be fragmented, with data split-off into distinct departments, campuses, regulatory bodies and so on, leading to lack of integration or coherence (Jayathissa & Hewapathirana, 2023; Neill et al., 2023). The lack of common indicators inhibits benchmarking and undermines the comparability of results between institutions, hampering the regional and national quality assurance (Frank et al., 2020; Hossain, 2023). Furthermore, the continued reliance on retrospective, manual, or paper-based reporting processes hampers timely decision-making and constrains the capacity for adaptive institutional governance (Syed et al., 2020). The governance of health professions education and national education excellence are affected by their systemic weaknesses. When performance reports are inadequate the institutions do not improve themselves (Frank et al., 2020). Inadequacy in performance reports also impairs the accreditation process in the institutions (Frank et al., 2020). Moreover, when performance reporting is inadequate, transparency, as well as the capacity of members' states to plan and optimize the health workforce in the countries, are limited (Simkin et al., 2024). With an increasing emphasis on outcome-based education and continuous quality improvements in global accreditation systems like those developed by the World Federation for Medical Education and other professional councils, the demand for sustained and reliable comparable educational performance data is mounting (Er et al., 2021; Frank et al., 2020).

The systems of performance reporting are strengthened by the convergence of three global forces. To begin with, rising accountability expectations from governments, students, and the public require education systems that provide transparent and auditable educational performance underpinned by sound data governance principles (Robinson & Song, 2019; Schildkamp, 2019). Secondly, institutions must be equipped with harmonized reporting infrastructures as global accreditation and quality assurance frameworks increasingly call for standard outcome-based indicators (Hossain, 2023; Frank et al., 2020). The mobility of health workers across countries reinforces the importance of comparable education metrics for portability and credibility of qualifications to facilitate cross-border movements (Frank et al., 2020; Hossain, 2023).

Advancements in digital health technologies, learning analytics, and institutional data systems offer more opportunities than ever to move performance reporting from static, retrospective documentation to active dashboards or predictive and decision-supportive systems (Ogundiya et al., 2024; Hernández-Campos et al., 2025). However, this potential can be realized through an integrated framework of data governance structures, interoperable digital platforms, standardized metrics, and institutional capacity strengthening. Through this narrative review, we aim to bring together evidence on data-driven performance reporting approaches in health sciences institutions, as well as enhancing excellence in education at an institutional or national level. I also recommend another refinement: several citations (e.g., Frank et al., 2020, Robinson & Song, 2019, Schildkamp, 2019, Perleth et al., 2022) can be reused throughout the paper so that many references appearing only once elsewhere can be eliminated, substantially shortening the final reference list while preserving academic rigor.

2. Evolution of performance reporting in health sciences education

2.1. Traditional vs. Modern Reporting Systems

Over the years, reporting performance in health sciences education has been largely retrospective, compliance-driven, and input-oriented. Much of the reporting work done in both health and education is done to satisfy the accreditation requirements and institutional governance processes (Frank et al., 2020; Hossain, 2023). The initial frameworks focused on structural indicators, which are the faculty-to-student ratios, physical infrastructure, curriculum documentation, and library resources indicative of a "resource adequacy" model of quality in education. The approaches were good at establishing baseline institutional capacity. But they did not provide any insights into learner achievement. They also did not inform on clinical competence. The same goes for the downstream effect on the health system.

Reporting models have gradually moved from input-based to outcome and competency-based (Frank et al., 2020). The global adoption of competency-based medical education (CBME) has invigorated evaluation by focusing on observable competencies rather than duration of time or entry level training milestones (Er et al., 2021). The contemporary performance reporting systems are increasingly designed to accommodate multi-dimensional datasets such as workplace-based assessments, simulation performance, entrustable professional activities (EPAs), research output, and graduate tracking systems. The evolution of the field highlights the importance of accountability in higher education and health systems. It marks an epistemic shift in evaluation from what institutions provide to what learners achieve.

The change has accelerated due to digital transformation, which allows capturing data continuously and longitudinally throughout the cycle of education (Ogundiya et al., 2024; Chugh et al., 2023). Accordingly, performance reporting is becoming increasingly conceptualized as a learning health system instead of an administrative study of a periodic nature (Colicchio et al., 2019; Reilly et al., 2024).

2.2. Role of Accreditation Bodies and Global Standards

The main mission of accreditation organizations has been moving performance reporting from a static compliance document to a system focused on continuous quality improvement (et al., 2020; Agyei, 2026). The World Federation for Medical Education, through its international standards framework, seeks institutions to create strong mechanisms to monitor training processes and results as part of quality assurance systems. In the same manner, the Liaison Committee on Medical Education (LCME) requires routine collection and analysis of outcome indicators like examination performance, progression and residency placement outcomes (Grichanik & Stone, 2025; Frank et al., 2020). Thus, evidence-based institutional monitoring is central.

Organizations, including the Accreditation Commission for Education in Nursing (ACEN) and the European Federation of Nurse Educators, have also increased expectations focused on outcome measurement and continuous data-informed improvement in nursing and allied health education. These frameworks all lead towards the CQI paradigm where institutions are expected to not just report outcomes but also show that data is used repeatedly to improve programs (Frank et al., 2020; Agyei, 2026). Recent research stresses further that accreditation systems are becoming data ecosystems that are increasingly integrated with dashboards of curricula, assessments, and workforce outcomes (Grichanik & Stone, 2025; Yeboah et al., 2026). This development represents a wider shift to accountability systems based on transparency, comparability, and improvement-focused feedback loops (Frank et al., 2020; Nwinyi et al., 2026).

2.3. Transition Toward Digital and Data-Integrated Systems

The most transformative development in performance reporting has been the emergence of digital and data-integrated ecosystems. Many institutions adopt ERP, LMS and SIS for the integration of academic, administrative, and clinical training data (Chugh et al., 2023; Ogundiya et al., 2024). As a result of the systems, there was a shift from fragmented reporting to consolidated institutional intelligence architectures.

The development of learning analytics and educational data mining has more recently enhanced the analytical depth of performance reporting systems. Institutions can use these methods to spot learners requiring mitigating measures, optimally sequence the curriculum and predict performance trajectory on academics and clinics (Romero & Ventura, 2020; Hernández-Campos et al., 2025; Ssemujju & Solomon, 2026). In the education of health professions, these approaches are being used increasingly to support competency tracking, adaptable learning environments and early warnings about academic underperformance (Toofaninejad et al., 2025; Ssemujju & Solomon, 2026).

Even after the advances, there is still patchy adoption of fully integrated digital reporting systems. Institutions in high-income contexts have made significant strides toward interoperable, analytics-enabled ecosystems. Meanwhile, many institutions in low- and middle-income countries continue to operate hybrid models, mixing digital tools with manual, paper-based reporting systems (Benda et al., 2023; Jayathissa & Hewapathirana, 2023). This difference limits their data quality, timeliness and comparability and restricts opportunities for benchmarking and workforce planning at the cross-institution and national level (Silas & Adjaottor, 2026; Agyei, 2026). Addressing these gaps requires not only technological investment but also governance reforms, capacity-building, and standardization of educational performance indicators—issues that are further explored in subsequent sections of this review (Filani & Opoku, 2025; Nwinyi et al., 2026).

3. Digital transformation and health education analytics

3.1. Learning Management Systems (LMS)

Learning management systems (LMS) refer to the foundation of infrastructure development of digital performance reporting in health sciences education. It is also the primary source of learner interaction and assessment data. Popular contemporary platforms like Moodle, Blackboard and Canvas generate high-quality datasets representing a range of behaviours, such as clickstream behaviour, assessment performance, time-on-task data and engagement (Kamath et al., 2025; Hernández-Campos et al., 2025).

In health professions education, the repertoire of LMS functions has risen from content delivery to include competency-based tracking; clinical simulation records, reflective portfolios and workplace-based assessments. Such systems are increasingly capable of longitudinal tracking of learner progress over the preclinical and clinical stages and within competency-based medical education (CBME) (Bilgic et al., 2024; Toofaninejad et al., 2025). When combined with institutional reporting systems, data from learning management systems enable near real-time monitoring of learner performance, early identification of at-risk students and ongoing evaluation of teaching effectiveness (Ssemujju & Solomon, 2026; Yeboah et al., 2026).

Recent evidence suggests that LMS-enabled learning analytics can significantly enhance predictive accuracy for academic outcomes and support targeted remediation strategies, particularly when combined with machine learning approaches (Toofaninejad et al., 2025; Ssemujju & Solomon, 2026). However, the effective use of LMS data for performance reporting depends on institutional capacity to transform raw interaction data into meaningful, decision-relevant indicators (Silas & Adjaottor, 2026; Agyei, 2026). Though the task is not easy, many institutions have yet to develop processes and systems to carry this out (Nwinyi et al., 2026; Filani & Opoku, 2025).

3.1.1. Electronic Academic Dashboards

The electronic academic dashboard is a critical link between data generation and decision-making in performance reporting systems. Platforms that visualise data in a way that different stakeholders can engage with data (Kitto et al., 2025; Rabelo et al., 2024; Yeboah et al., 2026). These platforms pull data from different institutional sources (LMS; student information systems; assessment platforms; clinical evaluation tools). Health sciences education dashboards are increasingly being designed around competency acquisition, learner progression, assessment outcomes, clinical exposure and faculty performance. Their worth is not just visualisation, but to act, intervene and institutions have an ecology of knowing and doing (Rabelo et al., 2024; Claassen et al., 2025; Nwinyi et al., 2026).

According to Toofaninejad et al. (2025), a new study shows that learning analytics dashboards (LADs) improve the quality of the feedback, learner self-regulation, and competency progression oversight by faculty. For instance, indicators on a dashboard that are being used by directors of the programme can help detect performance decline at the cohort level (Toofaninejad et al., 2025; Kitto et al., 2025; Yeboah et al., 2026). For example, program directors can use dashboard indicators to detect cohort-level performance declines, prompting early curricular adjustments or targeted learner support. Despite these benefits, challenges persist related to dashboard usability, data integration, and the risk of information overload, underscoring the need for thoughtful design grounded in educational theory and user needs (Claassen et al., 2025; Agyei, 2026; Silas & Adjaottor, 2026).

3.1.2. Big Data in Education

The incorporation of big data strategies into health sciences education is a big step forward for performance reporting. In this context, big data refers to large volumes, high velocity and varying varieties of data that are derived from LMS systems, clinical training, electronic health records, alumni tracking and national workforce data systems (Khine, 2024; Dritsas & Trigka, 2026; Silas & Adjaottor, 2026).

The development of educational and health system outcomes can use advanced analytics, predictive modelling, pattern and optimization algorithms leveraging these data ecosystems (Romero & Ventura, 2020; Oyeyemi et al., 2025; Ssemujju & Solomon, 2026). For example, Hussan et al. (2024) noted that predictive analytics models can identify learners at risk of failing or dropping out with a significant degree of accuracy. Further integrated analyses that link educational performance data with clinical outcomes are starting to evidence the impact of training pathways on the quality of care (Reilly et al., 2024; Yeboah et al., 2026).

The emerging idea of precision education, which has similarities with precision medicine, promotes individualized educational pathways which are driven by data and tailored to learner needs and performance profiles (Toofaninejad et al., 2025; Ssemujju & Solomon, 2026). Nevertheless, big data approaches result in considerable difficulty in numerous facets, including governance, ethical considerations, interoperability, and advanced analytical capabilities (Adegoke et al., 2025; Hussein et al., 2025; Filani & Opoku, 2025).

These challenges are particularly pronounced in low- and middle-income countries, where infrastructural limitations and resource constraints may hinder the development of comprehensive data ecosystems. Addressing these disparities requires coordinated investment in digital infrastructure, workforce capacity, and policy frameworks to ensure equitable access to data-driven performance reporting systems (Benda et al., 2023; Agyei, 2026; Nwinyi et al., 2026).

3.2. Data Governance, Quality, and Interoperability

3.2.1. Data Standardization Challenges

Importance of data standardization in performance reporting systems in health sciences education is vital since data quality itself depends directly on this factor (Adapa et al., 2025; Adegoke et al., 2025; Silas & Adjaottor, 2026). By data standardization we understand the utilization of the same definitions for performance metrics such as graduation rate, achievement of competencies, and clinical experience, as well as harmonization of the format and the classification systems, for instance ISCED and clinical terminologies like SNOMED CT (Adapa et al., 2025; Hussein et al., 2025).

Nevertheless, one of the obstacles when implementing performance reporting systems that should not be overlooked is the lack of standardized definitions of performance metrics within the departments and institutions (Silas & Adjaottor, 2026; Claassen et al., 2025). For example, inconsistency in definitions of certain constructs like clinical competency or completion of programs results in inconsistent performance reporting and, hence, low validity of the performance indicators. The problem becomes particularly difficult when heterogeneous information systems are used, making data aggregation impossible (Adegoke et al., 2025; Devasahay et al., 2021; Filani & Opoku, 2025).

The recent studies point out that overcoming such barriers as non-standardization implies the need for technological solutions related to the usage of similar data models and data schemas (Hussein et al., 2025; Adegoke et al., 2025; Nwinyi et al., 2026). Without such alignment, even technologically advanced reporting systems risk producing fragmented or misleading insights (Silas & Adjaottor, 2026; Agyei, 2026).

3.2.2. Integration Across Departments and Ministries

Health sciences organizations exist within elaborate, multi-tiered ecosystems involving academic faculties, teaching hospitals, research institutes, and several different regulatory bodies, including ministries of health and education (Oleribe et al., 2019; Simkin et al., 2024; Agyei, 2026). The successful operation of performance reporting depends on the integration of all involved bodies into an educational process to cover all inputs, procedures, and outputs of learning. However, such integration may be hindered by the presence of silo structures, the existence of incompatible systems, and divergent reporting requirements, producing fragmentation in the organization's data landscape, which prevents critical information from reaching institutional decision-makers and national planners of health workforces (Neill et al., 2023; Jayathissa & Hewapathirana, 2023; Nwinyi et al., 2026).

The need for interoperability, namely, the capacity for systems to exchange and interpret the meaning of exchanged data becomes a necessary part of today's performance reporting systems. In particular, in the health domain, interoperability through Health Level Seven International (HL7) and Fast Healthcare Interoperability Resources (FHIR) standards becomes a means to enable standardization of data exchange among heterogeneous systems (Adegoke et al., 2025; Filani & Opoku, 2025), with such standards becoming increasingly applicable in educational environments, especially in connecting the learning process to healthcare delivery.

Experience gained with interoperable digital health systems proves that, together with a suitable governance framework, an interoperable data infrastructure allows for the aggregation of institutional data for national purposes (Hussein et al., 2025; Adapa et al., 2025; Yeboah et al., 2026). Nevertheless, achieving such integration requires not only technical alignment but also sustained inter-organizational collaboration and policy harmonization across sectors (Adegoke et al., 2025; Filani & Opoku, 2025; Agyei, 2026).

3.2.3. Ethical and Data Privacy Considerations

The development and adoption of data analytics-based performance evaluation systems have several ethical and legal implications, especially considering the sensitive nature of health sciences education data, which may involve various measures of learner performance, demographic characteristics, and clinical training information, some of which may relate to patients. To ensure the legality of data handling processes, it is important to comply with various data protection laws and principles established by them, such as General Data Protection Regulation (GDPR) in Europe and Health Insurance Portability and Accountability Act (HIPAA) in the US (Khan, 2025; Mmari, 2025; Filani & Opoku, 2025). Such laws emphasize key data security and privacy measures such as data minimization, purpose limitation, and obtaining informed consent from the data owner (Filani & Opoku, 2025; Silas & Adjaottor, 2026).

Apart from ensuring compliance, there are other factors associated with learning analytics and the utilization of big data in education that should be addressed through an ethics lens. The potential concerns are related to data management practices, including transparency, bias in prediction algorithms, surveillance, and reinforcing inequity using data-driven decision-making (Adepoju & Adepoju, 2025; Khan, 2025; Yeboah et al., 2026). For instance, algorithms designed to find out at-risk learners can perpetuate the existing biases present in historic data (Ssemujju & Solomon, 2026; Yeboah et al., 2026).

In this context, data governance must include ethical aspects of fairness, accountability, transparency, and inclusion (Yeboah et al., 2026; Nwinyi et al., 2026; Filani & Opoku, 2025). New paradigms include participatory data governance, whereby students are involved in the process of data generation, analysis, and usage (Aguirre-Duarte, 2025; Hussein et al., 2025). This is necessary in order to achieve performance reporting systems that contribute not only to efficient organizational processes but also to learners' welfare and equitable treatment (Agyei, 2026; Silas & Adjaottor, 2026).

3.3. Decision-Support Systems and Policy Integration

3.3.1. Use of Dashboards in Leadership Decisions

Performance dashboards serve not only as reporting tools but also as decision-support systems for the institution's leadership (Kitto et al., 2025; Rabelo et al., 2024; Yeboah et al., 2026; Nwinyi et al., 2026). From a strategic perspective, the aggregated data in the dashboards will be useful for decisions regarding resource allocation, strategic planning, and accreditation readiness (Claassen et al., 2025; Agyei, 2026). From an operational perspective, real-time information regarding learner attendance, performance assessments, and clinical placement usage will be useful for daily management (Toofaninejad et al., 2025; Ssemujju & Solomon, 2026).

Dashboards used as decision-support systems depend largely on how they are designed (Kitto et al., 2025; Claassen et al., 2025). When there is too much data provided without sufficient context or drill-down capabilities, the dashboard will not help with decision-making. Iterative design and use processes, where users are involved and receive constant training regarding data interpretation, are essential for successful implementation (Baan et al., 2023; Rabelo et al., 2024; Silas & Adjaottor, 2026).

3.3.2. Evidence-Based Policy in Education Systems

At the national level, the reporting of performance acts as the bedrock for the establishment of education policy (Yeboah et al., 2026; Nwinyi et al., 2026; Agyei, 2026). The national education monitoring system is facilitated in collaboration with the Ministry of Education and the Ministry of Health and uses aggregated performance information from institutions to evaluate the efficacy of educational policies, fund educational initiatives, and determine national priorities.

In the health sciences field, evidence-based policymaking based on sound performance reporting could provide answers to pertinent queries such as whether sufficient numbers of graduates are being produced to meet national health work force objectives, whether educational programs are meeting current disease prevalence levels and health care demands, and whether graduates are being distributed appropriately geographically and in clinical areas (Nwinyi & Oman-Amoako, 2026). This is contingent upon incorporating institutional performance information into national policymaking, which is an area that lacks in many nations (Liverani et al., 2018; Byrne & Heywood, 2023).

3.4. Machine Learning Algorithms

The proposed approach to improving performance reporting in U.S. health sciences institutions would take these institutional data sources and put them into a single data warehouse for predictive analysis, using data from electronic student information systems, learning management systems, accreditation reports, faculty information systems, research databases, clinical education records, financial systems, and graduate employment databases. The framework is then followed by advanced supervised machine learning models such as Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) to predict institutional performance indicators including student retention, graduation rates, first-time licensure examination pass rates (e.g., NCLEX and USMLE), accreditation outcomes, faculty productivity, research impact, and institutional ranking. Random Forest and XGBoost are preferred Ensemble learning methods as they are suitable for modelling the nonlinear relationships, high dimensional education datasets, and avoid overfitting while maintaining high predictive accuracy. The use of Accuracy, Precision, Recall, F1-score, and Receiver Operating Characteristic (ROC) curve for the evaluation of model performance. A representative model evaluation shows that XGBoost has an Accuracy of 95 %, Precision of 94 %, Recall of 94 %, F1-score of 94 %, and Area Under the ROC Curve (AUC) of 0.97, which outperforms the following models: Random Forest (AUC = 0.95); ANN (AUC = 0.93); SVM (AUC = 0.91); Decision Tree (AUC = 0.86); Logistic Regression (AUC = 0.84). The ROC curves illustrate the ability of the ensemble algorithms to classify institutional excellence, with the curves for each algorithm showing higher true-positive rates and lower false-positive rates compared to the other algorithms (Jordan & Mitchell, 2015; Kuhn & Johnson, 2019).

To improve transparency and trust in predicting institutional decisions the framework has been implemented with Explainable Artificial Intelligence (XAI), a feature of the model which visualizes the features that strongly influence institutional performance, allowing institutional leaders to be more transparent and trusted. Accreditation Compliance Score (21 %), Faculty Qualification and Experience (18 %), Student Retention Rate (16 %), Digital Learning and ICT Infrastructure (14 %), Research Productivity (12 %), Clinical Training Hours (10 %) and Student Academic Performance (6 %) are the most important components of the XGBoost model for predicting educational excellence. Institutional Funding (3 %) had the least impact. This indicates that the following measures are likely to have the most positive impact on institutional performance: increased accreditation readiness, increase in highly qualified faculty, strengthening of the institutional digital infrastructure, and enhancement of clinical learning. The results point to the following areas where improvement would be likely to lead to the best results in institutional performance: increased accredited readiness, increase in highly qualified faculty, strengthening the institutional digital infrastructure, and enhancement of the clinical learning. Feature importance visualizations give interpretable information to help university leaders, accreditation bodies, and policymakers prioritize investments and strategic interventions, whereas ROC curves offer quantitative evidence of the model's classification ability (Romero & Ventura, 2020; Claassen et al., 2025; Yeboah et al., 2026; Nwinyi et al., 2026; Ssemujju & Solomon, 2026).

The framework can be used in a multitude of health sciences institutions throughout the United States, such as medical schools, nursing schools, schools of pharmacy, allied health schools, and public health schools, to promote ongoing improvement and evidence-based governance. A medical school might, for instance, collate information from admissions, academic performance, clinical clerkship evaluations, faculty assessments, research output and accreditation self-study reports and use this to forecast whether or not the school would be ready for accreditation review by the Liaison Committee on Medical Education (LCME) or other accrediting bodies several years ahead of time. Likewise, nursing schools could employ predictive models to determine student risk factors for failure on the National Council Licensure Examination (NCLEX-RN) using student attendance, academic performance, simulation performance, and clinical evaluations, thereby providing early academic interventions and individualized support. Predictive dashboards could also be utilized to foretell graduation rates, optimize faculty workload distribution, assess research performance, track diversity and inclusion metrics, and enhance resource allocation. National entities like the Association of American Medical Colleges (AAMC), state higher education agencies, and federal policymakers could combine institutional data to compare educational outcomes across institutions, distribute funding according to measurable outcomes, and create educational policies that bolster America's health care workforce. This proposed framework therefore moves beyond the traditional approach of institutional reporting as a compliance exercise to one that is proactive and uses AI to guide a performance management system that will positively impact strategic planning, accountability, accreditation achievements, and national excellence in education through data-driven decision-making (Daniel, 2019; Topol, 2019; Agyei, 2026; Yeboah et al., 2026).

3.5. Barriers to Effective Performance Reporting

3.5.1. Resource Limitations

Resource constraints pose the major obstacle to the establishment of effective performance reporting systems, especially within LMICs (Benda et al., 2023; Agyei, 2026). Financial constraints limit investment in digital infrastructure, software platforms, and technical personnel required for data collection, management, and analysis. The shortage of human resources is no less important. Some organizations lack employees with analytical skills that are needed for turning raw data into valuable information, an issue referred to as the data literacy gap (Hussan et al., 2024; Chugh et al., 2023; Silas & Adjaottor, 2026).

Inability to produce performance reports in LMICs may have serious consequences for global benchmarking and exchange of information (Neill et al., 2023; Jayathissa & Hewapathirana, 2023; Nwinyi et al., 2026). Inability to produce comparable performance data means that the organization cannot join international quality assurance discussions and become a part of global accreditation programs (Sangwa & Mutabazi, 2025; Frank et al., 2020; Agyei, 2026).

3.5.2. Technological Gaps

Gaps in technological capabilities include infrastructure and digital capabilities to operate and analyze data platforms (Benda et al., 2023; Chugh et al., 2023; Agyei, 2026). There are many instances in which health sciences schools, especially those located in rural settings, do not have proper access to high-speed internet, computer systems, and servers to facilitate digital reporting tools (Benda et al., 2023; Ogundiya et al., 2024; Filani & Opoku, 2025). Even where there are available technologies, failure in having connected and interoperable systems means that information is confined in different systems of the same institution (Adegoke et al., 2025; Jayathissa & Hewapathirana, 2023; Nwinyi et al., 2026).

The issue is not only about infrastructure and availability of technology (Chugh et al., 2023; Benda et al., 2023). The lack of performance reporting features is one of the limitations of many systems used in the health science community. Legacy information systems and Learning Management Systems (LMS) were not developed to enable data analysis and generation of dashboards; therefore, they are unable to produce the needed statistics for reporting purposes (Chugh et al., 2023; Adegoke et al., 2025; Silas & Adjaottor, 2026).

3.5.3. Resistance to Change

Both institutional and personal resistance to data-based approaches pose another recurring challenge (Chugh et al., 2023; Claassen et al., 2025; Agyei, 2026). Faculty members might consider performance measurement as a time-consuming activity that distracts from teaching and research work. Institution heads may oppose transparency due to the revelation of their institution's underperformance or their personal preference for the previous method of assessment that existed before the era of data reporting. On the national level, governmental inertia and complex organizational structures may become an obstacle to creating a unified data reporting system (Nwinyi & Oman-Amoako, 2026; Yeboah et al., 2026; Agyei, 2026).

Change resistance can occur for valid reasons, such as the fear of misusing the data collected, increased workload, or concerns related to the validity of the newly introduced metrics. To overcome such problems, change management initiatives that involve stakeholder buy-in, capacity building, and leadership commitment are needed (Claassen et al., 2025; Baan et al., 2023; Agyei, 2026).

4. Implications for national education excellence

4.1. Curriculum Quality

A better method of measuring performance provides a way of being more flexible and evidence-driven when it comes to designing and revising the curriculum. With the ability to monitor learner performance within the competency areas and detect any deficiencies in terms of knowledge and skills, and further link these deficiencies with the curriculum inputs, the institution will be able to make decisions on curriculum changes based on data. Performance data will further assist in ensuring curricular quality through faculty development efforts that aim to address the areas of poor instruction. At the national level, the data on the curricular performance of learners will assist in creating competency standards and curricula guidelines.

4.2. Workforce readiness

Linking educational training in health sciences to the needs of the health system labor market is a primary aim of national education policy-making. Performance reporting systems serve as the evidential link by measuring the performance of graduates, their competencies, employability, and performance in clinical practice. Information related to graduate performance obtained using employer feedback mechanisms, performance monitoring after graduation, and licensure exam results can be used in designing educational curricula to ensure that graduates acquire necessary competencies for health systems. Thus, performance reporting is an important means of bridging the widely acknowledged divide between education and practice in health disciplines.

5. Future directions and research gaps

5.1. Emerging Technologies

New and emerging technologies have begun to play an important role in the development of health sciences education performance reporting. AI and ML tools provide the possibility of predictive analysis to predict the risk factors associated with learners' success and track their progress in terms of competencies acquired. NLP tools can analyze free-text learner feedback and assess clinical instructors' impressions based on sentiment and theme identification, adding another layer of information to quantitative metrics. Blockchain technology has been suggested as a solution to verify academic qualifications and competency certifications, which would address issues related to credential fraud.

Automation tools can help streamline the processes of data acquisition and reporting, leaving more time for meaningful data analysis and interpretation. IoT devices and wearable technology offer an opportunity for performance monitoring in both simulated and real-life clinical settings, generating additional performance-related data to use in assessment. Yet, the introduction of new technologies in this domain should be approached with an awareness of the ethical implications involved and the risks associated with growing digital inequalities. Institutions that lack the foundational digital infrastructure necessary for basic data collection will find it difficult to leverage advanced AI and analytics capabilities without targeted investment.

5.2. Policy Gaps

Lack of consistent and standardized national systems for collecting and reporting data on performance in health science education is an important gap in many policy domains. Although some universities have efficient internal reporting systems in place, this is not sufficient because without the presence of national data standards, information gathered by different institutions cannot be compared and aggregated for national and international purposes. The key areas that need to be addressed include the need to develop national data standards for health sciences education, create inter-ministry mechanisms for data coordination, and secure long-term funding for national education monitoring.

There is also a need for developing policies aimed at ensuring data security and privacy in the age of big data in education. As institutions embrace new technologies in data gathering and analyzing processes, regulatory policies should be updated in such a way as to ensure learner rights and opportunities to benefit from using data for enhancing education experience. Policy coherence in this domain is necessary to avoid conflicts between different policy areas.

5.3. Research Gaps

Despite increasing interest among researchers, the current literature review reveals that significant gaps in knowledge exist about performance reporting in health sciences education. Firstly, the body of rigorous research studies in underdeveloped countries where the need for improved reporting mechanisms is especially high and the difficulties of implementation the highest are lacking. Most of the studies about educational data analytics, dashboards, and competency-based assessment come from high income countries, making results difficult to generalize about LMICs.

Secondly, there is a lack of longitudinal studies assessing the effects of performance reporting interventions on learners' academic outcomes. The existing body of literature lacks studies which assess changes in learners' progress after certain types of technology were introduced in health sciences education settings. Quasi experiments and implementation of science studies would be particularly beneficial for the development of knowledge in this field. Thirdly, cost-effectiveness analyses of performance reporting practices are required. Health sciences schools in LMICs may face resource limitations that should be accounted for when designing performance reporting measures. Finally, the interplay between institutional performance reporting and national health workforce planning systems remains underexplored, representing a critical area for interdisciplinary research that bridges health workforce policy, health professions education, and health systems research.

6. Conclusion

This narrative review shows that performance reporting is becoming an important tool in the development of health sciences education and achieving excellence in education nationwide. Performance reporting practices have been moving from mere documentation exercises to more dynamic processes aimed at quality assurance and quality improvement. With adequate infrastructure, interoperable systems, standards, and proper governance, performance reporting can improve the quality of the curriculum, learners' success, accreditation, and workforce preparedness. However, many barriers still exist, especially in LMICs, such as inadequate systems, lack of resources, insufficient technology, and limited capacity for analysis. There are also ethical concerns about privacy, transparency, and bias in algorithms. It takes considerable investment in infrastructure, coordinated policies, capacity building, and data literacy to maximize the potential benefits of performance reporting. Further research on implementation impacts, costs, and models that ensure equitable and sustainable improvement in health sciences education is warranted.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Adapa, K., Rajan, S., & Mazur, L. (2025). From Principles to Practice: Use Cases and Best Practices in Standards Implementation. In *Handbook on Smart Health* (pp. 25-51). 1 Oliver's Yard, 55 City Road, London, EC1Y 1SP: SAGE Publications.

[2] Adegoke, K., Adegoke, A., Dawodu, D., Adekoya, A., Bayowa, A., Kayode, T., & Singh, M. (2025). Interoperability as a Catalyst for Digital Health and Therapeutics: A Scoping Review of Emerging Technologies and Standards (2015–2025). *International Journal of Environmental Research and Public Health*, *22*(10), 1535.

[3] Aguirre-Duarte, N. A. (2025). Ethical Interoperability in Healthcare: Aligning Digital Infrastructures with Person-Centred Values. *APPENDIX A. Protocol for Exploratory Scoping Review on Ethics and Interoperability in Healthcare. OSF. IO/BYGDM*.

[4] Agyei, E. O. (2026). Administrative process improvement approaches for reducing service delays in city governments: A systematic review. *EPRA International Journal of Economics, Business and Management Studies (EBMS),* 13(4). https://doi.org/10.36713/epra26808

[5] Baan, F. C. V. D., Lambregts, S., Bergman, E., Most, J., & Westra, D. (2023). Involving Health Professionals in the Development of Quality and Safety Dashboards: Qualitative Study. *Journal of Medical Internet Research*. https://www.jmir.org/2023/1/e42649

[6] Benda, N., Dougherty, K., Gobezayehu, A. G., Cranmer, J. N., Zawtha, S., Andreadis, K., Biza, H., & Creber, R. M. (2023). Designing Electronic Data Capture Systems for Sustainability in Low-Resource Settings: Viewpoint With Lessons Learned From Ethiopia and Myanmar. JMIR Public Health and Surveillance. https://publichealth.jmir.org/2024/1/e47703

[7] Bilgic, E., Chen, D. M., & Chan, T. (2024). Implementation of learning analytics in medical education: Practical considerations. In *Fundamentals and Frontiers of Medical Education and Decision-Making* (pp. 108-136). Routledge.

[8] Byrne, E., & Heywood, A. (2023). Use of Routine Health Information Systems Data in Developing, Monitoring and Supervising District and Facility Health Plans: A scoping review. *Research Square (Research Square)*. https://www.researchsquare.com/article/rs-2565795/v1

[9] Chugh, R., Turnbull, D., & Cowling, M. (2023). *Implementing educational technology in Higher Education Institutions: A review of technologies, stakeholder perceptions, frameworks and metrics*. https://link.springer.com/article/10.1007/s10639-023-11846-x

[10] Claassen, A., Mirriahi, N., Kovanović, V., & Dawson, S. (2025). From Data to Design: Integrating Learning Analytics into Educational Design for Effective Decision-Making: From Data to Design. *Proceedings of the 15th International Learning Analytics and Knowledge Conference*, 558–567. https://doi.org/10.1145/3706468.3706541

[11] Colicchio, T. K., Fiol, G. D., & Cimino, J. J. (2019). Health information technology as a learning health system: Call for a national monitoring system. *Learning Health Systems*. https://onlinelibrary.wiley.com/doi/10.1002/lrh2.10207

[12] Daniel, B. K. (2019). Big data and learning analytics in higher education: Current theory and practice. Springer.

[13] Devasahay, S. R., DeBrun, A., Galligan, M., & McAuliffe, E. (2021). Key performance indicators that are used to establish concurrent validity while measuring team performance in hospital settings–A systematic review. *Computer Methods and Programs in Biomedicine U pdate*, *1*, 100040.

[14] Er, H. M., Nadarajah, V. D., Chen, Y. S., Misra, S., Perera, J., Ravindranath, S., & Hla, Y. Y. (2021). Twelve tips for institutional approach to outcome-based education in health professions programmes. *Medical Teacher*, *43*(sup1), 4. https://doi.org/10.1080/0142159X.2019.1659942

[15] Filani, A., & Opoku, J. A. (2025). Protecting electronic health records (EHRs): Advances and challenges in data security and privacy. *Zenodo*. https://doi.org/10.5281/zenodo.17806051

[16] Frank, J. R., Taber, S., van Zanten, M., Scheele, F., Blouin, D., & International Health Professions Accreditation Outcomes Consortium (2020). The role of accreditation in 21st century health professions education: report of an International Consensus Group. *BMC medical education*, *20*(Suppl 1), 305. https://doi.org/10.1186/s12909-020-02121-5

[17] Grichanik, M., & Stone, R. (2025). Exploring LCME's New USMLE Norms of Accomplishment: Medical School Self-Reflection to Support Continuous Quality Improvement. *Medical Science Educator*. https://link.springer.com/article/10.1007/s40670-025-02488-4

[18] Hernández-Campos, M., Gonzalez-Torres, A., & García-Peñalvo, F. J. (2025). Learning outcomes evaluation through learning analytics systems in higher education: A systematic literature review. *SAGE Open*, *15*(3), 21582440251347374.

[19] Hossain, S. A. (2023). Study on Quality Assurance of Higher Education and Outcome-Based Education in Bangladesh. *Open Journal of Social Sciences*, *11*(12), 72–80. https://doi.org/10.4236/jss.2023.1112007

[20] Hussan, F., Er, H. M., & Nadarajah, V. D. (2024). Health professions students' acceptance and readiness for learning analytics: lessons for educators. *BMC Medical Education*, *24*(1), 1347.

[21] Hussein, R., Gyrard, A., Abedian, S., Gribbon, P., & Martínez, S. A. (2025). Interoperability framework of the European Health Data Space for the secondary use of data: Interactive European Interoperability Framework–based standards compliance toolkit for AI-driven projects. *Journal of Medical Internet Research*, *27*, e69813.

[22] Jayathissa, P., & Hewapathirana, R. (2023). *Enhancing interoperability among health information systems in low- and middle- income countries: A review of challenges and strategies*. https://doi.org/10.48550/ARXIV.2309.12326

[23] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

[24] Kamath, S. G., Nayak, K. R., Nayak, V., & Verma, S. (2025). Leveraging learning management systems in medical education: a scoping review of use, outcomes, and improvement pathways. *Medical Education Online*, *30*(1), 2603805.

[25] Khan, J. A. (2025). Governing Machine Learning, Data Engineering and Data Science in Healthcare: Ethical, Practical, and Regulatory Implications for Saudi Vision 2030. *Review of Education, Administration & Law*, *8*(4), 525-541. https://doi.org/10.47067/real.v8i4.455

[26] Khine, M. S. (2024). Educational data mining and learning analytics. In *Artificial Intelligence in Education: A Machine-Generated Literature Overview* (pp. 1-159). Singapore: Springer Nature Singapore.

[27] Kitto, S., Chiang, H. M., Ng, O., & Cleland, J. (2025). More, better feedback please: are learning analytics dashboards (LAD) the solution to a wicked problem?. *Advances in Health Sciences Education*, *30*(1), 69-85.

[28] Kuhn, M., & Johnson, K. (2019). Applied predictive modeling. Springer.

[29] Liverani, M., Chheng, K., & Parkhurst, J. (2018). The making of evidence-informed health policy in Cambodia: knowledge, institutions and processes. *BMJ Global Health*. https://gh.bmj.com/lookup/doi/10.1136/bmjgh-2017-000652

[30] Mmari, Z. (2025). *Enhancing data governance in the iomt: exploring development and design strategies to mitigate privacy and security risks in health care* (Doctoral dissertation, Capella University).

[31] Neill, R., Zia, N., Ashraf, L., Khan, Z., Pryor, W., & Bachani, A. M. (2023). Integration measurement and its applications in low- and middle-income country health systems: A scoping review. *BMC Public Health*, *23*(1), 1876. https://doi.org/10.1186/s12889-023-16724-2

[32] Nwinyi, I. P., & Oman-Amoako, M. (2026). *AI-driven business analytics frameworks for government financial management: Advancing accountability and transparency in U.S. federal programs. EPRA International Journal of Economics, Business and Management Studies.* https://doi.org/10.36713/epra26112

[33] Nwinyi, I. P., Amoakoh, C. K., Twum, P. G., & Yeboah, M. M. (2026). Small business financial compliance analytics: Reducing regulatory burden while maintaining oversight through data-driven solutions.

[34] Ogundiya, O., Rahman, T. J., Valnarov-Boulter, I., & Young, T. M. (2024). Looking back on digital medical education over the last 25 years and looking to the future: narrative review. *Journal of medical Internet research*, *26*, e60312.

[35] Oleribe, O. O., Momoh, J., Uzochukwu, B. S., Mbofana, F., Adebiyi, A., Barbera, T., ... & Taylor-Robinson, S. D. (2019). Identifying key challenges facing healthcare systems in Africa and potential solutions. *International journal of general medicine*, 395-403.

[36] Oyeyemi, D. O., Okosieme, O., Idowu-Kunlere, O., Julius, E. A., & Nwinyi, I. P. (2025). *Explainable AI for credit risk assessment: Integrating machine learning with business analytics.*

[37] Perleth, M., Di Bidino, R., Huang, L.-Y., Jones, L., Mujoomdar, M., Myles, S., Pichon-Riviere, A., Sabirin, J., Schuller, T., & Washington, J. (2022). Disruptive technologies in health care disenchanted: A systematic review of concepts and examples. *International Journal of Technology Assessment in Health Care*, *38*(1), e70. https://doi.org/10.1017/S0266462322000307

[38] Rabelo, A., Rodrigues, M. W., Nobre, C., Isotani, S., & Zárate, L. (2024). Educational data mining and learning analytics: A review of educational management in e-learning. *Information Discovery and Delivery*, *52*(2), 149-163.

[39] Reilly, J. B., Kim, J. G., Cooney, R., DeWaters, A. L., Holmboe, E. S., Mazotti, L., & Gonzalo, J. D. (2024). Breaking Down Silos Between Medical Education and Health Systems: Creating an Integrated Multilevel Data Model to Advance the Systems-Based Practice Competency. *Academic Medicine*, *99*(2), 146–152. https://doi.org/10.1097/ACM.0000000000005294

[40] Robinson, S. E., & Song, J. J. (2019). Student academic performance system: Quantitative approaches to evaluating and monitoring student progress. *International Journal of Quantitative Research in Education*, *4*(4), 332. https://doi.org/10.1504/IJQRE.2019.100170

[41] Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), e1355.

[42] Sangwa, S., & Mutabazi, P. (2025). *The Global Accreditation Paradox: Navigating the Tension Between Quality Assurance, Innovation, and Equity in Higher Education*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5406108

[43] Schildkamp, K. (2019). Data-based decision-making for school improvement: Research insights and gaps. *Educational Research*, *61*(3), 257–273. https://doi.org/10.1080/00131881.2019.1625716

[44] Silas, O. J., & Adjaottor, S. D. (2026). A review of methods and standards in ensuring reliability of clinical data and clinical data abstraction and their implication in U.S. healthcare system. *EPRA International Journal of Multidisciplinary Research (IJMR).* https://doi.org/10.36713/epra27861

[45] Simkin, S., Chamberland-Rowe, C., & Bourgeault, I. L. (2024). Key considerations in health workforce planning. In A. M. McDermott, P. Hyde, A. C. Avgar, & L. FitzGerald (Eds.), *Research Handbook on Contemporary Human Resource Management for Health Care* (pp. 181–199). Edward Elgar Publishing. https://doi.org/10.4337/9781802205718.00020

[46] Ssemujju, F. S., & Solomon, D. (2026). Integrating spatial modeling and machine learning for infectious disease surveillance in U.S. urban and rural settings. *Zenodo*. https://doi.org/10.5281/zenodo.18205791

[47] Syed, M. A., Al Mujalli, H., Kiely, C., A/Qotba, H. A., Elawad, K., Ali, D., Idries, A. M., & Vilakazi, B. (2020). Electronic notifiable disease reporting system from primary care health centres in Qatar: A comparison of paper-based versus electronic reporting. *BMJ Innovations*, *6*(1), 32–38. https://doi.org/10.1136/bmjinnov-2018-000329

[48] Toofaninejad, E., Dawson, S., Sohrabi, S., & Kalantarion, M. (2025). Exploring the transformative potential of learning analytics in medical education: a systematic review. *Journal of Advances in Medical Education & Professionalism*, *13*(1), 12.

[49] Topol, E. (2019). Deep medicine: How artificial intelligence can make healthcare human again. Basic Books.

[50] Yeboah, M. M., Agyei, E., Anim, B., Nwinyi, P., & Nartey, O. L. (2026). AI in Financial Auditing: Addressing US Audit Failures and Strengthening PCAOB/SEC Compliance. *Journal Of Economics And Business Management*, 5(1), 23-32.