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# Integrating Artificial Intelligence and Data-Driven Decision Making to Enhance Educational Administration in the Digital Era

*An integrative conceptual review and proposed framework for school administration*

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**ABSTRACT**

Schools and other educational institutions hold large amounts of information about attendance, achievement, teaching, staffing, budgets, and student support. Yet having more data does not necessarily lead to better decisions. Records may be scattered across systems, staff may lack confidence in interpreting them, and useful findings may never translate into action. Artificial intelligence (AI) offers new ways to identify patterns, estimate risks, summarize records, and compare administrative options. Drawing on scholarship about data-driven decision making (DDDM), educational information systems, school leadership, and responsible AI, this article proposes a framework for AI-assisted school administration. It links data readiness, AI-supported analysis, professional interpretation, administrative action, and evaluation, with human oversight and governance running through every stage. Examples involving student support, instructional planning, staffing, and budgets show how the approach might work in practice. The article also considers ways to assess decision quality and addresses privacy, bias, reliability, organizational capacity, and unequal access. As a conceptual proposal, the framework still requires testing in real school settings. Its central argument is that AI can strengthen administrative judgment, but should not replace the people responsible for consequential educational decisions.

**Keywords:** *artificial intelligence; data-driven decision making; educational administration; school leadership; decision support; AI governance*

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## 1 Introduction

Schools generate information every day, from attendance and assessment results to staffing, student welfare, and expenditure. These records should help leaders recognise problems early, review programmes, and direct support where it is needed. In practice, however, useful evidence is often scattered across departments. Even when a dashboard brings the figures together, it cannot explain on its own why a problem has arisen or what a school should do next.

The OECD Digital Education Outlook 2023 highlights both the promise of educational data ecosystems and the difficulties of connecting learning-management platforms with institutional information systems (OECD, 2023). A principal, for example, may need to consult separate systems for attendance, grades, and pastoral support. Bringing those records together can take considerable time, delaying decisions about students who may need help.

AI may help schools move beyond routine reporting. Depending on the task and the quality of the available data, it can identify unusual patterns, estimate likely outcomes, or prepare summaries for review. The OECD Digital Education Outlook 2026 also considers generative AI in administrative and school-management work (OECD, 2026). These possibilities are useful, but they come with limits. A model that performs well on historical records may still produce misleading or unfair recommendations when circumstances change.

The central question is therefore not whether schools can use AI, but when its use leads to a better decision. This article argues that the answer depends on the wider process: asking a clear question, working with dependable information, choosing an appropriate analytical method, interpreting the results in context, acting responsibly, and checking what happened afterwards. AI has a place in that process, but it does not replace the people accountable for it.

## 2 Purpose and Review Approach

This article has four aims. It clarifies the meaning of AI, data-driven decision making (DDDM), and administrative decision making in schools. It then examines where AI may be useful in the decision process, develops an integrated framework linking analysis with professional responsibility, and identifies practical conditions and questions for future research.

The article uses an integrative conceptual review rather than a systematic literature review. It brings together selected

peer-reviewed studies of school leadership and data use, institutional guidance on digital education and responsible AI, and foundational thinking about decision processes. The literature was not gathered through an exhaustive search. Accordingly, the framework should be read as a reasoned proposal for further investigation, not as an intervention whose effectiveness has already been demonstrated.

The literature was selected for its relevance to three intersecting questions: how school leaders use evidence, what AI systems can contribute to administrative analysis, and which governance safeguards are needed for consequential decisions. The synthesis compares these strands to identify points of alignment and tension. Because no reproducible database search, screening protocol, or formal quality appraisal was undertaken, the review cannot establish the prevalence of particular findings or claim comprehensive coverage. This limitation should guide how its conclusions are interpreted.

### 2.1 Source Materials, Selection Logic, and Synthesis Procedure [REVISED]

The materials analysed in this conceptual study are published secondary sources, not student-level datasets, interview transcripts, or records collected from schools. Sources comprise peer-reviewed articles on school data use and leadership (e.g., Schildkamp, 2019; Schildkamp et al., 2019), educational data literacy (Mandinach & Gummer, 2016), AI explainability (Khosravi et al., 2022), and institutional guidance from OECD (2023, 2026) and UNESCO (2021; Miao & Holmes, 2023). Additional contextual literature on educational technology governance is considered where it bears directly on implementation (Williamson et al., 2020).

The synthesis was organised in four interpretive steps: (1) specify the administrative decision and its evidentiary requirements; (2) extract the data-use, analytical, professional-judgement, and governance concepts discussed in the selected sources; (3) compare overlaps and gaps, particularly where an AI output crosses into a consequential decision; and (4) translate those concepts into six operational components and provisional evaluation criteria. This was a purposive conceptual synthesis: no original institutional data were obtained, no participants were recruited, and no empirical implementation or formal search-screening counts are claimed. The selection is therefore illustrative rather than exhaustive, and the proposed framework remains unvalidated.

### 2.2 Framework Implementation in the Present Study [REVISED]

Implementation in this article means analytical application to an explicitly hypothetical school-attendance decision, not software deployment. The six components are mapped to the same example: data readiness establishes attendance definitions and authorised access; AI-supported analysis is compared with a simple absenteeism rule; human deliberation checks contextual explanations; administrative action specifies proportionate support and a named decision owner; evaluation considers both attendance and the delivery of support; and governance audits access, fairness, correction, and accountability throughout. Section 5 demonstrates the decision pathway and Figure 2 presents an illustrative interface mock-up. Neither is evidence of a tested application.

## 3 Theoretical Foundations

### 3.1 Administrative Decision Making

A school leader rarely has the luxury of making a decision from numbers alone. A rise in absenteeism, for example, may be visible in the records, but the reasons could involve transport, family circumstances, school climate, or difficulties with learning. Administrators must decide what the evidence can reasonably tell them, consider available responses, and weigh educational priorities, fairness, resources, and legal responsibilities before acting. This need to combine technical interpretation with professional judgement is consistent with Mandinach and Gummer's (2016) account of data literacy as a combination of knowledge, skills, and dispositions.

For the purposes of this article, decision quality has five dimensions. A decision should address a relevant problem, rest on credible evidence, arrive while action is still useful, have a rationale that others can understand, and treat those affected fairly. These dimensions should not be confused with outcomes. Even a carefully reasoned decision may have disappointing results if circumstances change or an intervention is not implemented as planned.

### 3.2 Data-Driven and Data-Informed Decision Making

DDDM involves using evidence systematically to understand educational problems and guide improvement. Schildkamp (2019) describes a recurring process of setting goals, gathering and interpreting evidence, taking action, and evaluating results. Relevant evidence extends beyond test scores to include classroom observations, formative assessments, interviews, administrative records, and research. Looking at several sources matters because a single indicator rarely tells the whole story. Mandinach and Gummer (2016) similarly argue that using data responsibly requires more than the ability to read indicators; educators need the skills to interpret evidence in its instructional context.

The literature uses data-based, data-driven, and data-informed decision making in partly overlapping ways. The term data-informed is particularly appropriate in schools because it leaves room for professional expertise and knowledge of individual circumstances. A prediction about a student should open a conversation and prompt closer examination. It should not settle the matter before anyone has considered the student's situation.

The organizational setting also shapes whether data are used well. Schildkamp, Poortman, Ebbeler, and Pieters (2019) identified five ways leaders can support effective data teams, including shared goals, individual support, professional learning, a safe climate for discussion, and connections across the school. Their work suggests that investing in software without investing in people is unlikely to be enough. This also helps explain why investing in analytical tools without

developing staff data literacy may have limited value (Mandinach & Gummer, 2016).

### 3.3 AI as an Analytical and Decision-Support Capability

Different tools answer different questions. Descriptive analysis shows what has happened, while diagnostic analysis explores possible explanations. Predictive models estimate what may happen next, but those estimates need testing, calibration, and regular review. Generative AI may help prepare a summary or organise policy options, yet it can also produce convincing errors. Schools should be careful not to call every dashboard or automated rule “AI”, especially when deciding whether a new system offers any real advantage. Holmes et al. (2019) describe a range of educational AI applications while drawing attention to their implications for teaching and learning. These applications should not be conflated with evidence that an automated recommendation is suitable for a particular school.

It makes more sense to begin with the decision than with the technology. A school concerned about attendance might first examine a simple trend report. If there is a clear reason to do so, it could then test a prediction model to identify cases for professional review. A language model might help draft a briefing using authorised documents. Each option carries different costs and risks, and each needs a level of oversight suited to the consequences of error.

There is a trade-off between analytical complexity and institutional accountability. More elaborate models may detect patterns that simple rules miss, but they can be harder for school staff to understand, challenge, or maintain. Conversely, a transparent rule may be easier to audit while overlooking meaningful interactions in the data. The appropriate choice depends on the seriousness of the decision, the evidence of comparative performance, and the school's ability to explain and correct errors.

### 3.4 Responsible AI and Data Governance

School records can reveal sensitive details about children and families, including health, disability, disciplinary matters, and socioeconomic circumstances. UNESCO guidance stresses human-centred use of generative AI, privacy, ethical assessment, and appropriate safeguards (Miao & Holmes, 2023). UNESCO’s Recommendation on the Ethics of Artificial Intelligence (2021) also addresses discrimination, transparency, privacy, and human rights. For schools, these are practical responsibilities that should shape decisions before a system is purchased or deployed. Slade and Prinsloo (2013) show that learning analytics raises questions about consent, surveillance, power, and the interpretation of student information, even when data collection is intended to support learners.

Responsible use requires more than a general commitment to ethics. Schools need to know why information is being used, who can see it, how long it will be kept, and who is responsible if something goes wrong. They also need ways to check the performance of AI tools and to review decisions that affect students or staff. An automated risk flag, for example, should never be mistaken for a diagnosis or a disciplinary finding. These concerns align with the sociocritical approach proposed by Slade and Prinsloo (2013), which treats the governance of educational data as a matter of institutional responsibility rather than technical compliance alone.

## 4 Proposed Integrated Framework

The proposed AI–DDDM Integrated Educational Administration Framework brings six connected activities into one decision cycle. Schools begin by checking whether their information and systems are ready. Analysis then produces evidence for staff to interpret, after which leaders select and implement a response. Evaluation shows what worked and what needs to change. Governance and human oversight apply throughout, rather than being added at the end. The framework builds on established approaches to school data use by making the possible role of AI, and the continuing responsibility of people, more explicit.

4.0a Conceptual Logic and Interactions Among Six Components [REVISED]

The framework consists of five sequential activities plus one cross-cutting control. Components 1–5 are connected by decision gates, rather than operating as independent categories. If data fail readiness checks, analysis should stop or revert to a descriptive baseline. If analytical evidence is uncertain or inequitable, the human review stage may reject the recommendation. Administrative action records the responsible person, the selected alternative, and a review date. Evaluation then feeds corrections into the original data definitions and the next decision cycle. Component 6, governance, constrains every stage through access controls, transparency, bias checks, and mechanisms for appeal. This structure differs from a generic data cycle by explicitly requiring comparison with a non-AI option and an accountable authorisation point before consequential action (Schildkamp, 2019; Khosravi et al., 2022).

FIGURE 1 • CONCEPTUAL MODEL




**Cross-Cutting Governance:** Human oversight, privacy, STOP/REVISE decision gates, and transparency audit apply continuously across all five stages.

Figure 1. Proposed interaction diagram (conceptual, not empirically validated): [1 Data readiness] → [2 AI or non-AI analysis] → [3 Human deliberation / challenge] → [4 Accountable administrative action] → [5 Evaluation and feedback] ↺ [1 Data readiness]. [6 Governance and human oversight] applies to all five stages. STOP / REVISE gates operate after data validation, analytical comparison, and professional review.

4.0b Distinct Conceptual Contribution [REVISED]

Western data-informed school-improvement research already emphasises goal-setting, evidence interpretation, collaborative data teams, intervention, and evaluation (Schildkamp, 2019; Schildkamp et al., 2019). The present proposal does not claim novelty for those established practices. Its bounded contribution is to specify the additional obligations created when AI is inserted into that process: validation against a transparent non-AI comparator, explicit documentation of professional override, and continuing checks for model drift and subgroup disparities. Work on explainable AI similarly cautions that a technically intelligible explanation must be designed for the educational stakeholder and task, rather than assumed to confer fairness or trust automatically (Khosravi et al., 2022).

The proposed contribution is not a new algorithm or a claim that existing data-use cycles are inadequate. Rather, the framework makes three distinctions explicit: analytical performance is different from decision quality; professional review must be documented rather than merely assumed; and the value of AI must be judged against simpler available approaches. These distinctions provide criteria for assessing when AI assistance is warranted and when conventional reporting or professional deliberation may be preferable.

The framework is intended to address a specific gap between producing analytical information and making an accountable administrative decision. Existing data-use cycles already emphasise interpretation, action and review; this proposal does not claim to replace them. Its added value is to identify three decision points at which AI creates additional obligations: checking whether a model is suitable for the local task, deciding who may act on its output, and comparing the resulting decision with a credible non-AI alternative. These obligations may be particularly important when an apparently accurate prediction influences support, staffing or resource allocation.

### Decision Rights and Escalation

An AI-generated output should have a named owner and a defined route to review. For low-impact tasks, such as preparing a draft summary of approved documents, an administrator may verify the source material before use. For decisions affecting an individual student or staff member, an authorised professional should check the underlying evidence, record the reasons for action, and provide an appropriate opportunity for correction or challenge. Where data quality is poor, uncertainty is high, or the likely consequences are disproportionate, the appropriate decision may be to suspend use of the model. These are proposed governance principles, not procedures shown to be effective in an evaluated school setting.

Table 1 Components of the proposed AI–DDDM integration framework

### 4.1 Data Readiness and Problem Definition

The starting point is the problem the school is trying to solve. Suppose attendance has declined. Before using an algorithm, leaders need to establish whether departments record attendance in the same way, whether the time periods are comparable, and what contextual information is missing. A large dataset is of little help if its definitions are inconsistent. As the OECD (2023) notes, connecting information systems and governing data use remain important challenges.

### 4.2 Analytical Support and Evidence Interpretation

Once the records are suitable for the task, analysis can help leaders see trends, identify cases for review, or compare possible responses. The difficult part is interpreting those outputs. A relationship between poor attendance and lower achievement, for example, does not show which causes the other. Leaders should ask what else might explain the pattern, how reliable the estimate is, and whether the tool performs differently for particular groups of students.

### 4.3 Human Deliberation and Accountable Action

School decisions benefit from discussion among people who see different parts of the problem. A principal may understand staffing constraints, a teacher may recognise a learning difficulty, and a counsellor may know about circumstances outside school. Their perspectives can change the meaning of an apparently straightforward data pattern. For consequential decisions, the school should record what evidence was considered, which alternatives were discussed, who made the decision, and why.

### 4.4 Monitoring and Organizational Learning

Taking action is only part of the process. Schools also need to find out whether the planned support was delivered and whether it helped. An attendance initiative may work well for one group of students but make little difference for another. That finding should lead to questions about implementation, access, and the original assumptions. It may also reveal that a data definition or analytical model needs to be revised.

This distinction matters because a technically successful system can still fail administratively. A model might correctly identify students with repeated absences, while the school lacks staff to contact families or offer appropriate support. In that situation, the analytical output has improved, but the decision process has not necessarily produced a better response. The framework therefore treats implementation capacity and evaluation as substantive parts of decision quality, not as tasks that follow automatically from accurate predictions.

**Table 1. Summary of Framework Dimensions**

| Component | Main question | Operational considerations |
|---|---|---|
| 1 Data readiness | Are the records fit for the problem? | Completeness, accuracy, timeliness, interoperability, lawful access |
| 2 AI-supported analysis | What patterns or options can be identified? | Task fit, model validation, uncertainty, explanatory evidence |
| 3 Human deliberation | What do the findings mean in this school? | Professional judgment, student context, consultation, alternative explanations |
| 4 Administrative action | Which response is justified and feasible? | Clear responsibility, resources, proportionality, documented rationale |
| 5 Evaluation and feedback | Did the action achieve its purpose? | Outcome and process indicators, unintended effects, model monitoring |
| 6 Governance across stages | Is the process accountable and fair? | Privacy, transparency, security, bias review, appeal and correction |

## 5 Illustrative Applications in School Administration

The situations that follow are illustrations, not accounts of tested school programmes. They show how an administrative question might move from records and analysis to a professional decision, and where safeguards would be needed along the way.

Table 2 Illustrative administrative applications and points of human review

### 5.1 Student Attendance and Early Support

Imagine a school where attendance, achievement, and student-support records sit in separate systems. After setting a clear goal and confirming the necessary permissions, a small team could bring together only the information needed to examine changes in attendance. A tested model might help identify cases for review, although a simple and transparent rule could work just as well. Teachers and counsellors would then consider the circumstances of each student, speak with the student or family when appropriate, and agree on suitable support. Leaders could subsequently check whether that support was delivered and whether attendance changed.

Such a system needs careful boundaries. A risk score cannot establish that a student will disengage from education. Missing information may be an administrative error rather than evidence of a student problem. An automated flag should lead to appropriate human review and support, not punishment or exclusion. Any threshold for intervention would need to be justified and tested in the local setting.

5.1a Worked Adoption Walkthrough and Illustrative Screen Mock-up [REVISED]

A future pilot could begin with an authorised attendance extract containing a pseudonymous learner identifier, week, attendance percentage, and documented support status. A data steward would check missingness, time-window consistency, and permitted use before producing any alert. A transparent rule (for example, repeated absence across a pre-specified period) would provide a comparator. A separately validated model, if available, could then be assessed on the same records. A counsellor would review flags against contextual evidence, record whether an alert was accepted or overridden, and authorise supportive follow-up. The team would assess whether follow-up occurred and whether outcomes differed by subgroup. All thresholds, metrics, and access rules must be set and evaluated locally; this article does not provide validated values.

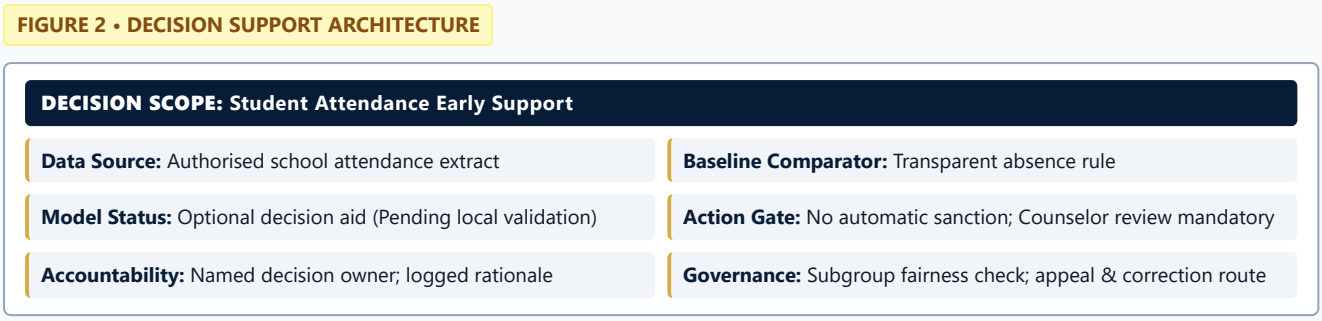



Figure 2. Illustrative future-project dashboard mock-up (not a screenshot of deployed software; entirely synthetic). SCREEN A | Decision: attendance support | Source: authorised school attendance extract | Data quality: pending local validation | Baseline: transparent attendance rule | AI model: optional / not validated | Flagged case: STUDENT-EXAMPLE | Professional interpretation: requires review | Action: no automatic sanction | Decision owner: designated counsellor | Follow-up: scheduled after support | Governance: access log, subgroup review, correction route. This mock-up demonstrates the fields and workflow a future project could implement; it contains no real student data or actual AI output.

### 5.2 Academic and Resource Decisions

Similar questions arise in teaching and resource management. An academic department might compare assessment patterns with curriculum coverage to identify where additional support could help. AI could organize the information, but teachers would still need to consider whether the pattern reflects teaching, assessment design, or differences between cohorts. Staffing and budget tools may make trade-offs easier to see, yet decisions must still account for workloads, student needs, regulations, and competing priorities. Technology should support discussion, not bypass it.

**Table 2. Illustrative School Administrative Areas and Decision Checks**

| Administrative area | Potential evidence | Possible AI support | Human decision and check |
|---|---|---|---|
| Student support | Attendance trends, grades, prior support contacts | Highlight patterns warranting review | Counsellor confirms context and agrees supportive response |
| Academic management | Assessments, curriculum coverage, formative feedback | Summarize gaps and compare trends | Academic team selects and evaluates instructional support |
| Staff allocation | Teaching assignments, schedules, workload records | Model alternative timetables | Leadership reviews equity, contracts, and staff needs |
| Budget planning | Project costs, procurement records, utilization | Compare allocation scenarios | Authorized committee checks feasibility and compliance |
| Quality assurance | Evaluation indicators, school improvement plans | Consolidate evidence and flag missing items | School team validates evidence before reporting |

## 6 Implementation Conditions and Evaluation

### 6.1 Institutional Readiness

A practical first step is to choose a problem that the school can define clearly and evaluate over time. Staff need dependable records, access to relevant systems, time to interpret findings, and agreed rules for protecting information. Before investing in AI, leaders should ask whether an ordinary report or transparent decision rule would do the job. For a smaller school, staff capacity and coordination may matter more than technical sophistication. The need for staff development is supported by Mandinach and Gummer (2016), who identify data literacy as a professional capability requiring deliberate preparation.

### 6.2 Phased Adoption

A gradual introduction gives staff a chance to test assumptions before a tool influences important decisions. Schools can begin by defining the problem and the consequences of getting it wrong. They can then check the available records, consider privacy requirements, and compare the proposed AI method with a simpler baseline. Limited testing should examine accuracy, uncertainty, and differences across groups. Staff should be involved in interpreting results, and the tool should be changed or withdrawn if it no longer performs adequately. This is a proposed sequence, not an implementation model that has already been validated.

### 6.3 Indicators for Future Evaluation

Future studies should look separately at how decisions are made, whether they are sound, and what happens to students and schools. Useful process measures include the time spent assembling evidence, the number of data-quality problems, how often reasons for decisions are recorded, and who takes part in deliberation. Researchers could also examine fairness and appropriateness across student groups. Outcomes would depend on the intervention, such as improved attendance or better-targeted support. Without comparison against an

appropriate baseline, improvement should not be attributed to AI.

Evaluation should also ask whether AI adds value over a simpler alternative. For example, a school could compare an AI-generated attendance alert with a transparent rule based on recent absences. Both approaches could be assessed for missed cases, unnecessary referrals, staff time, differential performance across student groups, and the usefulness of the resulting support decisions. An improvement in prediction accuracy alone would not demonstrate an improvement in student welfare.

The comparison should be defined before implementation. For example, a school could assess the same administrative task using its current workflow, a transparent rule-based approach and an AI-assisted approach. Outcomes might include time taken, completeness of documentation, errors identified during professional review, variation across student groups, and whether the eventual response was delivered. Because these outcomes measure different things, an improvement in processing speed should not be interpreted as proof of greater educational fairness or better student outcomes. Where feasible, independent reviewers should assess decision records without knowing which workflow produced them.

## 7 Risks and Limitations

AI systems can inherit the inequalities present in the records used to build them. If some students have historically received less support, a model may learn patterns that reflect that unequal treatment rather than their needs. Small datasets can make predictions unstable, and changes in student populations or curricula can make an apparently reliable model less useful. Generative AI adds another risk: a fluent summary may still contain factual mistakes or references that do not exist. Ethical analysis must therefore consider not only the model output but also the institutional response that follows it (Slade & Prinsloo, 2013).

Privacy becomes a particular concern when identifiable student information is sent to external services without clear legal, contractual, and technical protections. Schools should limit access and collect or share only what is necessary. They must also consider dependence on vendors, differences in infrastructure between schools, added demands on staff, and the risk that monitoring tools become instruments of surveillance. UNESCO (2021) places fairness, privacy, human rights, and accountability at the centre of responsible AI use. In educational settings, these concerns are especially important because students may have limited ability to challenge how their data are collected or interpreted (Slade & Prinsloo, 2013).

The framework remains a conceptual proposal. It has not been assessed by experts, tested in schools, or evaluated against alternative approaches. Future research needs to examine whether its components work together as intended, particularly in settings with different levels of staffing, funding, and data access. The article also offers no evidence that AI necessarily performs better than simpler statistical methods, established decision-support tools, or informed professional teams. The central test is not whether an AI tool produces a convincing output, but whether its use leads to a more defensible and equitable decision than the alternatives available to the school.

### 7.1 Discussion in Relation to Established DDDM and Recent AI Scholarship [REVISED]

Research on data-based decision making in European and North American school contexts offers a useful benchmark for this proposal. Schildkamp (2019) frames data use as an iterative school-improvement activity grounded in multiple evidence sources rather than test scores alone. Schildkamp et al. (2019) identify leadership practices that support collaborative data teams; these social and organisational conditions cannot be replaced by automated prediction. The proposed framework therefore retains the familiar DDDM sequence while adding explicit AI-specific decision gates. The added gates are a conceptual design choice, not evidence that the new process outperforms existing data teams.

Recent explainable-AI scholarship further qualifies the value of algorithmic outputs. Khosravi et al. (2022) examine the educational need for explanations that account for stakeholders, presentation choices, and potential pitfalls. This suggests that a dashboard displaying a risk score is insufficient unless staff can challenge its basis and identify an appropriate response. Williamson et al. (2020) also highlight that digital education technologies operate within wider institutional and political arrangements; data collection, procurement, and platform dependence therefore require scrutiny. Taken together, these studies support an implementation principle: evaluate an AI-assisted workflow not just for prediction quality but for contestability, equitable treatment, workload, and the practical delivery of support.

The comparative implication is deliberately modest. A transparent attendance rule may be more suitable than a complex model in a small school with incomplete records. Where an AI system offers measurable incremental benefit, it still requires authorised interpretation and continuing evaluation. Claims of effectiveness, transferability, or superiority cannot be made without prospective testing against the school's current workflow.

The framework also has conceptual boundaries. It is most applicable to recurring administrative decisions for which institutions have a legitimate reason to use relevant records and can review outcomes. It is less suitable for exceptional decisions, settings with unreliable records, or situations in which numerical indicators cannot capture the educational or ethical considerations at stake. The framework does not establish that its six activities are sufficient in every setting, nor does it specify an optimal technology or decision threshold.

A further limitation concerns competing goals. Earlier identification of students needing support could increase demand on counsellors and teachers without increasing the

resources available to respond. Similarly, more detailed monitoring may strengthen accountability but also encourage defensive record keeping or excessive surveillance. These trade-offs mean that the framework cannot be judged by predictive accuracy alone. Any evaluation should examine workload, trust, access to support and unintended consequences alongside administrative efficiency.

## 8 Implications for Research and Practice

For researchers, the framework offers questions that can be examined in real school settings. How does the quality of records affect the usefulness of AI-generated advice? What happens when an algorithmic recommendation conflicts with a teacher's knowledge of a student? Do governance arrangements change whether staff trust, question, or act on analytical outputs? Case studies could explore these processes, while comparative designs could test whether an AI-assisted workflow improves decisions over existing practice.

### 8.1 Propositions for Empirical Examination

The framework yields four provisional propositions. P1: Better data readiness will be associated with fewer errors in AI-assisted administrative evidence, although improvements may be limited when the underlying administrative question is poorly specified. P2: Explicit professional review and recorded decision rationales will improve the traceability of consequential decisions, but may increase processing time. P3: The advantage of AI-assisted workflows over transparent non-AI alternatives will vary by task complexity, data quality and institutional capacity rather than appearing uniformly across schools. P4: Ongoing monitoring of subgroup outcomes and opportunities for correction will help identify harmful differences that aggregate performance indicators can conceal. These propositions are hypotheses for future investigation, not findings established by the present review.

A useful research design would compare the proposed AI-assisted workflow with the school's existing decision process, rather than simply comparing outcomes before and after AI adoption. Researchers could document the same decision type across comparable periods or sites, assess the quality of evidence considered, and examine whether decisions were timely, justified, and open to review. They would also need to record implementation differences, staff workload, and changes in student circumstances. Such comparisons would not eliminate confounding, but they would make claims about AI's added value more credible.

For school leaders, the immediate priority may be less about acquiring new technology and more about improving conversations around evidence. A small team representing different school functions could begin with one recurring problem, review the available records, and document how its decisions are made. The leadership practices discussed by Schildkamp et al. (2019) provide a useful starting point. The test of any tool should be whether staff can explain its contribution and defend the decisions that follow. Professional learning should include interpreting evidence, questioning model outputs, and recognising when a simpler method is preferable (Mandinach & Gummer, 2016; Holmes et al., 2019).

## 9 Conclusion

AI may help school leaders make sense of information that is currently difficult to bring together. It can reveal patterns, organise evidence, and make possible responses easier to compare. Yet the responsibility to interpret that evidence, consider individual circumstances, and act fairly remains with people. The framework proposed here brings data readiness, analysis, professional deliberation, action, and evaluation into a single accountable process. Its value still needs to be tested in schools with different resources and needs. Until then, AI is best understood as a tool to support administrative judgement, not a substitute for it.

## Declarations

**Artificial Intelligence (AI) Usage:** Generative artificial intelligence tools, including ChatGPT (OpenAI), were used to proofread the article. The author is responsible for verifying the accuracy, originality, references and conclusions and approving the final manuscript.

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