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"Limits of Algorithmic Pedagogies in Indian Public Education"

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Limits of Algorithmic Pedagogies in Indian Public Education

Abstract

Algorithmic pedagogies have become increasingly central to contemporary education systems. They have been instrumental in different fields, such as artificial intelligence, data analytics, and platform-based technologies. These pedagogies are being increasingly integrated into the teaching and learning process across the globe. In this background, public education systems have emerged and are frequently positioned as key sites for algorithmic interventions. The reasons largely pertaining to the scale, administrative reach, and the capacity to generate large volumes of educational data. In this light, policy discourse has been framing algorithmic pedagogies as educational innovations. They have been tabled as having a lot of advantages like improved efficiency, personalized and better learning outcomes. Existing research in this field has been evaluating these systems via indicators like scale, platform usage, engagement metrics, and predictive accuracy.

In the context of India, there has been rapid advancements in the integration and adoption of these tools in the education sector. Covid 19 along with National Education Policy (2020) amplified this phenomenon with an intense focus on the deployment of platform-based learning and data driven educational governance like DIKSHA AND SWAYAM initiatives. From learning analytics to automated assessment tools and algorithmic recommendations, there have plethora of innovative interventions in this field.

The central argument of the paper is that these evaluations tend to treat these systems as technical tools, while assuming the presence of robust institutions. This over estimation of institutional capacity has made it difficult to capture the macro picture precisely. Here, the meaning and the scope of institutional capacity is not just limited to infrastructure availability, connectivity, or mere teacher training. Rather, it goes beyond to the realms of broader governance which has still remained underexplored. This gap has been more evident in Global South contexts for reasons concerning to institutional heterogeneity, uneven capacity, and complex governance arrangements. These arrangements challenge assumptions which are embedded in dominant models of algorithmic education.

This paper attempts to conceptualize algorithmic pedagogies as socio-tech systems that are embedded within public institutions rather than standalone educational technologies. It also contributes to the existing literature that algorithmic pedagogies are primarily governance interventions that recognize authority, accountability and decision making at all levels of public education systems. As a result, making the claim that the effectiveness algorithmic pedagogies ultimately depend on institutional coherence, data governance and sustained organizational learning. Henceforth, reiterating the argument that the limits of algorithmic education are the limits of institutional and governance capacity.

Keywords- Algorithmic pedagogies, Institutional capacity, public education governance, learning analytics, Datafication, Global South, National Education Policy, Platform based Governance, Algorithmic reccomenedations, Education.

CONTENTS

Introduction

The advent of artificial intelligence and other fast pacing algorithmic systems is rapidly transforming the educational landscapes globally by promising innovative approaches to teaching and learning. (Amiri, 2025) Consequently, The Indian education system is undergoing a significant transformation with the increase in deployment of digital platforms, algorithmic systems, and the pervasive trend of datafication. The exigencies of Covid 19 and the National Education Policy have been instrumental in accelerating this change with wide range of government led digital infrastructures like DIKSHA, PM e Vidya, and SWAYAM (Verma, 2025). Thus, reflecting a broader strategy to tech-mediated learning. This shift has produced large amounts of educational data by creating opportunities for advanced data driven interventions. The use of learning analytics and predictive modelling forecast student outcomes such as academic performance, engagement, and risk of dropout has seen a significant rise, Thereby, allowing institutions to design timely and targeted pedagogical interventions (Sghir et al., 2022), forming the bedrock for advanced algorithmic applications.

In order to limit the scope of the research for better insights, algorithmic pedagogies can be understood as educational practices and systems that are mediated by computational algorithms and designed to personalize learning and optimize instructional processes. (Siemens, 2013). This includes learning analytics, automated assessments, and educational recommender systems (Ferguson, 2012; Ihantola et al., 2010; Manouselis et al., 2011). Crucially, it is needed to make distinction between Ed Tech and Algorithmic Pedagogies. Algorithmic pedagogies differ from generic EdTech because they rely on algorithmic decision-making and data-driven personalization, which is not simply the digitization of existing materials, rather analysis of learner data to drive instructional decisions (Siemens, 2013).

To begin with, despite the promising nature of these technologies, existing literature emphasizes the pedagogical promise of algorithmic systems (Holmes et al., 2019; Siemens, 2013) with key themes ranging from personalization, efficiency, scalability to improved learning outcomes (Holmes et al., 2019; Luckin et al., 2016). The findings of these studies reflect the trend of treating algorithmic systems as neutral tools that can be deployed across contexts (Knox, 2020; Williamson, 2017). This leads to the problem of assumption of the presence of stable institutions which are capable of using algorithmic outputs effectively (Williamson, 2017;

Selwyn, 2019). It is also to be noted that here Institutional capacity is not limited to hardware, connectivity, or platforms. It factors in qualities like bureaucratic competence, administrative coordination, and organisational learning (Gulson & Sellar, 2019; Sellar & Gulson, 2021). It also determines how data is interpreted, how decisions are acted upon, and how systems are sustained (Williamson, 2017). Thereby shaping how pedagogical reforms which are then absorbed and routinised (Sellar & Gulson, 2021).

Since most of the frameworks and recommendations in this area originates in Global North with coherent bureaucracies, reliable data systems and clear accountability mechanisms, such assumptions tend to break down in the Global South due to institutional heterogeneity and federal complexity (Verger et al., 2016; Sriprakash et al., 2020). As a result, implementation challenges in countries like are often misinterpreted as resistance or inefficiency. This overlooks the structural misalignment part.

Building on the critical accounts of datafication and AI in education that emphasize the socio-technical nature of digital systems (Knox,2020; Williamson,2017), this paper reframes algorithmic pedagogies as being more social then technical. It analyses India's public education system to understand the social-political context in which these pedagogies operate. Thus, positioning it under governance area that requires strategized policy interventions. To achieve this objective effectively, this paper relies on qualitative, literature-based synthesis to identify conceptual gaps and analytical limitations in existing scholarship (Singh, 2021; Sriprakash et al., 2020).

Methodology and Limitations

Algorithmic pedagogies in Indian public education constitute an emerging and fragmented research area (Sriprakash et al., 2020; Singh, 2021). Empirical studies have been dispersed across education technology, learning analytic, governance and policy literature (Selwyn, 2019; Gulson & Sellar, 2019). Accordingly, no single dataset or field site can capture system- level institutional dynamics within the scope of this paper. Therefore, a literature-based approach has been adopted to synthesize the findings across disciplines and analytical traditions.

Moreover, Peer reviewed journal articles, Academic books, and edited volumes on education policy, institutional capacity and state capacity have been drawn on extensively.

Besides, institutional reports from multilateral organizations have also been extensively referred to wherever analytically relevant (Williamson, 2017; Verger et al., 2016). The paper has also prioritized post-2015 literature to reflect the datafication and algorithmic turn in education (Selwyn, 2019; Holmes et al., 2019).

Further, the limitations have been in terms of limited observation of classroom level practices and uneven availability of India specific empirical studies along with the dominance of Global North literature, which has shaped the framing for years. Thus, reflecting that findings have to be viewed as analytically generalizable instead of statistically generalizable (Sriprakash et al., 2020; Singh, 2021). Over and above this, the fast pacing, evolving nature of technology itself as a fundamental limitation has been duly noted and acknowledged. (Holmes et al., 2019).

Literature Review

Literature on algorithmic pedagogies has emerged primarily within the broader field of educational technology (Holmes et al., 2019; Selwyn, 2019). Many scholars have examined that the growing use of artificial intelligence, data driven systems and automated decision-making tools in teaching and learning processes (Holmes et al., 2019; Luckin et al., 2016) have shown tangible benefits at least on paper. There is also the observation that early scholarship framed algorithmic systems as instruments of innovation. They emphasized their potential to enhance efficiency, personalize learning trajectories, and address longstanding challenges of scale in education systems (Holmes et al., 2019; Siemens, 2013). Yet there has been a contradiction in terms of the environment in which it has been argued. Many of these claims have been typically developed in relatively controlled or well-resourced settings which limited attention to the heterogeneity of learners and resource constraints. These factors for the longest time shaped system-level implementation especially in developing countries like India (Selwyn, 2019; Sriprakash et al., 2020).

Additionally, in terms of methodology, literature has mostly been dominated by quantitative and experimental research designs. These largely include controlled experiments, quasi-experimental evaluations, platform-based analytics, and studies that focus on engagement metrics or predictive accuracy (Siemens, 2013; Holmes et al., 2019). These approaches have prioritized measurable performance while limiting the attention to institutional mediation and system level effects. There have been examples of these experiments being conducted in "innovative" schools, volunteer samples, or early-adopting jurisdictions, which have been a catalyst in limiting the relevance of these pedagogies to large, heterogeneous public systems (Gulson & Sellar, 2019; Sriprakash et al., 2020). This has reinforced a narrow understanding of how algorithmic systems have been operating within real word educational systems (Selwyn, 2012; Williamson, 2017). As a result, there has been a marked scarcity of qualitative, longitudinal, and governance-oriented analyses.

On the other hand, understanding capacity in this context is becomes very crucial. In much of the literature, capacity has been reduced to infrastructure or training. There has been limited consideration given to organizational learning, decision making routines or bureaucratic adaptivity (Gulson & Sellar, 2019; Sriprakash et al., 2020). Capacity in this context then is defined as the ability of institutions to absorb, interpret and govern algorithmic systems over time. This has mostly remained insufficiently theorized (Williamson, 2017).

A related problem has been in the matter of educational outcomes i.e., how educational outcomes are being measured and improved in the process. It has been in the mainstream discourse that studies on adaptive learning systems and learning analytics have always prioritised performance indicators such as test scores, engagement metrics, completion rates, and predictive accuracy. This outcome-oriented focus has ended up privileging technical effectiveness while pushing questions of institutional and administrative capacity to the margins (Siemens, 2013; Gulson & Sellar, 2019). For instance, scholarships on educational recommender systems draw heavily from work on digital platforms and e-commerce. This body of work has conceptualised learners as individual users navigating personalized content pathways Manouselis et al., 2011; Drachsler et al., 2015). However, even though these framing foregrounds engagement and choice, it tends to obscure curricular mandates, regulatory constraints, and institutional oversight. As a result, recommender systems have been rarely analysed as policy instruments that can and do mediate educational priorities (Drachsler et al., 2015; Williamson, 2017). Alongside this, research on automated assessment systems have highlighted efficiency, standardization, and scalability. While concerns about bias and accuracy have been duly acknowledged, they have often treated as technical challenges to be resolved through better design. (Ihantola et al., 2010; Keuning et al., 2018). Consequently, less attention has been paid to how automated assessment has been reshaping authority over evaluation. It has not been able to address the question of who governs algorithmic assessment and assessment decisions. This problem of redistribution of pedagogical judgement has been under explored across human and algorithmic actors (Ihantola et al., 2010; Keuning et al., 2018).

To compound this with the literature around teachers as primarily end users of algorithmic systems, we observe a different pattern. Research has mostly reported and recorded teacher acceptance, resistance, or digital literacy. This can be flagged as a major gap because by doing so, it has framed successful adoption as a matter of individual competence or attitude. Structural constraints like workload pressures, administrative requirements and institutional incentives have received little to no attention. (Selwyn, 2019).

On a parallel level, literature on digital platforms and algorithmic governance have highlighted the growing trend of automated systems increasingly functioning as infrastructures of public decision making. As initially they have been developed in the context of public administration, it has made education peripheral within this body of work (Gulson & Sellar, 2019; Williamson, 2017). These disconnects between educational technology and governance framework have limited the policy relevance of existing scholarships on algorithmic pedagogies. Consequently, algorithmic pedagogies have seldom analysed from the lens of governance mechanisms that reshapes institutional authority, accountability, and control in education systems (Williamson, 2017).

To account for this gap, a major reason that comes up is the origination of many influential studies mostly from Global North. The assumptions of institutional stability and administrative capacity as implicit stems from this issue to a great extent. For this reason, the differences in Global South have been framed as implementational challenges rather than theoretical limitations. This has limited the transferability of these dominant models. (Verger et al., 2016; Sriprakash et al., 2020). Another reason that justifies this gap is the focus of Indian scholarship primarily on access, inclusion and the digital divide. Algorithmic systems have often been discussed in aspirational or policy driven terms which has in turn limited the critical engagement in terms of institutional readiness and governance structures (Singh, 2021). Taken together, the existing literature privileges performance outcomes and technical effectiveness, while giving limited attention to institutional capacity, organizational learning, and algorithmic governance, particularly in Global South education systems (Williamson, 2017; Sriprakash et al., 2020).

Research Enquiry

The research question that emerges from this review are as follows:

1. How do institutional capacity and governance conditions shape the functioning of algorithmic pedagogies (AGs) in Indian public education system?
2. How does infrastructure and data readiness affect the reliability as well as effectiveness of AGs in Indian public schools? and
3. Why does algorithmic education show success initially in pilot setting but eventually struggle to scale at institutional level?

Analysis

Institutional capacity shapes what algorithms recognize as reality (Williamson, 2017; Kitchin, 2014).

Algorithmic pedagogies operate on attendance records, assessment scores and platform usage logs. These data points are produced by institutions, not generated independently. Therefore, the inputs for the algorithm, which is data in this case, has already been filtered, thus making them epistemically dependent on institutions (Ananny & Crawford, 2018). This can become a problem in large bureaucratic systems, for sometimes data is produced under factors like reporting deadlines, audit pressures and performance monitoring (Mayer-Schönberger & Cukier, 2013). This makes institutions prioritise completeness of data and visibility. For example, recorded indicators capture attendance, enrolment and usage but have not been successful in factoring depth of learning or pedagogical quality (Selwyn, 2020). As a result, algorithms trained on this compliance-oriented data have and can learn patterns of institutional reporting and emulating it. This pattern has also been visible on education platforms that show successful engagement (logins, completion) but weak evidence of pedagogical transformation (Williamson et al., 2020). Therefore, reproducing bureaucratic rationality rather than pedagogical intent.

Teacher mediation is structurally required by algorithmic systems but institutionally under-supported (Perrotta & Selwyn, 2020).

Algorithmic systems generate recommendations, alerts and adaptive pathways. These outputs are then expected to be contextualised and interpreted. In this process, teacher's capacity in digital literacy and openness to innovation is assumed in an accepting and over enthusiastic manner. This then tends to miss thorough analysis of workload, incentive structures and administrative burden (Ball, 2021).

In large public system like India's, teachers face high pupil teacher ratios, extensive non-teaching duties and frequent reporting requirements (NCERT, 2021). The limitation on time and cognition bandwidth, can make it cumbersome. Most teacher training in India have focussed primarily on completing modules and generating modules and not actually adapting recommendations to classroom realities (MHRD, 2020). This can lead to pedagogical scaffolding and minimal impact.

Algorithmic pedagogies scale poorly because institutions lack absorptive capacity (Selwyn & Pangrazio, 2021).

Algorithmic pedagogies are not one-time technologies. They require institutional learning via interpreting outputs repeatedly, adjusting practices over time, and recalibrating rules and routines. To understand this better, the factor of absorptive capacity should be taken into account. Absorptive capacity explains why pilots appear successful for they can concentrate resources, stabilise infrastructure and provide intensive support whereas Institutions differ in their ability to interpret feedback and modify workflows. Absorptive capacity is not about funding or training. It includes institutional memory, stable staffing and routinised reflection (Dodgson, 1993). This mismatch produces symbolic use, for algorithms continue to exist but stop sharing practice. In the absence of this, algorithmic outputs are then not iteratively used.

Algorithmic pedagogies are often framed as solutions to institutional weakness (Williamson & Hogan, 2020).

Policy and EdTech frequently position algorithms as compensation for teacher shortages, standardizing quality. This framing assumes that technology can substitute institutions and algorithmic rationality can replace human and organizational judgement (Eubanks, 2018). Contrarily, in practice algorithmic systems do not bypass institutions nor do they neutralize governance constraints. In fact, they amplify existing capacities and weaknesses (Kitchin, 2017). So, where institutions are strong, algorithms appear effective, but where institutions are weak, algorithmic functioning is distorted. Algorithmic breakdowns often reveal data quality frameworks, coordination failures, and weak feedback loops (Ananny, 2016). These are institutional characteristics which are then made visible by algorithms. India's scale and diversity tend to magnify this institutional variation with visible partial functionality, uneven effects, and governance dependent outcomes. India therefore functions as a stress- test case, not an outlier for its trajectory is similar to other countries with large but weak public-school systems (Azam et al., 2021).

Comparative Perspective: Algorithmic Pedagogies in India and Other Global-South Contexts

Empirical reviews show that learning analytics and AI enabled pedagogies are unevenly adopted across Global South education systems with activity concentrated in small number of countries and institutions (Prinsloo & Kaliisa, 2022). Even large parts of sub- Saharan Africa, Latin America and South Asia show low visibility of learning analytics research. This indicates limited institutional engagement with algorithmic pedagogies (Prinsloo & Kaliisa, 2022). Taking Africa as an example, few reports identified fewer than twenty peer reviewed studies on learning analytics across the entire content (Prinsloo & Kaliisa, 2022). Similar patterns can be seen in Latin America, where algorithmic and data driven education initiatives being common in elite and urban systems (Akpan, 2024).

Furthermore, Comparative studies also identify data availability and data quality as primary constraints on algorithmic pedagogies in Global-South education systems (Prinsloo & Kaliisa, 2022). There are many institutions that lack Integrated Learning Management systems. Even though, data systems exist, they often suffer from issues like missing values, inconsistent reporting formats and delayed uploads. This tends to limit their analytical processing.

Another finding reveals (bibliometric analyses) that research and innovation in digital education technologies are concentrated in countries with higher R&D investment, reinforcing global and regional inequalities (Akpan, 2024). This when analysed shows that algorithmic pedagogies are often designed for homogenous curricular and linguistic environments (Lim, 2018). Henceforth, in Global South with multiple languages and diversity, algorithmic systems get complicated due to lack of localisation. This makes it of symbolic use rather than real on ground change.

Empirical patterns

As per the National Data, there has been an improvement in access and device availability in recent years, even though it is uneven. According to UDISE+, the share of schools reporting from 22.3 % in 2019 to 53,9% in 2023-2024, showed a significant increase along with proportion of computers from 38.5% to 57.2% in the same period (UDISE+, 2024). However, these gains mask wide state level and district level variations. At the same time, national platforms exhibit large reach but limited evidence of uniform pedagogical integration. DIKSHA itself has reported millions of enrollments and course completions, but independent studies of teacher and classroom practice reflect uneven class adoption (NIEPA, 2023).

Similarly, learning assessments have consistently found foundational gaps despite expanded digital activity. ASER's recent findings highlight sizeable proportions of youth and children who cannot read age-appropriate texts or solve basic arithmetic, and NAS 2021 documents declines or weak gains in competency in several grades compared with earlier cycles (ASER, 2022; NAS, 2021). This reflects that algorithmic systems are being adopted faster than institutions adopting them. Thus, proving that they tend to function only partially and unevenly across India's federated school systems.

Recommendations

Algorithmic systems operate within complex institutional, political and socio-economic contexts. As per the central argument of this paper, their effectiveness is contingent on governance, institutional capacity and sustained administrative support (European Commission, 2021). These recommendations therefore outline enabling conditions and design principles. These are not meant to be prescriptive or universally applicable.

Algorithmic systems in public education systems should be explicitly positioned as decision support tools rather than performance evaluation mechanisms (UNESCO, 2023). Hence, their primary role should be to surface patterns, flag potential concerns and support professional judgement. High stakes use such as ranking schools, evaluating teachers and triggering punitive interventions should be restricted. To achieve this, clear governance guidelines are needed to ensure algorithmic outputs that inform decisions rather than support them.

Moreover, Data collection systems should be streamlined to focus on fewer but pedagogically meaningful indicators with consistent and reliable data flows (NITI Aayog, 2022). For this purpose, dashboards can be redesigned to foreground interpretability, communicate uncertainty and discourage mechanical reading of metrics. On the other hand, uniform nationwide deployment should be avoided. Implementation should follow a tiered model with lower capacity institutions focusing on foundational digital readiness and data reliability whereas higher capacity institutions should engage with more advanced algorithmic features (World Bank, 2022). This can also prevent algorithmic systems from reinforcing existing interstate and inter district qualities.

Along the way, pilot projects can be redesigned and used to identify governance bottle necks, assess coordination costs and evaluate administrative and cognitive load (OECD, 2023). Algorithmic tools can align with existing school routines, administrative reporting cycles and pedagogical planning process. Lastly, capacity building should move beyond short term technical training. In order to foster on ground change, Institutions require sustained reflection cycles, peer learning forums and stable administrative teams (MHRD, 2020) which should be realized through practice shared learning and contextual interpretations of the outputs of these systems. These mechanisms will enable schools and districts to learn how to work with algorithmic outputs and adapt practices iteratively over time.

Conclusion

Algorithmic pedagogies are commonly discussed as educational innovations. This paper has made an attempt to better understand these pedagogies as institutional interventions. It also brings to light that their impact relies to a great extent on how public algorithm function. This led to the core issue of institutional mediation. Similarly, current evaluation treats scale, usage and engagement as indicators of success. These indicators primarily measure administrative visibility rather than learning quality. This gives an illusion that these algorithmic systems are successful while producing limited pedagogical change. For this reason, success needs to be defined beyond dashboards and usage statistics. Without this shift, algorithmic interventions risk being misinterpreted as effective. As Selwyn (2019) cautions, educational technologies cannot be meaningfully assessed outside the social and organisational contexts in which they are embedded.

Digital and algorithmic systems in education are not neutral tools; they are shaped by the organisational cultures, governance arrangements, and power relations of the institutions. These conditions strongly influence how such systems function in practice (Selwyn, 2019). A central implication of this reframing also concerns how success is currently evaluated. It is noticed that much of the existing evaluation of algorithmic education systems relies on indicators like scale, platform usage, and engagement metrics. However, these indicators primarily capture administrative visibility rather than pedagogical transformation. Further, this paper demonstrated that algorithms do not in the first-place attempt fix the weaknesses of institutions or act like a substitute. They rather mirror and strengthen same data habits, priorities and governance structures that were initially set by institutions. Since, these algorithms depend on data such attendance, enrolment and so on, they mostly end up reflecting what schools already value rather than how well learning is actually happening. As explained by Williamson (2017), analytics systems trend to repeat the logic and assumptions which are built into their data sources.

When institutional data comes from strict reporting routines, the results produced by algorithms follow those same patterns. This means that the focus often stays on filling out reports and meeting targets rather than improving teaching or learning (Williamson, 2017). In these cases, algorithms show existing institutional conditions instead of changing them. The problem of feedback systems was also touched upon in terms of regular need of inputs for adjustments and making better adjustments. In the absence of such loops and classroom practice, algorithmic system then becomes stuck and lose their usefulness. This has been reiterated by. Fokkema et al. (2018) who point out that organisations do not learn from analytics, they in fact stop helping development.

This leads to another crucial point that the paper explains, why pilot projects often seem successful but fail when expanded, these pilot experiments usually run under stable conditions which do not last. So, when the same tools are scale, various problems keep resurfacing like low capacity, uneven infrastructure and administrative pressure. As rightly noted by Gulson and

Sellar (2019), that pilot projects often hide these problems, which tend to later show up during full implementation. Hence these challenges should not be viewed in isolation as technical breakdowns. These should rather be viewed as signs of deeper institutional limits. In the words of Beer (2017), Algorithms can act like mirrors, by exposing how organisations really function and where the weaknesses lie. This makes it imperative to bring attention to structural and governance problems, instead of giving solutions.

Overall, this paper argues that the success of any algorithmic tool in education depends on strong institutions first, followed by a better technology. They can only become useful when schools and systems can make sense of data and act on it in meaningful ways. To quote Daniel (2015), analytics are valuable when institutions have the skills to interpret and apply them. This brings us back to the central argument of the paper that the limits of algorithmic learning, reflect the limits of governance itself. This cannot be solved by technology alone. There should not be techno- optimistic dependence. However, it also not to be given up that technology truly has the power to transform educational systems. What will aptly make a difference is having a nuanced understanding. This will help avoid overestimating what algorithms can do and, in the process, encourages more realistic, context-based education policies.

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