

Applying Artificial Intelligence to Enhance Data-Informed Decision-Making in Saudi Secondary School Leadership

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Abstract: Artificial intelligence is gradually transitioning from being a tool used in the classroom to becoming an organizational capability that affects the way schools interpret evidence, distribute their attention, and coordinate their efforts for improvement. This study looks at how artificial intelligence can help leaders in Saudi secondary schools make data-driven decisions while at the same time keeping professional judgment, equity, and accountability intact. Unlike the reference study mentioned which looks at predictive models for academic outcomes in Saudi higher education, the present paper concentrates on leadership decisions and the organizational factors that make algorithmic evidence useful in the context of secondary schooling. Using a structured integrative review guided by the PRISMA 2020 principles, the review brings together peer-reviewed literature published between 2020 and 2025 as well as relevant Saudi and international policy documents. The evidence is arranged around four questions: which leadership decisions can make use of AI-powered analytics; what capabilities are needed to turn data into action; what ethical and regulatory protections are necessary; and how the introduction of AI can be carried out in the Saudi setting. The synthesis shows that AI is most useful when it aids in the interpretation of early-warning signals, in monitoring instruction, in prioritising resources, in analysing the school climate, and in forecasting operations, rather than taking over leaders' decisions. The benefits depend on the quality of the data, the level of data literacy among staff, the existence of collaborative practices, the explainability of the results, and clear governance. The paper suggests a human-centered decision cycle for secondary schools in Saudi Arabia, connecting the definition of purpose, data stewardship, interpretable analysis, deliberation, action, and monitoring. The review ends by stating that leadership capacity and the level of maturity of governance are more important in ensuring responsible value than the complexity of the algorithms alone.

Keywords: Artificial Intelligence, Data-Informed Decision-Making, Educational Leadership, Secondary Education, Saudi Arabia, Explainable AI, Vision 2030.

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1. INTRODUCTION

The situation in Saudi secondary schools is one in which heads of schools are expected to improve learning outcomes, enhance school performance, make effective use of digital tools, and help achieve the nation's objectives regarding human

capability. This situation comes at a time when there are rapid developments in artificial intelligence, learning analytics, predictive modelling, natural language processing and generative AI. In the field of education, AI is able to identify patterns in large amounts of data, classify risks, summarise

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information, predict likely results and produce recommendations which would be hard to create manually at the same speed. However, the fact that suitable tools are available does not mean that they will lead to better leadership. Data can be incomplete, indicators can be misunderstood, and a statistically accurate model can still result in decisions that are educationally inadequate or unfair. The main point therefore is not whether AI can work out things more quickly than a headteacher, but rather how the evidence generated by AI can be integrated into a defensible procedure of professional judgment.

The difference between data-driven and data-informed decision-making is significant. In a purely data-driven manner, it is possible that the metric will decide the action; in contrast, a data-informed approach regards the evidence as just one of several inputs, together with professional knowledge, the particular context of the school, the needs of the students, and ethical obligations. Research into the use of educational data indicates that having access to information by itself is not enough. Educators need established procedures for questioning the data, interpreting the patterns, testing explanations, and turning the findings into responses that are instructional or organizational. Visscher's review of intervention studies found that even when educators are able to interpret progress data, there remains great difficulty in turning those interpretations into specific actions. This gap is directly applicable to AI: although increasingly sophisticated predictions are being made, this does not eliminate the need for leadership involving sense-making. On the contrary, it increases the demand for leaders who are able to question, put the algorithmic outputs in context, and communicate them.

The reference paper by Albahli presented both the potential and the limitations of predictive analytics. Based on a large data set from Saudi higher education, the study finds that the neural-network method achieves very high predictive performance. It stresses the importance of explainable AI, socio-demographic variables, timely intervention, and institutional efficiency. Since these points are applicable to school leadership—where principals also deal with attendance, achievement, behaviour, engagement and background factors—the paper is of relevance. Nevertheless, the paper is about higher education and model performance, not the governance of secondary schools. The accuracy it reports is specific to the dataset and therefore cannot be applied to school settings without first being validated. The paper itself also mentions several constraints, including those relating to generalizability, omitted variables, changing educational conditions, privacy, and bias. This review thus uses Albahli as a conceptual and methodological

source on predictive and explainable analytics, but changes the unit of analysis from the model to the school leader and from prediction accuracy to decision quality.

It fills a significant gap. Although research into educational AI has developed quickly, a large part of it has focused on tutoring, personalisation, applications aimed at students, or technical prediction. On the other hand, research in the area of educational leadership has established a well-developed body of work covering the use of data, organisational culture, equity, and the practices of principals, but AI has still not been incorporated to a great extent into that area. The studies from Saudi Arabia provide an important contextual dimension: secondary-school principals stress achievement goals, teacher development, relationships with parents, academic excellence, and the school climate, while investigations into digital leadership and ministry-level transformation point to uneven readiness for leadership, cultural requirements, constraints relating to infrastructure, governance problems, and the need for support from top management. By combining these different lines of research, AI can be assessed as a form of support for leadership rather than as a standalone technology.

2. Saudi Context and Conceptual Framing

Saudi Vision 2030 and the Human Capability Development Program have identified education, digital capability, and future skills as closely linked national priorities. The National Strategy for Data and AI also regards data and artificial intelligence as strategic assets for the Kingdom. This policy context offers a positive outlook for evidence-based management in secondary schools, although it at the same time sets a higher bar for the responsible use of such data. Since school leaders are responsible for minors, sensitive educational records, information about families, evidence on teacher performance, and behavioural data, an AI initiative that enhances analytical speed but compromises privacy, fairness, or trust would go against the overall aim of modernising education. Governance has to be an integral part of the implementation of both the Saudi Personal Data Protection Law and the SDAIA's AI Ethics Principles rather than being treated as an optional technical addition.

The approach taken here is one that blends data-informed leadership with a human-centered use of AI. Data-informed leadership starts with an educational issue, not with the presence of a dashboard. Leaders have to set out the decision, determine the relevant evidence, examine the quality of the data, interpret the patterns together with their staff, select an action, and then keep an eye on the outcomes. Within this social process, algorithmic

systems are incorporated through human-centered AI. The progression proposed by Ouyang and Jiao from AI-directed to AI-supported and then to AI-empowered education is valuable since it shifts agency towards the people using the system. Just as explainable-AI research holds that an explanation must be meaningful to the individual who receives it rather than just technically accessible, so too does this apply in school leadership: the principal should be able to understand why a particular group of students, subject or operational area has been flagged, what data led to the result, what uncertainty is still present, and which action is in fact within the school's power to take.

It also presents decision quality as being multi-dimensional; although accuracy is important, school leadership decisions must also be timely, equitable, interpretable, lawful, feasible, and in line with educational goals. Wang warns that AI may enhance efficiency and accuracy at the same time as it magnifies existing bias or leads to conflicts with values like fairness and the principle of doing no harm. The key question then becomes whether AI enables the school to detect relevant patterns earlier, think more carefully about them, and respond in a more consistent manner. A valuable system should promote inquiry and accountability, not establish a new source of unquestioned authority.

3. Aim, Objectives and Review Questions

The purpose of this review is to critically examine the way in which AI-powered analytics can enhance data-driven decision-making among leaders in Saudi secondary schools, while at the same time safeguarding human judgment, equity, privacy, and accountability. This objective is intentionally different from the predictive-model study referred to, which aims at improving the prediction of individual academic outcomes. In the present case, the outcome under consideration is the quality of leadership decisions that is, how evidence is generated, interpreted, discussed, put into action, and monitored within a school organization.

The review is guided by four objectives. The first is to identify leadership decisions at which AI-enhanced evidence can provide practical benefit, such as those relating to academic monitoring, early intervention, teacher support, the allocation of resources, school climate, and operations. The second consists of bringing together the organizational factors that turn analytics into action, focusing on data literacy, digital leadership, collaborative routines, infrastructure, and trust. The third looks at the ethical and regulatory limitations that apply to secondary education in Saudi Arabia, with a special focus on explainability, bias, children's data, privacy, and accountability. The fourth involves creating an

implementation framework that is appropriate to the local context and which brings AI adoption into line with the educational priorities of Saudi Arabia as well as incorporating a human-in-the-loop approach to leadership. The relevant review questions are: Which AI-enabled practices are most appropriate for secondary-school leadership? What capabilities are needed for an effective use of such practices? What safeguards are required? And how can these elements be incorporated into a staged implementation model for Saudi Arabia?

4. REVIEW METHODOLOGY

An integrative review based on a structured approach was chosen since the subject area involves educational leadership, the use of data, artificial intelligence, K-12 practice, ethics, and Saudi digital transformation. A meta-analysis could not have been carried out since the evidence consists of qualitative leadership studies, conceptual papers, systematic reviews, implementation research, policy documents, and technical education studies which have incompatible outcomes. The integrative method allows for a critical comparison of these different types of studies while at the same time maintaining a clear selection rationale. The reporting adhered to the PRISMA 2020 principles concerning clear formulation of the questions, the eligibility criteria, identification of the sources, transparent synthesis, and the acknowledgement of limitations. Since the aim was conceptual integration and not the estimation of a pooled effect, no made-up numerical flow figures or effect sizes were included.

The review period extended from January 2020 to December 2025 and thus includes the rapid development of artificial intelligence in the field of education, the rise of discussions concerning explainability and the governance of generative AI, as well as the major Saudi digital transformation programmes. The search strategy was tailored to Scopus, the Web of Science Core Collection, ERIC, IEEE Xplore, ScienceDirect, SpringerLink, and publisher databases, and backward and forward citation checking was applied in order to link the leadership literature with the AI literature. The search strings combined terms relating to technology—namely artificial intelligence, machine learning, predictive analytics, learning analytics, explainable AI, and generative AI with terms relating to decision-making—such as data-driven decision-making, data-informed decision-making, principal, school leadership, and educational leadership—as well as terms referring to the setting, including secondary school, high school, K-12, general education, Saudi Arabia, and Saudi. Studies on Saudi leadership written in Arabic language were included if the bibliographic and methodological information was clear enough.

Inclusion meant that a study had to make a direct contribution to at least one of the four evidence areas: AI capabilities that are relevant to educational decisions; the use of data at the principal or school level; the leadership capabilities or readiness for digital transformation among Saudi schools; or the ethics, privacy, explainability, and governance of educational AI. We focused on peer-reviewed journal articles that were published in English or Arabic during the review period, since authoritative documents from SDAIA, Saudi Vision 2030, UNESCO, and the OECD were included as well, because legal and policy requirements cannot be deduced solely from the journal literature. Studies that were concerned only with higher education were generally excluded unless they had implications that could be transferred to school leadership. The Albahli article attached here was deliberately kept in as a comparative reference since it offers Saudi-based evidence on predictive analytics and XAI; at the same time, its focus on higher education is expressly regarded as a limiting factor rather than as evidence applicable to secondary schools.

The exclusion criteria included removing duplicate records, excluding studies on AI that were not educational, omitting vendor marketing material, excluding opinion pieces that lacked a defensible evidence base, excluding work published before 2020 except in those cases where it was part of the theoretical foundations of the reviewed studies, and

excluding purely algorithmic papers which had reported performance without any implications for human educational decisions. The sources were evaluated using a five-point matrix that looked at methodological transparency, the relevance to school leadership, the clarity of the data context, attention to governance or ethics, and the degree of transferability to Saudi secondary education. The appraisal was carried out in a comparative manner rather than being reduced to a single numerical score since a high-quality conceptual ethics paper and a qualitative study of Saudi leadership provide different types of evidence.

Synthesis followed thematic coding. Evidence was first coded into leadership decision domains, AI functions, enabling organizational conditions, risks, and governance responses. A second cycle examined relationships between themes, particularly where technical capability failed without leadership capacity or where governance requirements altered the design of an AI use case. Contradictory findings were preserved rather than averaged away. For example, literature supporting predictive efficiency was considered alongside work showing the limits of data translation, explainability, and fairness. The final synthesis produced two outputs: an evidence map connecting AI capabilities to leadership work and a human-centered decision cycle for implementation. Figure 1 summarizes this review architecture.



Figure 1: Review architecture linking evidence identification, appraisal, thematic coding, and synthesis into a leadership-focused framework

5. Synthesis of Evidence

5.1 AI-Enabled Decision Domains

The existing literature indicates that the most promising leadership applications start with questions that are already important to the

principals. Academic monitoring is the best example of this. Schools collect data on assessments, attendance, assignments, behaviour, and use of the platforms, yet typically look at these different indicators separately or only after problems have

become apparent. Predictive techniques are able to combine various signals in order to detect patterns that deserve attention, while descriptive and diagnostic analytics can show which subjects, groups of students, or time periods are most responsible for a decline. In a secondary school, the appropriate output is not an automatic label such as "high-risk student" which would determine the kind of intervention to be taken. It should be a prioritised signal for staff to examine: which students or groups need a more detailed investigation, what evidence underlies the alert, and what kind of intervention is appropriate? This difference transforms prediction into early inquiry instead than automatic judgment.

AI can also assist with instructional leadership. The established practices of Saudi principals entail setting achievement goals, developing their teachers, concentrating on scholastic excellence, and forming the school climate [16]. These responsibilities can be enhanced if leaders are given timely trend information rather than just the static end-of-term summaries. Detection of trends at the subject level may show which units are causing many students difficulty; analysis of assessment items can highlight misconceptions; patterns relating to attendance and punctuality can point to engagement problems; and text analytics can summarize the recurring themes in structured feedback. When used with care, these capabilities aid leaders in deciding whether coaching, changes to the timetable, enrichment activities, or focused support are required. Nevertheless, evidence regarding the use of data indicates that interpretation has to be linked to collaborative routines and instructional knowledge. While professional development can improve data literacy and effectiveness, turning the evidence into action is still a matter for humans and organizations.

A second area of practical concern is that of operational decisions. Secondary-school heads are responsible for matters such as staffing, the use of rooms, the scheduling of examinations, supervision, maintenance, communication, and dealing with competing requests for resources. Forecasting can be of help in estimating patterns of absenteeism, peaks in workload, demands for support, or the need for resources. Natural-language tools could cut down the time required for sorting non-sensitive management documents or for summarising recurring problems. Since these applications involve a lower level of educational risk than predictions concerning students' performance, they may be appropriate for pilot schemes. Yet the same questions about governance remain: what data are being processed, whether the purpose is legitimate, whether the outputs can be verified, and who is ultimately accountable for the final action.

5.2 Moving from Prediction to Professional Judgment

One consistent conclusion from the evidence examined is that AI should be used to assist rather than to take the place of leadership. Wang specifically advises viewing AI as a tool for decision support since the ability to carry out computations on a large scale can increase efficiency, even though biases and value conflicts are still likely. Research into explainable AI supports this view by demonstrating that transparency has to be customized to the stakeholders in question: an explanation that is useful to a data scientist might not aid a principal in deciding what action to take. For leaders, explanations must highlight the variables that have an influence, the direction of that influence, the level of uncertainty, the absence of information, and the limitations of the model. An interpretable alert such as "persistent absence and declining mathematics assessments contributed most to this flag" is more useful in practice than a risk score given without any reasons.

The Saudi study referred to shows why it is wrong to focus only on accuracy when assessing a model. Albahli finds that the neural-network model reaches an extremely high level of classification performance and points out that XAI can be used as a means of carrying out practical interventions [1]. While this provides good evidence of the technical potential, acceptance by school leaders will depend on further investigations: Does the model perform just as well in all schools and among different groups of students? Are the predictors available and dependable in the secondary setting? Could a false positive result in unnecessary labeling? Might a false negative result in a delay in receiving support? Can school leaders explain the model's output to teachers and to families? Is the model still valid following changes to the curriculum, assessments, or policies? Hence, an evaluation aimed at leadership purposes must take into account calibration, subgroup fairness, interpretability, temporal stability, and consequences, and not rely solely on accuracy.

5.3 Data Culture, Capability, and Digital Leadership

The use of data is a collective activity. Research involving principals and teachers reveals that they may interpret different kinds of evidence, assign different meanings to official and informal data, and need to follow common procedures in order to develop a common understanding. The expectations set by the district or the system equally influence whether leaders concentrate mainly on performance averages and on the disaggregated patterns related to equity. This point is important for Saudi secondary schools since an AI dashboard on its own will not produce a data culture; it is up to leaders

to set up regular routines for reviewing the evidence, encourage challenge rather than blind acceptance, link data discussions to instructional priorities, and make the distinction between signals that call for an immediate response and those that call for further investigation.

The evidence from Saudi Arabia indicates that readiness is not entirely missing but instead varies. Alqahtani and his team found that secondary school principals already carry out goal setting, teacher development, handling family relationships, maintaining an academic focus, and providing leadership regarding the school's climate. Research into digital leadership shows that there is stronger practice in certain professional and evaluation areas, yet weaker performance in terms of vision, organizational development, team preparation, or the establishment of a helpful culture. At the ministry level, Alojail and colleagues list technology, employee engagement, partnership with vendors, budget, top-management support, culture, and strategy as critical success factors, while governance, data, infrastructure, cost, organizational problems, and opposition to change are still regarded as challenges. It therefore follows that AI adoption must be seen as a matter of organizational development; it will not suffice to train only a technical administrator, since principals, deputies, counselors, department heads, and data owners all require different skills.

5.4 Ethics, Privacy, and Equity

The moral obligations become more intense in the case of secondary education since students are minors and the data may affect expectations, the kind of support given, disciplinary actions, and opportunities available to them. The ethics literature in the field of international AIED regularly highlights fairness, accountability, transparency, privacy, human agency, inclusion, and the avoidance of harm as key issues. Saudi governmental regulations also include mandatory local requirements. The Personal Data Protection Law gives a broad definition to the processing of personal data and requires organisations to treat collection, use, sharing, storage and deletion as activities that are governed. The AI Ethics Principles issued by SDAIA include interpretability, bias detection, risk management, accountability, privacy, security, reliability and respect for human interests throughout the AI lifecycle. A school cannot therefore simply justify the indiscriminate collection of data just because a greater number of variables could improve the model.

Equity also affects the way that leaders should interpret apparently successful results. A model could reproduce historical differences if past patterns relating to attendance, discipline,

achievement, or access have led to unequal opportunities. Roegman's research into how principal data is used demonstrates that breaking down the evidence can shift focus from overall performance to the inequities at the group level. The same principle should apply to AI monitoring. Leaders should regularly compare error frequencies and outcomes among relevant groups, check whether a feature functions as an unfair proxy, and must avoid using prediction to assign a fixed identity. Alerts should remain temporary hypotheses that encourage support and verification. Actions of a high stake's nature for example, disciplinary escalation, restriction of placement, or decisions that have a major impact on a student's future should never be based on an opaque model without proper human review and a means by which corrections can be made.

5.5 Developing AI Literacy in the Context of Leadership Responsibilities

Although AI literacy in the K-12 sector is frequently seen as a matter that should be addressed within the curriculum for students, the underlying skills are just as important for leaders. Evidence from systematic reviews points out the need to understand what AI can and cannot do, how data and models influence the outputs, and the social consequences of its use. For principals, literacy should be focused on specific tasks. Leaders do not need to become machine-learning engineers; instead they should consider whether the training data is similar to that of their school, what the target variable stands for, how missing data are dealt with, whether performance is broken down by group, how explanations are produced, and how the tool is monitored once it has been deployed. Just as UNESCO and OECD guidance do, the idea of AI and digital education is presented as ecosystems that require policy, capacity, infrastructure, and governance rather than simply being purchased in isolation.

A direct result of this is that assessing vendors has to be included within a school's leadership capabilities. Schools must be able to ask for information regarding the origin of the data, the purpose of the model, how it has been validated, its known limitations, data retention policies, access controls, the procedures for updates, and the approach to dealing with incidents. Statements like "AI-powered" or "99 percent accurate" are not adequate unless they are accompanied by context. The evidence offered should be evaluated in relation to a specific educational issue and compared to a simpler alternative. In certain situations, a well-designed rule or a descriptive dashboard can be just as useful and more transparent than a complicated model. Responsible AI leadership therefore requires the ability to judge when it is appropriate not to use AI.

Table 1: Evidence domains linking AI capabilities to school-leadership decisions

Decision domain	Typical data	AI / analytics role	Leadership output	Main risk
Academic progress	Assessment, course marks, prior achievement	Trend detection; risk prioritization	Targeted academic review and support	Over-labeling; model drift
Attendance & engagement	Attendance, punctuality, platform activity	Anomaly detection; prediction	Early inquiry and family/student support	Proxy bias; context loss
Instructional leadership	Item results, subject trends, teacher/team evidence	Pattern discovery; summarization	Coaching, curriculum focus, resource targeting	Reduction of teaching to metrics
School climate	Behavior patterns, structured feedback, incident categories	Text / pattern analytics	Identify recurring issues and prevention needs	Sensitive inference; stigmatization
Operations	Timetables, staffing, service requests, utilization	Forecasting; optimization	Scheduling and workload prioritization	Automation bias; poor data quality
Governance & assurance	Model logs, subgroup performance, access records	Bias checks; monitoring; explainability	Approve, modify, pause, or retire AI use	False assurance from compliance

6. Human-Centered Implementation Framework for Saudi Secondary Schools

The synthesis outlines a six-stage decision cycle that is centered on human needs: Purpose, Stewardship, Interpretation, Deliberation, Action, and Monitoring. The Purpose stage starts with a definite leadership question and a decision that is clearly defined. For example, "Improve attendance among Grade 11 students" is better than the broad aim "use AI for attendance". Stewardship then determines which data are needed, who is allowed to access them, how quality is ensured, for how long they are kept, and what PDPL and institutional requirements apply. This stage is intentionally placed before model selection since responsible design must begin with purpose and data governance, not with the procurement of technology.

The interpretation of data involves turning it into clear and understandable evidence. Models must be validated using data that mirrors the environment for which they are intended, and the outputs have to include explanations, a statement of uncertainty, and relevant comparisons. The deliberation stage is the leadership checkpoint at which principals and the appropriate staff compare the AI signal with their existing knowledge of the situation, consider other possible explanations, examine the equity implications, and decide if any further evidence is

required. Action is taken only if the suggested response is appropriate in an educational sense and is in line with policy. Monitoring completes the cycle by investigating whether the intervention was effective, whether the model's errors have changed, whether any group has been put at a disadvantage, and whether the tool is still needed. Thus, the cycle views AI as a component of ongoing improvement rather than as a one-off installation.

The implementation should proceed in stages depending on the level of risk. For low-risk administrative analytics, confidence can be gained regarding the quality of the data, the workflows, and the staff's capabilities. More moderate-risk applications—such as early-warning systems which trigger supportive reviews will need more thorough validation, clearer explanations, and closer monitoring. High-impact applications that have an effect on discipline, student progression, access, or student rights must have the most rigorous controls and may indeed be unsuitable for automated recommendations altogether. Table 2 turns the framework into specific actions at the school level, and Figure 2 illustrates the way in which leadership, analytics, governance, and outcomes interact. The basic idea is that the more important the decision, the greater the need for transparency, human review, evidence of fairness, and documented accountability.

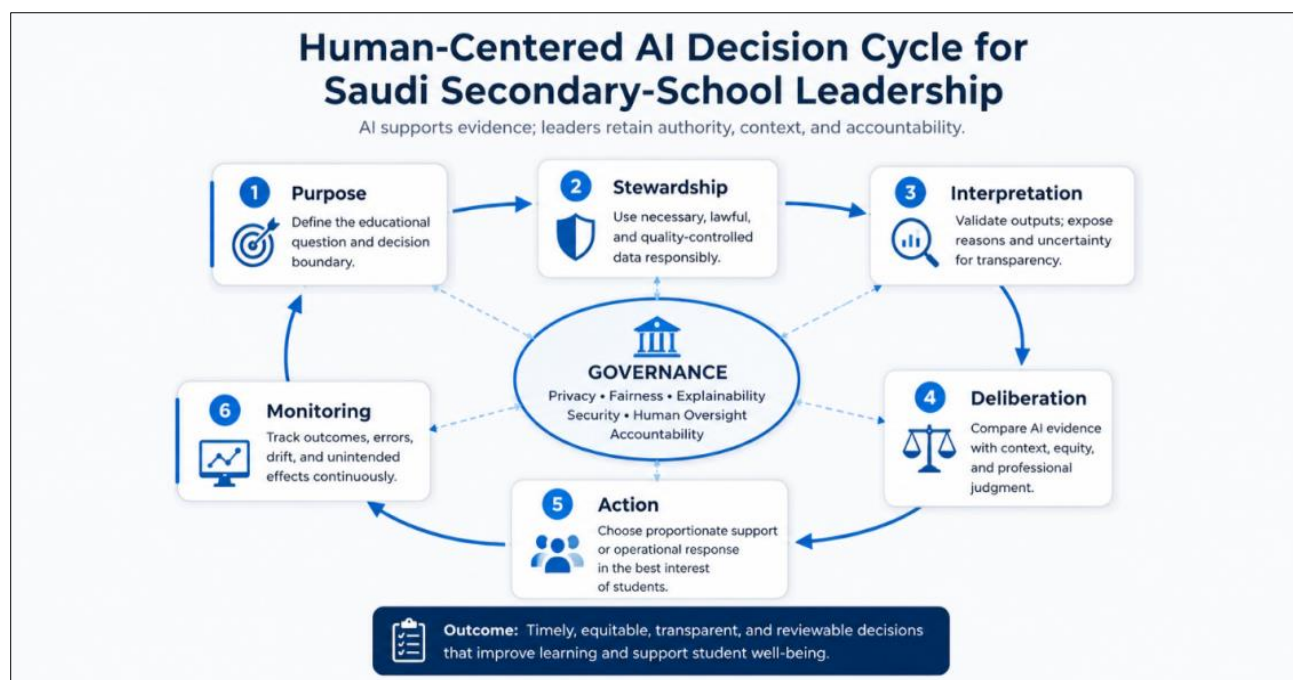


Figure 2: Human-centered AI decision cycle for Saudi secondary-school leadership. Governance surrounds every stage rather than operating as a final compliance check

Table 2: Staged implementation framework for Saudi secondary schools

Phase	Leadership action	Data / AI requirement	Governance control	Readiness indicator
1. Purpose	Define one bounded decision problem and intended benefit	Baseline indicators; simple benchmark	Purpose limitation; named decision owner	Problem, users, and success measure documented
2. Stewardship	Assign data owners and check quality	Data dictionary; missingness and lineage review	PDPL basis; access, retention, minimization	Reliable fields and permissions confirmed
3. Pilot	Compare AI with current practice on limited scope	Local validation; subgroup tests; baseline comparison	Risk assessment; security and vendor controls	No unacceptable disparity; output reproducible
4. Explain & deliberate	Review reasons with relevant staff before action	Interpretable output; confidence / uncertainty	Human review; escalation; correction path	Leaders can explain and challenge outputs
5. Act & monitor	Apply proportionate intervention and record rationale	Outcome tracking; error and drift monitoring	Audit log; fairness review; incident process	Evidence of benefit without disproportionate harm
6. Institutionalize	Scale only after evidence; train wider leadership team	Interoperability; versioning; performance dashboard	Periodic reapproval; contract and deletion controls	Capability embedded in routine improvement cycle

7. DISCUSSION AND IMPLICATIONS

The review presents three arguments. It alters the way in which the adoption of AI is seen, moving the focus from a problem linked with the acquisition of technology to one that is related to the design of leadership. The current body of literature does not support a deterministic sequence in which more data leads to better models and better models, in turn, automatically result in better decisions.

Studies on decision-making based on data show that interpretation and translation still act as continuous bottlenecks, and research into AI ethics reveals that technically efficient systems can still produce unfair or opaque results. The appropriate unit of change is therefore the decision process: that is to say, who defines the problem, which data are included, how the evidence is presented, who has the opportunity to

challenge it, what action is taken, and how the consequences are examined.

Secondly, the circumstances in Saudi Arabia involve both advantageous factors and some limitations. The Vision 2030 programme, the Human Capability Development Programme, the National Strategy for Data and Artificial Intelligence, and the expansion of digital education all help to ensure a strategic concentration on responsible analytics. However, local research shows that digital leadership, a helpful culture, the required infrastructure, good governance, as well as readiness for change must not be assumed. Even if a national or regional platform can provide common infrastructure and standards, it is still the leadership at the school level that determines whether the data are used in a constructive manner or are employed as compliance indicators. Capacity building should therefore include not solely technical literacy yet also the principal's ordinary responsibilities such as instructional leadership, teacher development, communication with families, keeping up a positive school climate, and planning for improvement.

Thirdly, the review clearly explains the role of the referenced study. It does not offer a ready-made model for secondary schools, instead demonstrating that Saudi educational data can be used to make sophisticated predictions and that explainability can connect the model's outputs to specific interventions. Likewise important are the study's limitations: the specificity of the dataset, the omission of certain variables, temporal changes, the computing requirements, data protection concerns, and bias all show the need for a school-leadership framework to go beyond just considering model metrics. The right next step should not be to reproduce an accuracy figure, but rather to look at whether a smaller number of transparent and well-governed use cases could improve the quality and speed of actual school decisions.

8. Limitations and Future Research

The review is not meta-analytic but integrative and the Saudi evidence which directly connects AI with secondary-school leadership stays very limited. It is therefore necessary to draw certain conclusions from international research into the use of data and from studies on digital leadership in Saudi Arabia. Subsequent research should include longitudinal, mixed-method studies that examine real-life applications in schools and evaluate decision quality, the timing of the interventions, workload, trust, fairness towards different groups, and student outcomes. Comparative studies involving different regions and types of school should assist in determining how far the findings can be transferred, and implementation research must look into Arabic-

language explainability, communication with families, and governance practices in the context of PDPL. Independent verification is especially important before predictive systems are used to influence important student decisions.

Research should also investigate how leaders deal with disagreements between the signals from algorithms and their professional judgement. Such situations are valuable from an analytical point of view because they show the underlying assumptions that are held both by the model and by the organisation. For example, a manager may come to the conclusion that an apparent fall in attendance is the result of a change in the timetable, a short-term transport problem, a delay in reporting or the admission of a new group rather than because students have become disengaged. If it is recorded why staff accept, modify or reject the recommendations, an audit trail will be created for the purpose of learning and this will assist developers in advancing future systems. It will also allow researchers to distinguish between appropriate human overrides and resistance that is based on habit or a misunderstanding. Another important area is procurement governance. Ministries and schools should have clear criteria for comparing vendors, for testing claims, for specifying who owns the data, for limiting its secondary use, for requiring security measures, and for making certain that schools can export or delete their information when their contracts finish. Interoperability deserves particular attention since fragmented systems can cause leaders to have to reconcile inconsistent definitions across attendance, assessment, behaviour and learning platforms. More useful than sophisticated modelling when the underlying evidence is inconsistent are shared data dictionaries, clearly documented definitions of indicators and common quality checks. Finally, research should look at how workloads are distributed. Even though AI may reduce repetitive analysis for some staff it may create new tasks entailing verification, documentation and escalation for others. It is essential to measure these changes if we are to know whether the system in fact enhances leadership capacity or simply shifts the administrative burden. Putting these questions is likely to take the field beyond simple demonstrations of predictive performance and towards providing evidence about sustainable use in real schools.

Future research needs to also involve a comparison of schools that are using the same AI tools but have different leadership procedures, varying levels of staff involvement, and differing degrees of data quality. Such a comparison could reveal whether the benefits that have been seen are due to the algorithm itself, to the organizational practices connected with it, or to the way these parts

interact. Researchers must note the instances when principals accept, question, modify, or ignore AI recommendations and then investigate whether such actions have a positive impact on subsequent outcomes. Attention should also be given to the opinions of students and families since trust may depend on whether the people in question understand what information was used, why an alert was issued, and how inaccurate records can be corrected. Arabic-language interfaces and explanations should be evaluated on the basis of understanding and not regarded as effective merely because they have been literally translated. The studies should also examine whether the dashboards promote productive inquiry or instead result in a greater emphasis on metrics. Finally, implementation research should assess the total cost of ownership, cybersecurity support, interoperability, staff turnover, dependence on the vendor, the maintenance of the model, and the way in which the new validation tasks are distributed among the various school roles. Open reporting of these factors would help to distinguish between sustainable institutional capability and short-lived pilot successes and would give Saudi education leaders stronger evidence on which to base responsible decisions about scaling the initiative across distinct regions, school types, and student populations.

9. CONCLUSION

Artificial intelligence can help improve evidence-based decision-making in secondary schools in Saudi Arabia by helping leaders to spot patterns earlier, connect evidence from different sources, decide which questions to pursue, and keep an eye on progress. Yet its value is not automatic and depends on a number of factors. It is the quality of the data, the abilities of the leaders, the level of collaboration when interpreting the information, the extent of explainability, attention to privacy, fairness, and accountability that determine whether technical outputs lead to responsible action. A human-centered approach that follows the cycle of Purpose, Stewardship, Interpretation, Deliberation, Action, and Monitoring provides a practical means of achieving governance from the very beginning of the process. The most effective strategy for the Saudi school systems is to begin with clearly defined, lower-risk leadership issues, to build up data and AI literacy in relation to real work processes, to try out the tools in a local context, and only to increase automation when there is enough evidence and suitable safeguards in place. In this approach, AI does not replace the principal's judgment; rather, it makes that judgment more informed, faster, more transparent, and open to review.

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