Research Paper

Learning analytics and data-driven decision-making in educational institutions: a policy perspective

Saman M. Almufti*
*Department of Information Technology, Technical College of Duhok, Duhok Polytechnic University, Duhok, Iraq.

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ABSTRACT

The term of learning analytics (LA) is a recently introduced novel paradigm in the field of education that focuses on collecting, processing and analyzing the amount of student generated data to rational support pedagogical or administrative decision-making. While many technologies, including learning dashboards, predictive modeling and early-warning systems have developed at a fast pace, there has been little progress on policy frameworks addressing their ethical and transparent use, and responsible applications. This paper explores the policy challenge of Data Driven Decision Making (DDDM) in educational institutions in particular, as well as the governance, ethical and institutional challenges arising from Implementing Learning Analytics. A Systematic Literature Review was performed for articles published from 2012 to 2025 in the databases: Scopus, IEEE Xplore, SpringerLink and ERIC. The literature reviewed was classified in four categories: conceptual underpinnings of DDDM; institutional integration and training; predictive analysis and early-warning systems; and privacy, ethics, and data protection. The results suggest that learning analytics enhances personalized learning, student support, institution effectiveness, yet at the same time, concerns about privacy and control of data, algorithmic bias, student surveillance, transparency, and educator autonomy have been raised. The paper outlines a four levels policy practical framework in the pedagogical alignment, operational governance, technical governance, ethical and legal protections, and strategic institutional leadership. Robust governance combined with data literacy, informed consent, continuous monitoring of algorithmic fairness, and adapting policies to promote responsible, equitable, and trustworthy implementation of learning analytics is needed for sustainable implementation.

Corresponding Author:
Saman M. Almufti
Department of Information Technology, Technical College of Duhok, Duhok Polytechnic University, Duhok, Iraq.
Email: saman.almofty@gmail.com

1. INTRODUCTION

In the last ten years, education live a more subtle and profound shift in the decision-making process on the curriculum, student support, and institutional strategy. With the growth of learning management systems (LMS), students' information systems and digital assessment solutions, an unprecedented amount of behavioral and achievement data has emerged. A systematic process of collecting, analysing and using such data to guide practice, it is also referred to as Data-driven decision-making (DDDM) and has been called a “perfect time” for education systems to transition away from intuition-based governance to evidence-based management [1]. The sub-field of learning analytics (LA), which focuses on measuring and analyzing data regarding learners and their contexts, has increasingly emerged as the key technical means by which DDDM is implemented in classrooms, learning platforms and in administration.

The promise of Learning Analytics is quite simple: if a student (or group of students) displays undesirable behaviour, or a provision is proving poorer than anticipated, or a cohort is not being reached by current provision, then intervention can precede matters spiraling out of control. However, the very same infrastructure that would support early intervention can repattern authority and judgment within an institution in such a way as to create structural change. There has been considerable debate about the way data-driven platforms shift the locus of pedagogical decision making from the teacher to the usual suspects of private technology companies and the presentation of what constitutes "real" evidence for learning advanced by the platform, as well as tacit modification of learning goals by the platform [2]. Structural consequences are not subjected to the same degree of discussion as other more visible decisions in curriculum, partly because the use of technology in education happens on a tool-by-tool and vendor-by-vendor basis, without a policy framework.

This policy space is critical in situations where institutions have limited resources and experience in developing countries implementing a policy or institutional gap in their ability to interpret and apply the results of analytics meaningful to the goals of a policy in a responsible and responsible way in the presence of the same developed countries' analytics platforms that are marketed globally. In such contexts, learning analytics is often part of an effort to modernise education or ‘modernise the school’ (and there are contexts like a lot of the Middle East where this is the case), meaning it is adopted as a new tool (a new dashboard, a new LMS module) without an institutional plan in place that outlines who is allowed to view student data, for what purposes and under what conditions of protection. The technical and policy dimensions of LA are inseparable as per this paper: without the policy, the technical will be harm; and if there is no technical then the policy would be irrelevant.

In this context the present paper sets out to have three aims. First, it reviews the current state of research on learning analytics and data-driven decision making for three different application domains: institutional adoption, forecasting and early-warning systems, and data privacy and ethics. Second, it explores the connections between these technical developments and links them to educational policy at the institutional and national level, which all too often today remains out of step with them. Third, it outlines a policy framework to support the implementation of the analytic capability by those who govern and help administrators make better use of evidence in practice. In the rest of the paper we will develop our arguments as follows. Related work is surveyed in Section 2, under the four thematic areas listed in the above. The methodology adopted for literature review to identify and review the literature is represented in section 3. The results are presented and discussed in section 4, alongside a suggested governance framework, which are discussed in the context of the policy implications. The paper is concluded in section 5 which states the future research directions.

Before beginning it is important to explain the meaning of several concepts which are similar and will be used throughout this paper. In this context ‘learning analytics’ is defined as the measurement, coming together and analysis of learning data and its contexts, for the purpose of understanding and adjusting learning and its contexts. But "educational data mining" has been a small and related, albeit methodologically different tradition that is interested in uncovering new patterns from educational data, typically utilizing a technique developed from the fields of computer science and statistics; learning analytics has the overall focus on applying existing models to make educators' and learners' decisions in real time. Both are covered under the umbrella of "data-driven decision making," along with externally oriented administrative decisions like allocation of resources and planning for enrollments out of the focus of instructional analytics. This paper focuses on the policy implications which emerge at the stage of using data of any of these types at the point where their use may affect the learning of individual pupils, as distinctions in the purpose of using data for purposes of governance become particularly acute at that point, rather than at the point of its collection.

It is best to consider this paper not a technical paper, but a policy oriented one, since the remainder will be read. Those readers who wish to have detailed descriptions of specific machine-learning algorithms used in the field of predictive analytics or detailed descriptions of the software architecture of contemporary learning-management systems are referred to the technical literature quoted in the context of the various sections. The contribution here is to collate findings across the different subfields of technical science that are often published in different disciplinary journals—for example, computer science, information ethics and educational psychology—so as to generate an effective summary, one that synthesizes the various findings before they get to the ear of policy makers or decision makers at institutions, and that could serve as a useful starting point for institutions when making procurement and governance decisions.

2. RELATED WORK

2.1 Conceptual Foundations of Data-Driven Decision-Making

DDDM in education threads back to the conceptual foundations of the development of learning analytics systems before them, focusing on how to make school improvement processes more systematic and evidence-based. Early delineations described the difference between the amount of data available and the amount of use made of it, noting that having a lot of data on a student doesn't necessarily translate into improved decision making unless teachers have the capacity, motivation, and organizational support to interpret it [3]. The divide between data and data literacy hasn't faded from the discipline and continues to be a focus. Further research has demonstrated that data literacy needs to be declared as a separate teaching skill that is a given effort, not a natural outcome of technology adoption [4]. Comparative cross-cultural and cross-institutional studies also show that conceptions of the legitimacy and effectiveness of DDDM among teachers vary greatly across settings and cultures, and that negative experiences teachers may have had with high-stakes testing regimes may be one source of skepticism about data-driven practices.

One consistent message that runs throughout this literature is the contrasting concepts of “data for accountability” and “data for improvement.” Data systems which focus on external reporting and compliance will likely create compliance behaviors and not real instructional change in schools. Conversely, where the use of data is part of a more culturally collaborative community of inquiry, it is linked to improved equity for historically underserved students [5]. For the purposes of this equity dimension, this is important because the issue isn't just about whether institutions should employ data-driven practices but what the institutions' governance structures create is either decrease or increase disparities.

2.2 Institutional Adoption and Learning Analytics Infrastructure

There have been many studies that have taken a systematic approach to the diffusion of LA, mostly concentrated on the higher-education sector. Much as is reported repeatedly in the literature, there are many LA initiatives at the institutional level that are successfully established on small scale, single-course deployments, and not creating embedded institutional practice, despite years of pilot projects [6].

Challenges to wider adoption include inconsistent analytics data infrastructure, a lack of commitment within institutions, lack of clarity with IT departments and academic units over who owns analytics initiatives, and the ongoing shortage of staff who are competent in interpreting dashboards [7]. A systematic review [8] specifically targeting distance and Online Education identified learning analytics applications in these contexts focus on engagement and interaction metrics based on log information of the learning platform, but with interventions that have not been assessed with respect to their impact on learning outcomes.

Reviews at the secondary-level report that learning analytics applications are even more immature; the vast majority of learning analytics practices at the secondary level are still at an exploratory stage, and have received little application to formal school-improvement policy [9]. A more comprehensive analysis of the factors used to analyze learning outcomes in the higher-education analytics landscape also identified that the majority of factors analyzed are around engagement and platform behavior, rather than and/or self-assessment and demographic data, which tends to be the most relevant variables for equity interventions [10]. These findings related to the technical capacity to collect data and institutions' capacity to set their measurement agenda and purpose together suggest that the capabilities to measure have been much prior to the capability to define what should be measured and for what.

There are two other threads of writing that intersect infrastructural issues related to adoption. First, interoperable data-collection standards (such as the Experience API) have been developed to allow for the collection of learning activity data from different tools to all be conveyed to a single analytic pipeline, necessary for institution-wide DDDM, but not the same as the analytic use of individual tools that is currently available. Second, research in the design of analytics dashboards has focused on the need to involve end users, teachers and students, in the validation of the analytical tools and visualizations provided on the dashboards, as a poorly designed dashboard [11] can mislead as well as inform [12]. The results of both strands converge to a policy-relevant conclusion: analytic infrastructure decisions (data standards, dashboard design, interoperability) impact upon how fairly and accurately resources are accessed via data-driven decisions.

2.3 Predictive Analytics and Early-Warning Systems

Predictive analytics is the most "policy-sensitive" implementation of L.A. as this output guides limited attention and support of the institution towards particular learners. Historical engagement and performance data are effective for indicating potential for failure and have been shown to have positive impacts when used for early-warning systems with timely and targeted interventions to boost retention rates [13]. Following a systematic review of predictive learning analytics over a decade, it has been observed that the complexity of predictive models has steadily improved from logistic regression to ensemble models and deep learning models, but that most frequently published models are not deployed in real-world settings, and that most authors only evaluates predictive accuracy, not the effectiveness of intervention [14].

This discrepancy in predictive accuracy and explainable output has recently spurred the interest in explainable artificial intelligence (XAI) for dropout prediction because an accurate predictive model able to provide predictive knowledge but lacking knowledge about why a student was flagged as dropping out will be of limited value to an advisor, in determining how to intervene [15]. Empirical studies in local national contexts show the potential for utility as well as problems with this approach: predictive dropout models were created for a distance university in South Korea which proved useful to prioritize advising resources, yet the models' accuracy was highly dependent on the completeness of the institution's data pipeline and these models needed regular updates due to shifts in student populations [16]. These results further support the overarching policy concern: the predictive models trained on the patterns of one institutional context may not generalize well to another, and thus it is essential to be mindful of this when foreseeing the widespread implementation of predictive models, trained and validated in a different context, by developing-country institutions.

2.4 Privacy, Ethics, and Data-Governance Frameworks

The fourth policy area, which arguably is the most relevant to policy, is Ethical and Legal Governance of Student Data. Basic research in this field proposed to divide the analytic process into stages: pattern-finding and intervention, with each stage requiring specific safeguards so that the mere finding of a pattern in the student's data does not mean that they should have an individual intervention without appropriate safeguards [17]. It is possible to distinguish between a set of principles developed for a European learning-analytics toolbox, which presented "how to ensure that personal data collected for LAs is not used for purposes that it was not originally gathered for" [18]. These proposals suggest an overall consensus that informed consent is a prerequisite and essential governance mechanism, but is not enough in itself; student consent is often not anticipated when they enroll, and informed consent may be difficult to determine when it becomes clear years later how their information will be used; it is also often impossible to withdraw consent after the fact.

In the wake of these initial proposals, subsequent research has introduced more sweeping sets of ethical and privacy directives to guide institutional learning-analytics policy, for instance by outlining how to be transparent about the types of data being gathered, specifying who will have access to the data, and providing students the opportunity to challenge analytics decisions about them [19]. There has been empirical research on the topic of student data privacy, and a systematic study of this research confirms that these principles are poorly applied in practice: there is often a lack of documented data protection policy for student data specific to learning analytics; where such policies exist, they are often not communicated to students in an accessible form [20], [21]. Rather, it has been argued from an information-ethics perspective that protecting student data is more than just a legal requirement in regulations like those for data protection—as students sit in a structural vulnerability position relative to the institutions and vendors that control information about them [22]. In addition, a thorough system of contradictory ethics that are still under conceptual and etiological debate in the field has yielded a wealth of conceptually-based and principle-based guidance but relatively little work examining how implementations of learning analytics principles and concepts affect ethical outcomes for students [23].

The literature summarized in the preceding section shows the field has progressed significantly in technical sophistication, research on adoption and adoption studies, and ethical theory, but has failed to achieve a joined-up policy over technical, adoption and adoption theory issues. The process for secondary synthesis of this body of literature is detailed in the next sections along with the presentation of a policy framework to address that gap.

A second strand of research in this core literature explores the socio-structural environment in which data-driven practices become (or do not become) entrenched. Research into school improvement efforts has determined that the existence of a data system is not a strong indicator of the extent that meaningful data use takes place in the institution; what's more predictive of the actual and meaningful use of data is having regular protected time for staff to review data together, and whether or not the institutional leaders use data when making decisions, instead of relying on only a junior staff at the school or a consultant to review data. These organizational aspects are often underestimated and do not form the crux of conversations that concentrate on technical "savvy" in dashboards and analytic platforms but regularly appear in conversations regarding the factors that drive the success or failure of implementation in the literature on the adoption discussed in Section 2.2.

3. METHODOLOGY

There are a number of reasons for not using the conventional empirical research methodology for the type of study and purpose this paper has outlined here: first, because it has a policy-perspective and does not test an empirical hypothesis; second, because this is a synthesis literature review that follows a narrative approach, which aligns already presented or already taught information from the various sources reviewed; and third, because the method of literature synthesis defines the categories of material chosen for the review process. The process of review consisted of four steps, namely search, screening, thematic coding, and synthesis.

The identified peer-reviewed literature from 2012 to 2025 was taken from the following databases: Scopus, IEEE Xplore, Springer Link, Science Direct, and ERIC, for the various combinations of the following terms: "learning analytics," "data-driven decision-making," "educational data mining," "predictive analytics in education," "early-warning system," "student data privacy," and "educational policy. To identify key systematic reviews not found by the keyword search, a snowballing sampling methodology was employed and reference lists of key reviews were hand searched, following the usual practice of narrative and scoping reviews in rapidly evolving technical fields.

Note that in the screening stage sources were included where they (a) met the condition of addressing learning analytics (or data-driven decision making) directly in a formal education setting, (b) were published in a peer-reviewed journal, conference proceedings, or an established institutional or governmental report, and (c) were substantive to one of the four thematic areas defined in Section 2. Sources that only referred to the use of data analysis for exclusive corporate training or in contexts beyond educational were excluded, except for sources that were preprints without a peer reviewed equivalent that covered a topic of direct relevance to education.

In these retained sources, the thematic coding was an inductive process into the themes that have been identified and organized under the four themes discussed in Section 2: conceptual foundations, institutional adoption, predictive applications, and privacy/ethics governance. Sources that covered more than one theme were assigned to the more important one and cross-referenced where appropriate to the other themes. During the synthesis stage, each theme finding was compared to other findings to seek commonality, areas of tension, and areas of non-overlap that were not identified in existing research, and data from these discussions was integrated into a four layer policy framework (Section 4) developed to address the key challenges identified. Since it is a conceptually and policy related paper and not a "work with human subjects" there is no need for primary data, only secondary data that has been published to others.

4. RESULTS AND DISCUSSION

There is a consistent structural pattern in the literature reviewed in Section 2 with more rapid, and not everywhere equal, improvement in technical and analytic capacity, and "gaps" or weaknesses in the governance structures required to guide that capacity to equitable and trustworthy outcomes. This section defines that pattern in greater detail, summarises it in tabular form and offers a four-layered pattern of policy orientation, thought to help solve the pattern.

4.1 Cross-Cutting Findings

The thematic review leads to three cross cutting findings. Firstly, as shown by enormous adoption studies, the focus on using learning analytics is never as a method to build a capability within institutions, but rather as a string of individual tool deployments [7], [9]. A similar trend – that of being technically advanced and governance-consuming – is seen in all of the four thematic areas analyzed in this paper Table 1.

Second, as sound as predictive and early-warning applications have proven to be in improving student retention when used effectively, they are prone to issues of context-transfer: the models work well for learning under a certain set of conditions and may perform poorly when implemented in a different context without recalibration [14], [16]. For institutions in the developing regions where implementation of this policy may be desirable, this is a direct policy concern as predictive tools may be developed and validated mostly in North American or European settings.

Third, a significant amount of literature has emerged in the fields of privacy and ethics that provides principle-based guidance for privacy and ethics, including consent, transparency and purpose limitation, but relatively little evidence that institutions do consistently align their practices with principles, and even less evidence that implementation has an impact on student outcomes [20], [21], [23]. An issue this paper sees as the most important gap between principle and practice and as a policy vulnerability described in the literature is the disconnect between the ethical legitimacy of learning-analytics programs at present relying more on institutional intention without verified, auditable practice. As can be seen in Figure 1, this increase in the disparity in policy readiness and technical capability over the course of this review.

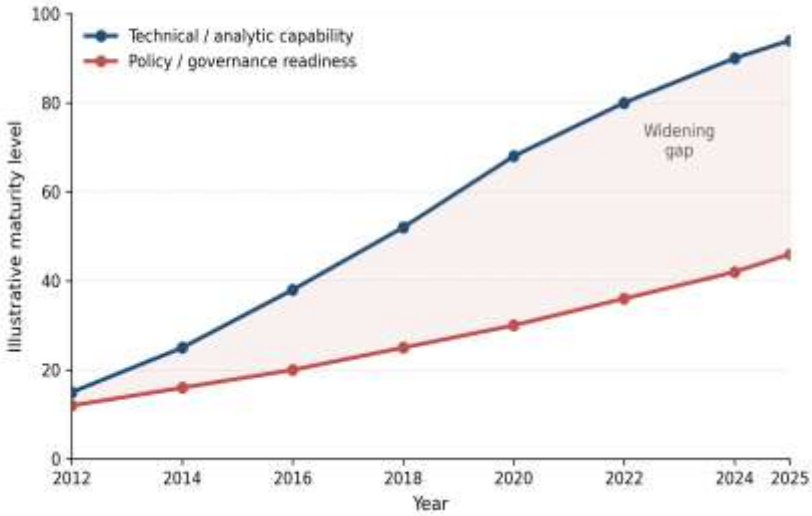

Figure 1. Widening Gap between Technical/Analytic Capability and Policy/Governance Readiness (2012–2025, Illustrative)

Table 1. Summary of Technical Maturity and Policy Readiness across Thematic Domains

Thematic Domain	Technical Maturity	Typical Policy Readiness	Representative Sources
Institutional adoption / infrastructure	Moderate–High	Low: ad hoc, tool-by-tool governance	[7], [10]
Predictive analytics / early warning	High	Low–Moderate: limited context validation	[13], [16]
Privacy, ethics, data protection	Moderate: principles well developed	Low: weak institutional implementation	[17], [23]
Data literacy / educator capacity	Low–Moderate	Low: rarely embedded in preparation programs	[1], [4], [6]

4.2 A Four-Layer Policy Framework

Drawing on the cross cutting dynamics discussed in the previous paragraphs, this paper suggests a four-level policy framework that could support the connection of institutions' analytic capacity to governance responsibility. The structure of the framework is designed to also tackle different failure modes outlined in literature.

The first layer, data governance, sets-out formal rules on what student data can be collected, how long stored data will be held, who stocked data can be accessed by, and under which conditions its data may be reused. On this layer, the absence of consent is certainly not enough when data is used for a period of time [17], [18] and conveys purpose-limitations and transparency requirements laid out in the ethics literature [19]. The second tier is institutional capacity, which focuses on a long-standing issue in adoption research related to data-literacy i.e., the need for specific investment in training faculty, advisors, and administrators to interpret dashboards and to act on predictive outputs, but not expected to understand how to do these incidental skills. The third layer of pedagogical alignment involves assessing and considering any intervention that is designed based on the data generated by analytics, not just its predictive reliability, but also the way in which it affects the children's teaching and learning practice, refuting the challenging dichotomy of predictive reliability and impact that has surfaced in the predictive-analytics literature [14], [15]. Meanwhile, the fourth layer (ethical oversight) creates an institutional review mechanism through regular audits that can confirm that analytics systems that are currently in use continue to meet the institution's stated data-governance and equity commitments, as the principle-practice gap identified as most significant vulnerability in Section 4.1 [20], [21], [23] has been reported. The above four layer structure is schematically given in Figure 2.

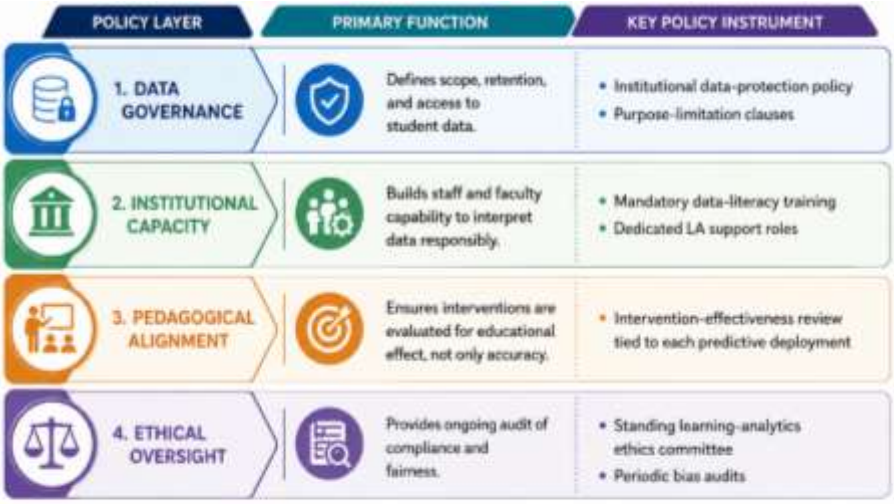

Figure 2. Proposed Four-Layer Policy Framework for Learning Analytics Governance

Table 2. Proposed Four-Layer Policy Framework for Learning Analytics Governance

Policy Layer	Primary Function	Key Policy Instrument
1. Data governance	Defines scope, retention, and access to student data	Institutional data-protection policy; purpose-limitation clauses
2. Institutional capacity	Builds staff and faculty capability to interpret data responsibly	Mandatory data-literacy training; dedicated LA support roles
3. Pedagogical alignment	Ensures interventions are evaluated for educational effect, not only accuracy	Intervention-effectiveness review tied to each predictive deployment
4. Ethical oversight	Provides ongoing audit of compliance and fairness	Standing learning-analytics ethics committee; periodic bias audits

4.3 Implications for Developing and Resource-Constrained Contexts

The policy framework at hand is of special interest to educational institutions in developing and resource-limited environments, such as universities and technical institutions in the Middle East, characterized by an urgent need for expanded livelihoods and employment. In the developing and resource-constrained regions, including the Middle East, technical institutions, and universities are especially relevant to the proposed policy Table 2 framework because the need for expanding livelihoods and employment opportunities is urgent. However, it is common for institutions that implement learning management and analytics platforms not to also implement supporting mechanisms like data protection policies, ethics committees and faculty data-literacy programs.

This imbalance puts at risk the use of predictive models and analytics dashboards that may be built in different educational and legal environments, but deployed without proper local validation, thus potentially impacting on fairness, transparency, and privacy of student data. Shared policy resources, such as the harmonization of data governance frameworks, consent templates, and the development of protocols for auditing algorithms at the national or regional level by higher education authorities, however, can help build governance capacity.

The role of technical departments, and specifically those focusing on information technology and computer science, can be key in the scenario of evaluating the performance of algorithms, assessing practices to deal with the data and backing the evidence-based decisions of procurement. The reform of the curriculum is also necessary. Though there are many institutions providing technically competent students who can design analytics systems, the education on ethical, legal, and policy issues of learning analytics is still limited. Even in the absence of comprehensive changes to a national policy, the implementation of learning analytics principles of data governance, privacy, informed consent and algorithmic fairness in IT curricula will boost the capacity of institutions and equip future professionals to handle learning analytics with responsibility.

4.4 Limitations

This paper does not present a quantitative measure of thematic classificatory inter-coder reliability nor is it a systematic review, as would be recommended by PRISMA protocols. Its findings should consequently be read more as a synthesis of the already voluminous and highly dynamic literature or as a sample of the field rather than as comprehensive or simply statistically representative. Based on a formal systematic review approach or as a formal empirical experiment through institutional case studies, the governance recommendations put forward here could be validated and characterised with a certain level of refinement in the future.

5. CONCLUSION

Learning analytics has shown to have substantial potential to transform educational decision-making in terms of timeliness, evidence and need responsiveness. But this lit review shows that tech and analytic skills have always been more in abundance than policies to effectively manage them. While steady progress has been made across a range of issues, including the development of predictive models, adoption frameworks, and ethical principles, there haven't been enough strides toward incorporating those ethics into auditable, enforceable institutional practice. This proposed 4-layer policy framework (data governance, institutional capacity, pedagogical alignment, and ethical oversight) hereby substantively contributes to bridging this gap and is intended as a first attempt of an institutional policy agenda—it is not the end of all policy efforts. Closing the divide between the capacity of the academic and policy levels is expected to be particularly difficult for institutions in developing and resource-poor areas, and will take coordinated investment efforts by national education authorities and individual institutions. Ultimately, it will be the power of the governance systems used to deploy the algorithms from learning analytics that will decide whether they are useful in education or not, rather than the sophistication of their algorithms themselves. Empirical tests of governance models, including this one, should be done and evaluated in the future; the performance of predictive models that can be compared across a range of asymmetric institutional settings (longitudinal studies) should be measured; and analysis of policy differences across national education systems should be undertaken.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Saman M. Almufti	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization   I : **I**nvestigation   Vi : **Vi**sualization

M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

Conflict of Interest Statement

The author has no conflict of interest to disclose related to the content of this article.

Informed Consent

Not applicable. There were no human subjects used in this study and no primary information was gathered from humans.

Ethical Approval

Not applicable. This study is a literature review (policy analysis) study and does not need an institutional review board for its ethical approval.

Data Availability

For this study, data sources were not gathered, and no new data was analyzed. All of the sources that were used in this review are peer-reviewed, and they are publicly available.

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BIOGRAPHIE OF AUTHOR

Saman M. Almufti, is a faculty member in the Department of Information Technology at the Technical College of Duhok, Duhok Polytechnic University, Duhok, Iraq. His research interests include information technology applications in education, data-driven decision-making, learning analytics, and educational technology policy. He has contributed to research and academic activities aimed at strengthening the integration of information technology into teaching, learning, and institutional governance within higher education. Email: saman.almofty@gmail.com