



Potential Contribution of Generative Artificial Intelligence to School Calendar Planning by Secondary School Principals

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ABSTRACT: School calendar planning is a constraint-intensive management task involving national regulations, instructional-time requirements, teacher and room availability, assessment periods, extracurricular activities, meetings, holidays, local disruptions, and equity considerations. This structured integrative review examines the potential contribution of generative artificial intelligence (GenAI) to this task, with particular attention to secondary-school principals. Eight search strands covering GenAI and school leadership, educational administration, timetabling optimization, decision support, resource allocation, administrative workload, and resource-constrained settings were used to build an analytical corpus of 85 publications from an initial pool of 160 records. Evidence was coded by type, educational context, planning function, expected or observed benefit, risk, and proximity to annual or term-level school calendar planning. The review reveals a marked asymmetry: educational timetabling optimization is technically mature, whereas direct evidence on GenAI-assisted annual school calendar planning remains scarce. Recent K–12 leadership studies nevertheless support the plausibility of gains in document preparation, information synthesis, communication, scenario generation, and delegation of routine administrative tasks. The evidence also indicates that large language models should not be used as autonomous constraint solvers because they may omit rules, hallucinate availabilities, or produce superficially coherent but infeasible schedules. We therefore propose a hybrid GenAI-Assisted School Calendar Planning model (GASCP), combining conversational GenAI for constraint elicitation and explanation, a formal optimization engine for feasibility and trade-off management, and accountable human validation. The model generates testable hypotheses concerning planning time, feasibility, pedagogical quality, equity, robustness, acceptability, traceability, and principals' cognitive workload. The central conclusion is that GenAI is most defensible as an interface for responsible planning rather than as an autonomous decision-maker.

KEYWORDS: generative artificial intelligence, school calendar, school principal, secondary education, timetabling, decision support.

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I. INTRODUCTION

The organization of school time is one of the most visible and sensitive responsibilities of secondary-school leadership. A poorly designed calendar can create overlapping activities, insufficient instructional periods, clusters of examinations, underused facilities, uneven teacher workload, poorly synchronized meetings, and repeated mid-year adjustments. Conversely, a coherent calendar provides the temporal architecture within which curriculum requirements, staff availability, assessment, remediation, professional development, and school-community activities are coordinated. Research on school-leader workload also shows that time poverty and administrative intensification are persistent management concerns.²⁰

A distinction is essential between the school calendar and the weekly timetable. The school calendar operates at macro and meso levels: the opening and closing of the school year, terms or semesters, instructional weeks, holidays, examination windows, staff meetings, cultural and sporting activities, remediation periods, professional-development days, and contingency periods. Weekly timetabling, by contrast, assigns lessons, teachers, classes, and rooms to specific time slots. The two are connected but not interchangeable. The scientific literature is mature on school timetabling and constraint optimization,^{54,74,16} whereas the use of GenAI for annual or term-level calendar planning is still poorly documented.

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The emergence of large language models changes the nature of computer assistance. Traditional optimization tools require constraints to be formalized in advance, while GenAI can receive requirements in natural language, ask clarifying questions, reformulate rules, generate scenarios, explain rejected options, and rapidly draft communications. This creates a plausible new role for GenAI as a cognitive interface between school leaders and rigorous optimization engines. Recent work on AI-supported school leadership reports growing use for communication, document preparation, information synthesis, program planning, and other administrative tasks.^{11,38,27,71}

At the same time, several decades of operational-research scholarship show that complex allocations of teachers, classes, rooms, and periods can be modeled with integer programming, constraint programming, local search, metaheuristics, and hyper-heuristics.^{5,72,74,16} The scientific issue is therefore not whether machines can contribute to planning, but how the conversational flexibility of GenAI can be combined with computational mechanisms that guarantee feasibility while preserving human accountability.

This question is especially relevant in secondary schools operating under resource constraints, late teacher appointments, variable infrastructure, centralized examinations, intermittent connectivity, or disruptions that reduce available teaching days. In such environments, the value of an intelligent system lies not only in generating a calendar quickly, but also in making constraints visible, simulating the consequences of changes, proposing contingency options, and supporting transparent trade-offs. Human–AI leadership frameworks consistently caution that strategic, relational, ethical, and value-laden judgments remain the responsibility of educational leaders.^{79,21,6,43}

Research question and objectives

The central question is: To what extent can generative artificial intelligence contribute reliably, responsibly, and operationally to school calendar planning by secondary-school principals? The review pursues five objectives: (1) map direct and indirect evidence; (2) identify planning functions for which GenAI offers a plausible advantage; (3) specify the risks that prevent autonomous delegation of the decision; (4) propose a hybrid conceptual model; and (5) formulate indicators and hypotheses for empirical validation in secondary schools.

School-time planning as a socio-technical problem

Timetabling research conceptualizes planning as a multi-constraint, multi-objective combinatorial problem. Hard constraints are non-negotiable requirements such as mandated teaching days, teacher unavailability, room capacity, minimum instructional hours, or forbidden examination overlaps. Soft constraints represent preferences or quality objectives such as reducing idle time, balancing assessments, protecting professional-development days, or limiting fragmentation. Explicit formalization of both types of constraints is central to useful solutions.^{5,72,85}

Annual calendar planning adds objectives that cannot be reduced to mathematical feasibility. A calendar can be computationally feasible yet pedagogically poor. Assessment spacing, learning rhythms, remediation periods, fatigue, local holidays, transport, climatic conditions, and community activities require contextual interpretation. For this reason, human–AI decision frameworks emphasize complementarity between analytical efficiency and human judgment grounded in values, equity, and relationships.^{80,21} GenAI adds an interaction layer that classical solvers lack. It can transform an instruction such as 'avoid mathematics and physics examinations in the same week for final-year students' into an explicit rule, ask whether the requirement is absolute or preferential, and explain trade-offs among feasible options. However, a language model is not inherently a constraint solver. It can generate a calendar that looks coherent while containing hidden conflicts, omitted rules, invented availabilities, or silently altered assumptions. Research on LLMs in education repeatedly identifies risks of inaccuracy, bias, and over-trust.^{36,77} The most defensible role is therefore assistance with elicitation, explanation, and scenario generation, coupled with a deterministic or optimization engine and human validation.

II. METHOD

Review design and sampling logic

A structured integrative review was chosen rather than a narrowly defined effectiveness review because the research question lies at the intersection of GenAI, school leadership, educational administration, decision support, and operations research. Restricting the search to the exact phrase “generative AI school calendar planning” would have produced an artificial impression of no evidence. The integrative design therefore distinguished three levels of evidence: direct or very close evidence, related transferable evidence, and contextual or structuring publications.

Eight search strands were explored: (a) GenAI and school leadership/management; (b) AI and school timetabling; (c) educational administration, planning, and decision support; (d) AI adoption by principals; (e) timetable and examination optimization; (f) resource allocation and educational governance; (g) administrative workload and time savings; and (h) African or resource-constrained settings. The initial screening covered 160 records, yielding 130 unique items after deduplication. Titles, authors, publication years, journals, and available DOIs were then checked against traceable bibliographic or publisher records. A targeted

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update conducted on 29 September 2026 incorporated the most recent K–12 leadership evidence while keeping the analytical corpus fixed at 85 publications.

Eligibility and prioritization

- Included: empirical articles, structured reviews, and conceptual frameworks on AI/GenAI in school leadership, educational administration, data-informed decision-making, planning, and timetabling; optimization studies with mechanisms transferable to secondary-school planning; mainly 2019–2026 publications, with older foundational timetabling studies retained where necessary.
- Excluded: commercial pages, promotional material, tutorials without a scientific protocol, publications focused exclusively on student learning with no administrative or planning relevance, and records with insufficiently traceable metadata.
- Prioritized: K–12/secondary settings, real school data, PRISMA/scoping reviews, studies involving school leaders, and work explicitly addressing constraints, resources, time, or administrative decision-making.

Coding and synthesis

Each publication was coded across seven dimensions: publication year, evidence type, educational level/context, planning stage, AI/GenAI function, observed or expected benefit, risk/limitation, and proximity to annual or term-level school calendar planning. Because outcomes and designs were highly heterogeneous, no pooled effect size was calculated. The analysis combines descriptive frequencies with thematic synthesis of recurrent mechanisms. Importantly, evidence from weekly timetabling was treated as a technical basis for transfer, not as direct proof that GenAI improves annual calendar planning.

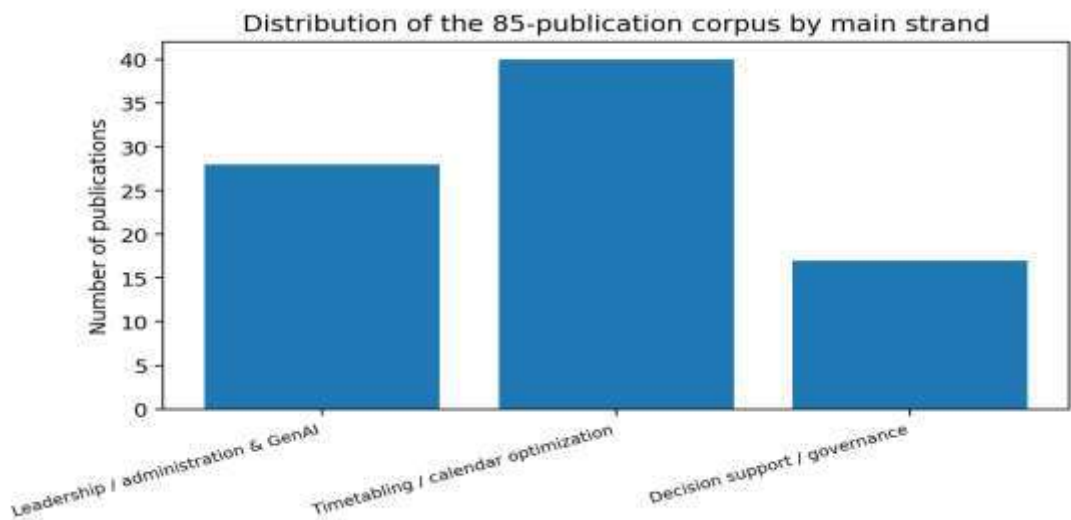


Figure 1: Distribution of the 85-publication analytical corpus by main strand.

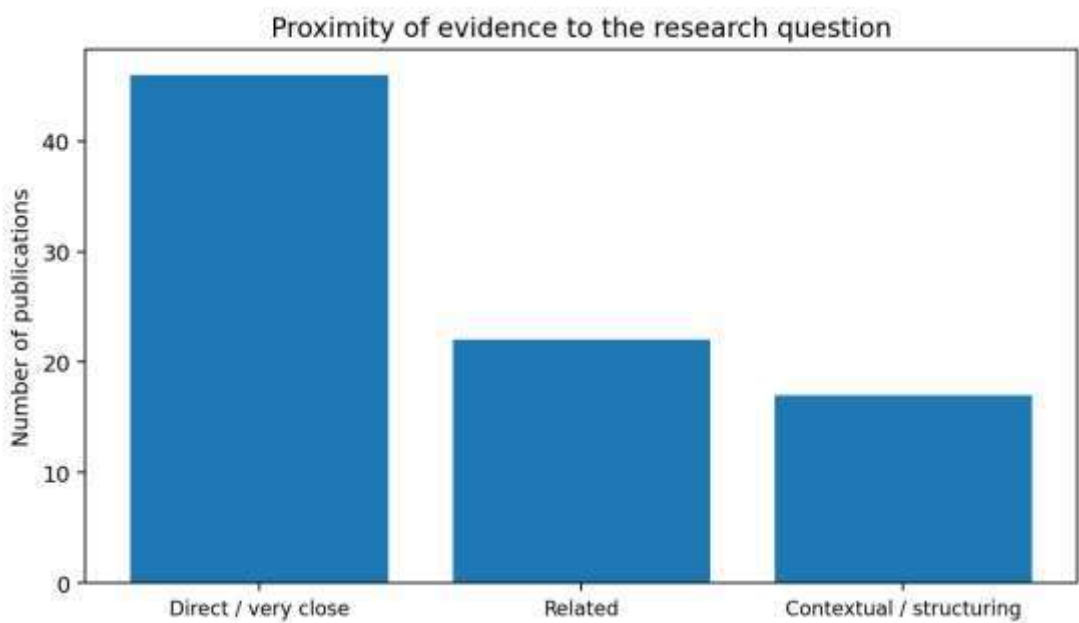


Figure 2: Proximity of the evidence to annual or term-level school calendar planning.

III. RESULTS

1. A mature optimization literature but little direct GenAI evidence

The first result is a pronounced asymmetry. Automated timetabling is technically mature: the field formalizes constraints, maintains international benchmarks, and compares families of algorithms.^{54,74,16} In contrast, GenAI and school leadership constitute a recent literature still dominated by adoption surveys, reviews, qualitative studies, and conceptual frameworks. The 2026 update narrows this gap only slightly: recent studies document GenAI use among educational leaders and K–12 principals, but none directly tests the production of a better annual or term calendar with GenAI.

The two evidence streams nevertheless converge in a meaningful way. Operations research shows that authentic school-planning problems can be decomposed into constraints, objectives, allocations, and scenarios and solved efficiently,^{74,72,85} while leadership research indicates that GenAI is entering management routines for documentation, communication, synthesis, and planning-related tasks.^{11,27,71}

2. Constraint elicitation and formalization

Planning often fails before optimization begins because rules are implicit, contradictory, or dispersed across official circulars, institutional routines, staff preferences, and local constraints. GenAI can act as a structured interviewing assistant: it can ask which days are unavailable, what contingency margin is required, which activities must precede others, which periods are reserved for assessment, and which teachers have specific constraints. It can then produce a constraint matrix for principal validation. In this role, GenAI reduces the cognitive cost of formalization without assuming decision authority.

Timetabling studies consistently show that solution quality depends on the quality of the constraint model. Models that include availability, preferences, compactness, and synchronization are more useful than models limited to avoiding overlaps.^{72,85} GenAI's distinctive contribution may therefore be less about 'solving' the schedule than about helping leaders construct a better problem for the solver to solve.

3. Scenario generation and understandable trade-offs

Calendar decisions rarely have a single acceptable solution. Several scenarios may satisfy hard constraints while distributing holidays, examination weeks, professional-development days, remediation periods, and school events differently. Optimization methods can produce Pareto-efficient or near-optimal solutions; GenAI can translate those differences into managerial language. For example, it can explain that one scenario reduces examination conflicts but compresses departmental meetings, while another protects remediation time at the cost of a smaller contingency reserve. Such explanations can make team deliberation more transparent.

This addresses a recurrent problem in AI-assisted decision-making: analytical speed is insufficient if leaders do not understand the assumptions, reasons, and consequences behind recommendations. Transparency, traceability, and contestability are therefore functional requirements rather than merely ethical add-ons.^{80,21}

4. Rapid replanning after disruptions

A school calendar is not static. Strikes, power outages, severe weather, site closures, delayed staff appointments, unexpected official activities, or changes in examination dates may require replanning. Local-search, metaheuristic, and decomposition approaches show that a feasible plan can be adjusted without rebuilding the entire schedule. In a hybrid architecture, a principal could describe a disruption in natural language—such as “three instructional days were lost in the second term; preserve the final examination window”—and receive several verified recovery strategies with explicit trade-offs.

5. Reduction of peripheral administrative workload

A substantial share of calendar work occurs around the schedule itself: meeting invitations, circulars, summary tables, versions for teachers and parents, explanations of changes, minutes, and briefing documents. Recent evidence among educational leaders suggests that GenAI can save time in document preparation and communication and can support delegation of lower-level administrative tasks.^{27,71} For calendar planning, these peripheral savings may be as important as optimization, provided that regulatory and contextual verification remains human.

6. Equity and calendar quality under explicit conditions

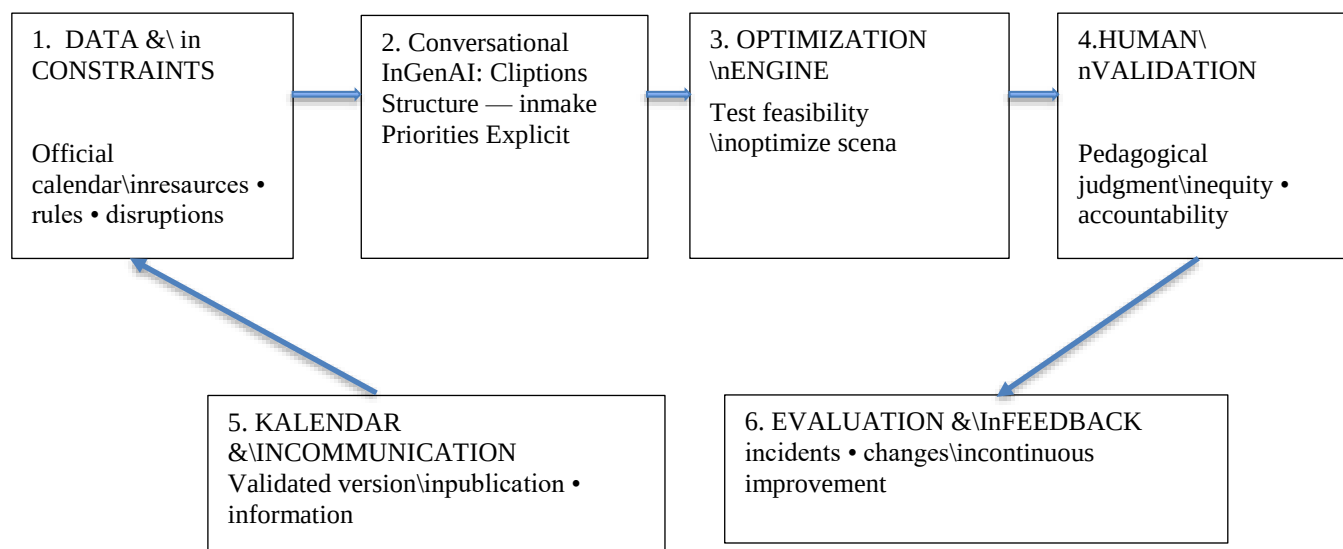
Optimization can incorporate equity objectives such as distributing undesirable periods, limiting excessively long days, balancing examination load, protecting preparation time, distributing invigilation duties, and reducing idle time. However, equity depends on the objective function and available data. A system can optimize what is measured while neglecting underrepresented interests. Participation by teachers, students, and parent representatives in defining criteria is therefore advisable.

Proposed conceptual model: GenAI-Assisted School Calendar Planning (GASCP)

Based on the convergence of the reviewed evidence, we propose the GenAI-Assisted School Calendar Planning model (GASCP). Its originality lies in functional separation among natural-language understanding, mathematical optimization, and accountable human judgment. The model comprises six components connected through a feedback loop: (1) data and constraints; (2)

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conversational GenAI; (3) an optimization engine; (4) human validation and governance; (5) calendar production and communication; and (6) evaluation and feedback.



Principle: GenAI proposes and explains, the solver verifies; the principal arbitrates and remains accountable.

Figure 3: Proposed GASCP model derived from the literature synthesis.

Operational components of GASCP

- Data and constraints: official calendar, instructional-time requirements, examination windows, holidays, teacher and room availability, institutional events, local constraints, and—where legally appropriate—historical disruption data. Sensitive data should not be uploaded to unauthorized GenAI services.
- Conversational GenAI: elicits ambiguous constraints, requests confirmation, structures rules, proposes priorities, and explains alternatives. It does not certify feasibility.
- Optimization engine: applies constraint programming, integer programming, or metaheuristics to satisfy hard constraints and optimize soft objectives. This layer provides calculable guarantees that text generation alone cannot provide.
- Human validation and governance: the principal, preferably supported by a small planning committee, assesses scenarios against regulation, pedagogy, equity, social context, and information that may be absent from the system. Major changes to constraints must remain traceable.
- Production and communication: once validated, the calendar is converted into stakeholder-specific versions and accompanied by a contingency plan.
- Evaluation and feedback: implementation data—conflicts, changes, overloads, delays, absenteeism, and disruptions—feed the next planning cycle.

Implementation challenges and risks

The main technical risk is hallucination or omission: a generated calendar may appear plausible while violating a rule, inventing an availability, or overlooking a conflict. LLM scholarship documents these reliability limitations.^{36,77} A professional system should therefore prevent publication until machine-verifiable constraints have been checked and a responsible human has confirmed the result.

A second challenge is data quality. AI cannot compensate for incomplete or outdated staff assignments, room capacities, transport information, or official dates. Data maturity is a prerequisite for useful optimization. Third, calendars may contain personal or sensitive information, requiring data minimization, approved tools, access controls, and—where possible—anonymization or pseudonymization. Fourth, bias can be embedded in objective functions: a solution may be efficient on average yet systematically disadvantage a group. Equity criteria must therefore be explicit, measurable, and contestable.

A fifth challenge is dependency and possible erosion of planning competence. Human-in-the-loop leadership frameworks argue that AI should augment rather than replace leaders' understanding and responsibility.^{6,79,21} Finally, in resource-constrained settings, intermittent internet, electricity, limited information systems, and uneven AI literacy may favor lightweight hybrid architectures, local solvers, and offline continuity procedures over cloud-dependent automation.

Recent school-leadership research further indicates that access to the tool alone is insufficient; organizational support, policy clarity, digital/AI literacy, and innovation culture shape responsible adoption.^{27,43,11}

Evaluation indicators and testable hypotheses

Empirical validation of GASCP should go beyond principals' satisfaction. A credible comparative protocol should measure at least: planning efficiency (time and iterations); feasibility (hard-constraint violations and conflicts); pedagogical quality (assessment distribution, instructional continuity, remediation margins); equity (distribution of workload and undesirable periods); robustness (ability to absorb disruptions); acceptability (perceived transparency, fairness, and usefulness); traceability (proportion of major decisions linked to an identifiable constraint); and calibrated trust/cognitive workload (ability to understand, challenge, and correct AI suggestions).

- H1: Hybrid GenAI + solver assistance reduces planning time relative to usual practice without increasing hard-constraint violations.
- H2: Hybrid assistance increases the diversity of scenarios considered and improves the quality of decision justifications.
- H3: Effects on calendar quality are mediated by input-data quality and the principal's AI literacy.
- H4: Team-based validation increases stakeholder acceptability and perceived fairness.
- H5: GenAI used alone produces lower feasibility than a GenAI + solver + human-validation architecture.
- H6: In infrastructure-constrained settings, usefulness depends more on interface simplicity, local/offline capability, and prior data digitization than on the raw power of the language model.

IV. DISCUSSION

The principal contribution of this review is to shift the question from “Can GenAI make the school calendar?” to “Which planning functions should be assigned to which component of a socio-technical system?” The evidence suggests that GenAI is strongest at manipulating language and semi-structured knowledge, while operations-research methods are strongest at verifiable constraint satisfaction. Recent K–12 leadership studies reinforce this functional division: GenAI is associated with administrative efficiency, synthesis, communication, and delegation of routine work, while contextual expertise, relationships, strategic judgment, and accountability remain human responsibilities.

This interpretation is consistent with human–AI symbiosis models in educational leadership.^{6,79,21} AI can process many conditions and alternatives rapidly, but the principal must define purposes, protect equity, contextualize rules, and assume responsibility for consequences. GenAI can make decisions more informed; it cannot turn value-laden educational choices into purely technical problems.

The word “potential” must therefore be retained in the article title and conclusions. The strongest evidence demonstrates the effectiveness of optimization algorithms for timetabling and documents increasing AI/GenAI adoption in administrative and leadership work. The September 2026 update strengthens both observations without closing the decisive gap: no experimental or quasi-experimental study identified in the corpus directly establishes that a principal produces a better annual or term school calendar with GenAI. This gap is precisely the empirical justification for GASCP and its validation agenda.

The review has three main strengths. First, it does not confuse direct evidence with extrapolation: timetabling research is used as a technical foundation, not as proof of GenAI effectiveness. Second, it integrates school-leadership scholarship with operations research, two domains that rarely communicate. Third, it produces a testable model with measurable outcomes. The review also has limitations. The literature is changing rapidly; several 2025–2026 publications are online-first or appear in emerging outlets. The review was not preregistered as a systematic review with independent double screening and coding. Older technical studies were retained because they remain foundational to timetabling optimization. Finally, the September 2026 update was targeted rather than a complete rerun of every bibliographic database.

Practical implications for secondary-school principals

In the short term, the safest use of GenAI is as a planning-preparation assistant: inventory constraints, convert notes into rule tables, flag potentially inconsistent dates, propose alternative term structures, draft communications, and generate verification checklists. Final decisions and conflict validation should remain outside the language model. In the medium term, school-management systems could connect a conversational module to a solver so that principals express goals in natural language, the system converts them into parameters, optimization is executed, residual conflicts are displayed, and scenario differences are explained. In the longer term, planning could become adaptive, using recurrent disruption data to estimate risk periods and propose safety margins, but such development requires governance, auditing, and continuous evaluation of organizational effects and bias.

V. CONCLUSION

Generative artificial intelligence has credible potential to improve school calendar planning, but the evidence remains predominantly indirect. The strongest bodies of evidence concern, on one hand, algorithmic optimization of timetables and resources and, on the other, the growing use of AI/GenAI in school administration and leadership. Recent studies suggest that educational leaders can gain efficiency in document preparation, synthesis, communication, and delegation of routine tasks while confirming that strategic, relational, and ethical functions require human control. The proposed GASCP model therefore reframes GenAI from an autonomous

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schedule generator into an interface for responsible planning. Its core architecture combines conversational GenAI, formal constraint optimization, and accountable human validation. The next scientific step is to implement and test the model on real secondary-school calendars, measuring planning time, feasibility, pedagogical quality, equity, robustness, acceptability, traceability, and principals' capacity to maintain calibrated, autonomous judgment.

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VII. DISCLOSURE

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