



Prioritizing Key Factors of GenAI-Induced Changes in School Education: A Spherical Fuzzy DEMATEL Approach

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ARTICLE INFO

Article history:

Received 12 July 2026

Received in revised form 20 August 2026

Accepted 4 October 2026

Available online 10 October 2026

Keywords:

Generative artificial intelligence; School education; Spherical fuzzy sets; DEMATEL

ABSTRACT

Generative artificial intelligence (GenAI) is changing how schools approach student learning, teaching, assessment, and administration. Existing research has identified many of these changes but has provided limited evidence on how they influence one another or which factors warrant priority. This study examines twelve factors associated with GenAI-induced changes in school education using an adapted spherical fuzzy DEMATEL (SF-DEMATEL) procedure. Six teachers from primary, junior secondary, and senior high schools evaluated the direct influences among the factors. Their judgments were aggregated as spherical fuzzy numbers and then converted into real-valued influence scores for subsequent DEMATEL analysis. The findings identify teacher facilitating skills, teacher AI literacy, and AI education in schools as the most prominent factors. Administrative attitude toward GenAI shows the strongest net influence, while teacher AI literacy and teacher curriculum leadership are both central and influential. Interdisciplinary teaching emerges as the strongest net receiver among the factors. These results suggest that clear school-level direction and sustained teacher development may provide a foundation for changes in classroom practice. The study offers a structured basis for prioritizing GenAI-related initiatives in school education.

1. Introduction

The rapid advancement of generative artificial intelligence (GenAI) has substantially expanded the capacity of AI systems to produce novel text, images, audio, and other forms of content in response to user instructions [1]. Following the public release of ChatGPT, GenAI tools such as ChatGPT and Midjourney have quickly entered educational settings, where they can function as learning assistants, tutors, content generators, and design aids [2]. Their accessibility allows students to retrieve and reorganize information, engage in human-like dialogue, and generate written or visual materials within a short period, reshaping how they acquire knowledge and produce learning outcomes. Recent evidence also indicates that well-designed GenAI interventions can improve students' academic performance, particularly when their interactions with these tools are supported

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by teachers [3]. The same capabilities raise concerns regarding inaccurate outputs, excessive dependence, plagiarism, copyright infringement, and the possible weakening of critical thinking skills.

These developments highlight the growing significance of GenAI in school education. However, its educational implications are multifaceted and cannot be fully understood by focusing only on technology adoption or classroom use. Recent studies have shown that GenAI is associated with changes in student learning, teacher roles, assessment practices, and school administration [2]. In student learning, the growing presence of GenAI has increased the importance of AI literacy, critical reasoning and thinking, digital, media and information literacies, and generic skills. From the perspective of teacher learning and teaching, educators are expected to strengthen their curriculum leadership, develop sufficient AI literacy, acquire new skills for facilitating student–GenAI interactions, and engage more actively in interdisciplinary teaching. Assessment practices also require reconsideration because conventional approaches and assessment dimensions may not adequately capture the knowledge and skills needed in GenAI-supported learning environments. At the administrative level, GenAI creates opportunities for evidence-based decision-making and more efficient completion of routine tasks, accompanied by a need to examine the awareness and attitudes of school administrative teams toward its use. Taken together, these findings indicate that GenAI-induced changes in school education constitute a set of interconnected developments affecting what students learn, how teachers support learning, how learning outcomes are assessed, and how schools organize administrative work.

Existing research on GenAI in education has developed along several related streams. One stream has examined the adoption and use of GenAI, with particular attention to teacher and student acceptance, intentions to use ChatGPT, and perceptions of its educational value. A second group of studies has investigated the application of GenAI in learning and teaching, including its effects on learning performance, personalized learning, automated or adaptive feedback, and instructional support. Another body of research has addressed the risks and challenges associated with its educational use, such as academic integrity, hallucinated or inaccurate outputs, ethical concerns, privacy risks, and excessive dependence on generated content. More recent qualitative research has moved beyond the immediate functions of GenAI tools by identifying the broader educational changes associated with their introduction into schools. Based on the perspectives of teachers and school leaders, Chiu [2] classified these changes into four domains: student learning, teacher learning and teaching, assessment, and administration. This line of inquiry differs from studies of learning and teaching applications because it seeks to identify system-level changes in educational roles, practices, and priorities rather than evaluate the effectiveness of a particular tool or intervention. Despite these contributions, existing studies have generally examined individual domains separately or provided qualitative descriptions of the identified changes, leaving their relative importance and causal interrelationships insufficiently understood. A systematic analysis of how these GenAI-induced changes influence one another within school education remains underdeveloped.

Although existing studies have identified a wide range of GenAI-induced changes in school education, most have concentrated on identifying and describing these factors rather than determining their relative importance. Such findings clarify which educational changes may matter yet provide limited guidance on which factors should receive priority when schools allocate resources or design interventions. The identified factors are also interdependent rather than isolated. For example, teacher AI literacy may strengthen teachers' facilitating skills, which can subsequently support students' critical thinking, while changes in student competencies may create further pressure to redesign assessment practices. Treating these factors as independent elements may therefore obscure their direct and indirect relationships and make it difficult to distinguish driving factors from resulting factors. The Decision-Making Trial and Evaluation Laboratory (DEMATEL)

method offers a suitable means of revealing these interdependencies and constructing a causal structure among the identified changes. A further methodological challenge arises from the uncertainty inherent in expert judgement. Educational experts may find it difficult to express the influence of one factor on another using precise numerical values, whereas linguistic assessments such as low, medium, and high more closely reflect how such judgements are formed. Spherical fuzzy sets provide a flexible environment for representing degrees of membership, non-membership, and hesitation contained in these assessments. Accordingly, this study employs a spherical fuzzy DEMATEL approach to prioritize GenAI-induced changes in school education and examine the causal relationships among them under uncertain decision conditions.

To address the identified research gaps, this study aims to prioritize the key factors associated with GenAI-induced changes in school education and clarify their underlying causal structure. A spherical fuzzy DEMATEL framework is applied to transform experts' linguistic judgements into structured decision information while retaining the uncertainty and hesitation involved in the evaluation process. The prominence values derived from the analysis are used to determine which factors occupy more central positions within the system, while the relation values distinguish causal factors from effect factors and reveal how these factors interact. The findings are expected to help school leaders, teachers, and policymakers identify priority areas and develop more targeted strategies for responding to GenAI-induced educational changes. Accordingly, this study addresses the following research questions:

RQ1: What are the relative prominence levels of the key factors associated with GenAI-induced changes in school education?

RQ2: What are the cause-and-effect relationships among these factors?

The methodological choice of spherical fuzzy DEMATEL reflects the interconnected nature of GenAI-induced changes and the imprecision of expert evaluations. Within school education, these changes may reinforce or constrain one another through complex causal pathways. DEMATEL traces the influence transmitted and received by each factor, providing a prominence value that indicates its overall significance in the system. The resulting causal values further separate the factors into cause-and-effect groups. Expert opinions on emerging educational issues are often accompanied by ambiguity, hesitation, and subjective interpretation. Spherical fuzzy sets capture these characteristics through three components: membership, non-membership, and hesitancy degrees. Combining the two approaches makes it possible to preserve the uncertainty embedded in expert assessments while mapping the causal structure of the interconnected educational factors.

This paper contributes to understanding the key changes induced by GenAI in school education under uncertain decision conditions. The main contributions of the study are summarized as follows:

- i. The qualitative findings reported in previous research are extended through a quantitative prioritization of GenAI-induced changes in school education. The resulting prominence values provide a clearer indication of which factors occupy central positions in the educational change system.
- ii. A spherical fuzzy DEMATEL framework is applied to explore the causal interrelationships among the identified factors. This framework moves beyond independent factor ranking by distinguishing the cause group from the effect group and tracing the influence transmitted across educational domains.
- iii. The identification of key causal factors provides practical evidence for school-level GenAI planning. The findings can assist school leaders, teachers, and policymakers in determining which educational areas should receive earlier attention when resources and intervention capacity are limited.

The remainder of this paper is organized as follows. Section 2 reviews research on GenAI-induced changes in school education and spherical fuzzy DEMATEL. Section 3 describes the factors and the adapted SF-DEMATEL procedure. Section 4 presents the data analysis and discusses the prominence and causal roles of the factors. Section 5 summarizes the findings, offers practical suggestions, and outlines the study's limitations and directions for future research.

2. Literature Review

2.1 GenAI-Induced Changes in School Education: Identification of Enablers

The influence of generative artificial intelligence (GenAI) on school education has gradually moved beyond the use of individual technological tools. Its capacity to generate text, images, explanations, examples, and feedback has begun to affect what students are expected to learn, how teachers organize instruction, how learning outcomes are assessed, and how schools process information. Earlier research on artificial intelligence in education mainly examined adaptive learning, automated feedback, intelligent tutoring systems, and learning analytics. The rapid diffusion of GenAI has extended this discussion to curriculum content, learner agency, assessment validity, teacher competence, and institutional decision-making. A systematic review by Chiu *et al.*, [4], covering 92 studies, organized the educational implications of AI around learning, teaching, assessment, and administration. Chiu [2] subsequently examined GenAI in the school context and identified four corresponding themes and twelve subthemes. The present study adopts this four-theme, twelve-subtheme framework as the basis for its evaluation criteria, with the subthemes corresponding to the twelve factors examined in the analysis.

The twelve factors were retained from Chiu [2] rather than generated through a new process of factor selection or conceptual merging. Additional literature on AI literacy, educational practice, assessment, and responsible technology adoption was used to clarify and support their operational definitions for expert evaluation. These sources informed how each factor was described within the context of GenAI-related changes in primary and secondary education; they were not used to introduce additional factors or alter the four-domain structure. The resulting framework comprises four student-learning factors, four teacher-learning and teaching factors, two assessment factors, and two administration factors.

Student learning

Student learning constitutes the first area in which GenAI produces identifiable changes. Access to conversational systems enables learners to obtain explanations, examples, summaries, and preliminary feedback with relatively little delay. Such access may support personalized learning and independent inquiry. The educational value of these functions depends on whether students understand how AI systems operate and whether they can judge the quality of the generated material. GenAI-supported learning requires knowledge that goes beyond the mechanical use of a chatbot.

AI education in schools forms the first factor. Students need an age-appropriate understanding of how AI systems produce outputs, what types of tasks they can perform, and why their responses may contain errors or bias. Responsible use also involves privacy, attribution, fairness, and the social consequences of automated decisions. Ng *et al.*, [5] reviewed AI literacy education in secondary schools, examining pedagogical approaches, teaching tools, learning content, and assessment methods. Their review provides a school-based foundation for defining AI education as the integration of AI-related knowledge, skills, and ethical understanding into the curriculum. Ng *et al.*, [6] organise this literacy around understanding AI, applying it, evaluating its outputs, and addressing ethical issues.

Critical reasoning and thinking represent a separate requirement. GenAI can produce fluent responses without ensuring their factual accuracy, evidential quality, or contextual suitability. Students must examine the assumptions embedded in prompts, compare generated claims with reliable sources, identify unsupported conclusions, and explain why an answer should or should not be accepted. Kasneci *et al.*, [7] note that the educational use of large language models requires awareness of bias, possible misuse, and the continuing need for human oversight. Tlili *et al.*, [8] similarly report concerns related to misinformation, manipulation, cheating, and the reliability of chatbot-generated content.

Digital, media and information literacies acquire additional importance because GenAI complicates the origin and status of digital content. Learners need to locate information, distinguish generated material from verified evidence, check authorship and provenance, and communicate content with appropriate acknowledgement. Traditional information literacy remains relevant, although verification now includes the examination of generated text, synthetic images, invented references, and algorithmically shaped representations [9].

Generic skills development forms the fourth student-related factor. Effective work with GenAI involves problem formulation, creativity, communication, collaboration, self-regulation, and independent learning. The quality of a generated response frequently depends on how learners define a task, refine a prompt, compare alternatives, and revise the resulting material. Group activities may also require students to explain how GenAI was used and negotiate which outputs should be retained. These practices shift attention from answer production alone to the broader processes through which students formulate, evaluate, and improve their work.

Teacher learning and teaching

GenAI also repositions teachers' professional roles and required competencies. Teachers remain responsible for the educational purposes, intellectual demands, and ethical boundaries of classroom activities. Their work increasingly includes decisions about when GenAI is appropriate, how its use should be disclosed, and what forms of human judgment must be preserved. The teacher-related subthemes identified by Chiu [2] comprise curriculum leadership, teacher AI literacy, facilitating skills, and interdisciplinary teaching.

Teacher curriculum leadership refers to teachers' role in interpreting curriculum aims and translating them into suitable GenAI-supported learning experiences. Existing curriculum documents rarely provide detailed guidance for every emerging AI application. Teachers must decide whether GenAI use supports the intended learning outcome, redesign tasks when automated content generation weakens their educational purpose and establish classroom expectations that suit students' age and level of development. Curriculum leadership also includes the sequencing of prerequisite knowledge. Students need sufficient subject understanding to recognise when an AI-generated response is incomplete or inaccurate [10].

Teacher AI literacy includes an understanding of GenAI functions, limitations, risks, ethical implications, and possible pedagogical applications. Technical knowledge alone is insufficient. Teachers must be able to judge whether a system is suitable for a particular class, recognise biased or fabricated outputs, protect student information, and explain acceptable use [11]. Teacher AI literacy therefore combines technological, pedagogical, evaluative, and ethical knowledge.

Teacher facilitating skills concern the guidance students require while interacting with GenAI. Classroom facilitation may include helping learners construct purposeful prompts, comparing generated responses, verify claims, reflect on the reasoning process, and document the contribution made by AI. Dialogue remains necessary because students may accept fluent outputs without recognising weak evidence or logical gaps. The teacher's role shifts towards structuring inquiry,

monitoring cognitive engagement, and ensuring that students do not transfer the entire learning task to the technology.

GenAI systems can draw together language, visual information, data, and subject-specific explanations within a single task. Such affordances create opportunities for learning activities that connect science, mathematics, languages, social studies, and the arts. Interdisciplinary designs can also provide an authentic setting for discussing the technical, ethical, and social implications of AI. Successful implementation requires coordination across subject boundaries and clear identification of the disciplinary knowledge that students must contribute. Therefore, the factor concerns teachers' capacity to design learning experiences that combine knowledge and methods from multiple subjects rather than the incidental use of the same tool in separate classes.

Assessment

The widespread availability of GenAI challenges several assumptions underlying school assessment. Homework and unsupervised written assignments no longer provide straightforward evidence of what a student can produce independently. A polished response may reflect extensive machine generation, limited student revision, or a more substantive process of human–AI collaboration. The educational meaning of the final product consequently becomes difficult to determine without information about the process through which it was created.

Assessment approaches refer to changes in formative and summative assessment methods. Teachers may place less weight on conventional homework and greater weight on in-class performance, staged assignments, portfolios, project work, oral questioning, and the defence of submitted work. Formative assessment can incorporate prompt records, drafts, source-verification notes, and student reflections to make the learning process visible. Summative assessment may combine written products with oral explanation or supervised tasks. The purpose of these adjustments is not simply to detect unauthorised AI use. Their main function is to obtain more credible evidence of students' understanding, reasoning, and authorship.

GenAI changes both the assessment method and the competencies that require assessment. Disciplinary knowledge remains essential, while critical judgment, generic skills, AI literacy, responsible use, and the ability to verify generated information become increasingly relevant learning outcomes. Students may need to demonstrate why they accepted, revised, or rejected an AI response. Assessment criteria may consequently address the quality of reasoning and verification in addition to the correctness of the final answer. Assessment is therefore not merely another independent issue but is closely related to changes in student competencies and teaching practices.

Administration

School administration forms the fourth domain. GenAI can assist with routine tasks such as drafting notices, preparing preliminary reports, organising documents, summarising feedback, and generating initial versions of schedules or proposals. These applications may reduce the time devoted to repetitive work. Administrative use also carries risks involving confidentiality, accuracy, accountability, and inappropriate reliance on automatically generated recommendations. Human review remains necessary whenever generated information informs decisions about students, teachers, or school policy.

School leaders frequently work with survey responses, policy documents, performance data, meeting records, and stakeholder feedback. GenAI may help organise or summarise such material and present alternative interpretations for consideration. The resulting output should serve as decision support rather than a substitute for professional responsibility. Evidence must be checked against its original source, and recommendations must be evaluated in relation to the school's context and educational priorities.

Table 1
Key factors of GenAI-induced changes in school education

Dimension	Code	Factor	Definition.	Literature supporting the operational definition
Student learning	C1	AI education in schools	The incorporation of foundational AI concepts, the operation and limits of GenAI, responsible use, and social and ethical implications into the school curriculum.	Chiu [2]; Ng <i>et al.</i> , [5]
Student learning	C2	Critical reasoning and thinking	Students' capacity to question prompts, examine the logic and evidence behind generated responses, detect errors or bias, and justify whether an output is credible and appropriate.	Tlili <i>et al.</i> , [8]
Student learning	C3	Digital, media and information literacies	The ability to locate, interpret, verify, create, and communicate information across digital and media environments, including the attribution and evaluation of AI-generated content.	Ng <i>et al.</i> , [6]
Student learning	C4	Generic skills development	The development of transferable capabilities such as creativity, communication, collaboration, problem solving, self-regulation, and independent learning in GenAI-supported tasks.	Chiu <i>et al.</i> , [4]; Kasneci <i>et al.</i> , [7]
Teacher learning and teaching	C5	Teacher curriculum leadership	Teachers' role in interpreting curriculum aims, redesigning learning sequences, and establishing context-sensitive rules for the pedagogically appropriate use of GenAI.	Chiu <i>et al.</i> , [4]
Teacher learning and teaching	C6	Teacher AI literacy	Teachers' knowledge of GenAI principles, functions, limitations, risks, ethics, and pedagogical applications, together with their ability to evaluate AI-supported practices.	Chiu [2]; Ng <i>et al.</i> , [6]; Ng <i>et al.</i> , [12]
Teacher learning and teaching	C7	Teacher facilitating skills	Teachers' ability to guide prompting, dialogue, source checking, reflection, collaboration, and self-regulated learning when students work with GenAI.	Kasneci <i>et al.</i> , [7]; Tlili <i>et al.</i> , [8]
Teacher learning and teaching	C8	Interdisciplinary teaching	The design of learning experiences that connect knowledge and methods from multiple subjects to address complex tasks supported by GenAI.	Chiu [2]
Assessment	C9	Assessment approaches	Changes in formative and summative methods, including reduced reliance on unsupervised homework and greater use of process evidence, projects, in-class performance, dialogue, and oral assessment.	Kasneci <i>et al.</i> , [7]
Assessment	C10	Dimensions of assessment	The broadening of assessment targets to include disciplinary understanding, generic skills, critical judgment, AI literacy, and students' capacity to use and verify GenAI responsibly.	Chiu [2]; Ng <i>et al.</i> , [12]
Administration	C11	Effective work with evidence	The use of GenAI to assist routine administrative work and to organise, summarise, and interpret evidence for school planning and decision making while retaining human review.	Chiu [2]; Chiu <i>et al.</i> , [4]
Administration	C12	Administrative attitude toward GenAI	School leaders' awareness, acceptance, risk perception, policy orientation, and willingness to provide training and organisational support for responsible GenAI adoption.	Akgun and Greenhow [13]; Chiu [2]

Administrative attitude toward GenAI captures leaders' awareness, acceptance, risk perception, and willingness to provide organisational support. Leadership attitudes influence whether schools develop coherent policies, provide professional learning, allocate resources, and establish safeguards for responsible use. Limited understanding may lead either to uncritical adoption or to broad restrictions that prevent potentially useful applications. Training can support more informed attitudes by helping administrative teams distinguish realistic educational opportunities from technical claims.

Accordingly, this study uses the twelve factors adopted from Chiu's four-domain framework to examine GenAI-induced changes in school education. Student learning is represented by C1–C4, teacher learning and teaching by C5–C8, assessment by C9–C10, and administration by C11–C12. Table 1 presents the operational definition of each factor and the literature supporting that definition. Chiu [2] provides the source framework for all twelve factors, whereas the additional references support their operational interpretation in the present study. These factors are treated as interrelated elements because changes in one domain may affect several others. For example, stronger student AI literacy may alter assessment design, whereas administrative support may influence teachers' opportunities to develop AI-related competencies.

2.2 MCDM in Educational Research

Multi-criteria decision-making (MCDM) methods have been increasingly used to support complex decisions involving multiple and potentially conflicting criteria. Their structured procedures allow expert judgments to be converted into comparable values for evaluating alternatives, determining criterion importance, and identifying priorities. Educational researchers have applied MCDM methods to performance evaluation, resource allocation, programme selection, e-learning systems, student assessment, and the analysis of factors influencing educational outcomes. A systematic review of 328 educational studies found that the use of MCDM has grown considerably, with AHP, TOPSIS, and fuzzy AHP among the most frequently adopted techniques. BWM and fuzzy DEMATEL have also gained attention in recent educational research [14].

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method provides a different analytical perspective. It converts expert assessments into a structured influence network and considers both direct and indirect relationships among factors. The resulting prominence values indicate the overall importance of each factor, while the relation values separate factors into cause-and-effect groups. DEMATEL can therefore identify influential drivers as well as factors that are mainly affected by other elements in the system. Its ability to represent interdependence and construct cause-and-effect diagrams makes it suitable for complicated problems in which the criteria cannot be regarded as independent [15].

Applications in educational research have demonstrated the value of this relational perspective. For example, Aldowah *et al.*, [16] applied DEMATEL to identify the core factors associated with student dropout in massive open online courses and to reveal the causal relationships among those factors. Similar reasoning is relevant to GenAI-induced changes in school education. Student AI literacy may affect assessment design, teacher facilitating skills may influence students' critical reasoning, and administrative attitudes may shape curriculum leadership and professional training. These factors form an interconnected system rather than a collection of isolated educational issues. DEMATEL is consequently adopted in this study because it can simultaneously prioritise the identified factors, model their interaction structure, and distinguish the driving factors from the affected factors. Its integration with spherical fuzzy sets further allows uncertainty and hesitation in experts' linguistic judgments to be represented during the evaluation process.

2.3 Spherical Fuzzy DEMATEL and Research Gaps

Expert evaluations of educational change commonly contain ambiguity, hesitation, and incomplete information. Crisp numerical scales may not fully represent such judgments, particularly when experts are asked to assess the influence of emerging technologies with uncertain long-term consequences. Fuzzy set theory was introduced by Zadeh [17] to describe imprecise information through a membership degree. This representation was extended by Atanassov [18], whose intuitionistic fuzzy set incorporates both membership and non-membership degrees and derives the remaining hesitation from them. Pythagorean fuzzy sets subsequently relaxed the restriction imposed on these two degrees by requiring the sum of their squares to be no greater than one, thereby offering decision makers a larger domain for expressing uncertain evaluations [19].

Spherical fuzzy sets provide a three-dimensional representation consisting of membership, non-membership, and hesitancy degrees. Each component can be independently assigned within the interval from zero to one, provided that the sum of their squared values does not exceed one. This structure allows experts to express support, opposition, and hesitation more explicitly than traditional fuzzy and intuitionistic fuzzy representations [20, 21]. The wider preference domain is particularly useful when experts cannot provide fully certain judgments about the relationships among newly emerging educational factors.

Gül [22] integrated spherical fuzzy sets with DEMATEL and introduced the SF-DEMATEL method. The approach incorporates experts' hesitation when evaluating the strength of influence between criteria while retaining DEMATEL's ability to determine factor prominence and causal direction. SF-DEMATEL is therefore suitable for analysing GenAI-induced educational changes, since teachers may agree that two factors are related while remaining uncertain about the precise strength of that relationship. The spherical fuzzy representation preserves this uncertainty during the aggregation of expert judgments, and the DEMATEL component reveals the resulting structure of direct and indirect influences.

The preceding literature review indicates three research gaps. A substantive gap concerns the treatment of GenAI-induced changes in school education. Existing studies have identified changes related to student learning, teacher competencies, assessment, and administration. These factors are usually discussed as separate themes or examined through qualitative evidence. Limited attention has been paid to determining their relative importance within a unified analytical framework.

A relational gap is also evident. Changes in school education do not occur independently. Teacher AI literacy may shape curriculum leadership and facilitating practices. Students' critical reasoning may influence the design of assessment, while administrative attitudes may affect training opportunities and school-level implementation. The interdependencies and causal relationships among these factors remain insufficiently understood. A simple ranking cannot show which factors initiate change and which factors mainly receive influence from other parts of the educational system.

A methodological gap arises from the limited integration of expert-based causal analysis with an uncertainty-handling environment in research on GenAI and school education. Qualitative studies can provide detailed descriptions of educational change, while conventional ranking methods can establish an order of importance. Neither approach alone fully captures causal interaction and expert hesitation. Existing research has rarely used a structured method capable of addressing both issues when prioritising GenAI-induced changes in school education.

To address these gaps, this study applies SF-DEMATEL to prioritise the identified factors and reveal their causal structure. The method supports a systematic comparison of the twelve criteria, distinguishes cause factors from effect factors, and represents the uncertainty contained in teachers' judgments.

3. Methodology

This study employs the spherical fuzzy DEMATEL (SF-DEMATEL) method to examine the causal structure among GenAI-induced changes in school education. Spherical fuzzy sets are used to represent uncertainty and hesitation in expert assessments. DEMATEL is then applied to trace direct and indirect influences among the selected factors.

3.1 Preliminaries

This subsection presents the definitions and operations required in the subsequent analysis.

Definition 1 [21]. Let X be a universe of discourse. A spherical fuzzy set (SFS) $\tilde{A}$ in X is defined as $\tilde{A} = \{(x, \mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x), \pi_{\tilde{A}}(x)) \mid x \in X\}$ (1)

where $\mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x), \pi_{\tilde{A}}(x) \in [0,1]$. The three functions denote the membership, non-membership, and hesitancy degrees, respectively. They satisfy

$$0 \leq \mu_{\tilde{A}}^2(x) + \nu_{\tilde{A}}^2(x) + \pi_{\tilde{A}}^2(x) \leq 1 \quad (2)$$

A spherical fuzzy number (SFN) is therefore expressed in the compact form $\tilde{A}_e = (\mu_e, \nu_e, \pi_e), (e = 1, 2, \dots, m)$ (3)

denote the SFN provided by evaluator e . The corresponding weight is ω_e , where $0 \leq \omega_e \leq 1$, $\sum_{e=1}^m \omega_e = 1$.

These three degrees can be specified independently within the constraint. This structure permits hesitation to remain explicit in expert assessments. No differentiated evaluator weights are assigned in this study. Each judgment receives the same weight:

$$\omega_e = \frac{1}{m}, e = 1, 2, \dots, m \quad (4)$$

Definition 2. Let $\tilde{A} = (\mu_A, \nu_A, \pi_A)$ and $\tilde{B} = (\mu_B, \nu_B, \pi_B)$ be two SFNs. Their spherical fuzzy addition is defined by

$$\tilde{A} \oplus \tilde{B} = \left(\sqrt{\mu_A^2 + \mu_B^2 - \mu_A^2 \mu_B^2}, \nu_A \nu_B, \sqrt{(1 - \mu_B^2) \pi_A^2 + (1 - \mu_A^2) \pi_B^2 - \pi_A^2 \pi_B^2} \right) \quad (5)$$

For a positive scalar λ , multiplication of an SFN by λ is expressed as $\lambda \tilde{A} = \left(\sqrt{1 - (1 - \mu_A^2)^\lambda}, \nu_A^\lambda, \sqrt{(1 - \mu_A^2)^\lambda - (1 - \mu_A^2 - \pi_A^2)^\lambda} \right), \lambda > 0$. (6)

The scalar operation is required when weighted spherical fuzzy information is combined.

Definition 3. Consider a set of SFNs $\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_q$ and the corresponding weight vector $\omega = (\omega_1, \omega_2, \dots, \omega_q)$ subject to $\omega_k \in [0,1], \sum_{k=1}^q \omega_k = 1$. The spherical weighted arithmetic mean (SWAM) is written as

$$SWAM_\omega = \left(\sqrt{1 - \prod_{k=1}^q (1 - \mu_k^2)^{\omega_k}}, \prod_{k=1}^q \nu_k^{\omega_k}, \sqrt{\prod_{k=1}^q (1 - \mu_k^2)^{\omega_k} - \prod_{k=1}^q (1 - \mu_k^2 - \pi_k^2)^{\omega_k}} \right) \quad (7)$$

The operator combines individual evaluations while retaining their spherical fuzzy form. Gül [22] employs SWAM to obtain the aggregated direct-influence matrix from the judgments of several decision-makers.

Definition 4. score function is required to convert an SFN into a real value. Following Gül [22], the score of $\tilde{A}$ is calculated as

$$S(\tilde{A}) = (2\mu_{\tilde{A}} - \pi_{\tilde{A}})^2 - (\nu_{\tilde{A}} - \pi_{\tilde{A}})^2. \quad (8)$$

A larger score represents a stronger assessed influence. In this study, the score function is applied after the individual evaluations have been aggregated. The fuzzy information is therefore retained during group aggregation and converted into real numbers before the DEMATEL matrix operations.

3.2 SF-DEMATEL

The DEMATEL method is used to examine interdependent factors within a complex system. Its matrix-based procedure measures direct and indirect influences among the factors. DEMATEL also distinguishes factors that mainly drive the system from factors that are mainly affected by other elements.

Two indicators support the interpretation of the results. Prominence represents the overall involvement of a factor in the system. Relation indicates whether the factor belongs to the cause group or the effect group. These measures make DEMATEL suitable for identifying the key factors associated with GenAI-induced changes in school education.

The conventional DEMATEL procedure operates on real-valued influence matrices. In the proposed method, spherical fuzzy information is retained until the group evaluations have been aggregated. The aggregated SFNs are then converted into real numbers. Normalization, total-relation calculation, and causal analysis are subsequently performed using ordinary real-number matrix operations.

The proposed procedure consists of a spherical fuzzy aggregation stage and a real-number DEMATEL stage. Spherical fuzzy operations are applied to the linguistic judgments and their aggregation. Real-number matrix operations begin after the aggregated spherical fuzzy matrix has been defuzzified.

Step 1. Construct the individual direct-relation matrices.

First, let $C = \{C_1, C_2, \dots, C_n\}$, denote the set of factors associated with GenAI-induced changes in school education. The directional influence of factor C_i on factor C_j is evaluated using four linguistic terms. Their corresponding spherical fuzzy numbers are presented in Table 2.

Table 2

Linguistic scale for influence assessment

Linguistic term	Abbreviation	Spherical fuzzy number(SFN)
No influence	NI	(0.00,0.30,0.15)
Weak influence	W	(0.35,0.25,0.25)
Moderate influence	M	(0.60,0.20,0.35)
Strong influence	S	(0.85,0.15,0.45)

The four-level scale is adapted from the SF-DEMATEL method developed by Gül [22]. Data codes are used to record the evaluations. The corresponding spherical fuzzy triples are used in the calculations.

For evaluator e the linguistic direct-relation matrix is written as $L^{(e)} = [l_{ij}^{(e)}]_{n \times n}$, ($e = 1, 2, \dots, m$)

Each off-diagonal element $l_{ij}^{(e)}$ indicates the assessed influence of C_i on C_j . The matrix is directional and is not required to be symmetric. Hence, the evaluation of C_i influencing C_j may differ from the evaluation of C_j influencing C_i . The diagonal elements are assigned a value of zero:

$$l_{ii}^{(e)} = 0 \quad (10)$$

Code 0 is reserved for the main diagonal and is not treated as an additional linguistic category. Each off-diagonal linguistic evaluation is replaced by the corresponding SFN in Table 2 The individual spherical fuzzy direct-relation matrix is expressed as

$$\tilde{Z}^{(e)} = [\tilde{z}_{ij}^{(e)}]_{n \times n} \quad (11)$$

where

$$\tilde{z}_{ij}^{(e)} = (\mu_{ij}^{(e)}, \nu_{ij}^{(e)}, \pi_{ij}^{(e)}), \quad i \neq j \quad (12)$$

And

$$\tilde{z}_{ii}^{(e)} = (0, 0, 0) \quad (13)$$

Step 2. Aggregate the individual spherical fuzzy matrices.

The individual matrices are combined into a group spherical fuzzy direct-relation matrix. For each ordered pair (i, j) , the SWAM operator is applied as follows:

$$\tilde{z}_{ij} = \text{SWAM}_w(\tilde{z}_{ij}^{(1)}, \tilde{z}_{ij}^{(2)}, \dots, \tilde{z}_{ij}^{(m)}) = (\bar{\mu}_{ij}, \bar{\nu}_{ij}, \bar{\pi}_{ij}) \quad (14)$$

The aggregated membership degree is calculated as

$$\bar{\mu}_{ij} = \sqrt{1 - \prod_{e=1}^m [1 - (\mu_{ij}^{(e)})^2]^{w_e}} \quad (15)$$

The aggregated non-membership degree is

$$\bar{\nu}_{ij} = \prod_{e=1}^m (\nu_{ij}^{(e)})^{w_e} \quad (16)$$

The aggregated hesitancy degree is

$$\bar{\pi}_{ij} = \sqrt{\prod_{e=1}^m [1 - (\mu_{ij}^{(e)})^2]^{w_e} - \prod_{e=1}^m [1 - (\mu_{ij}^{(e)})^2 - (\pi_{ij}^{(e)})^2]^{w_e}} \quad (17)$$

Step 3. Convert the aggregated spherical fuzzy matrix into a real matrix.

Early defuzzification is performed after the group matrix has been obtained. The score of each aggregated SFN is calculated using the score function introduced in Equation (18):

$$s_{ij} = (2\bar{\mu}_{ij} - \bar{\pi}_{ij})^2 - (\bar{\nu}_{ij} - \bar{\pi}_{ij})^2 \quad (18)$$

The score s_{ij} represents the collective assessment of the influence exerted by C_i on C_j .

DEMATEL elements indicate influence intensity and therefore require non-negative values. A non-negative boundary is introduced when constructing the real direct-relation matrix $A = [a_{ij}]_{n \times n}$:

$$a_{ij} = \begin{cases} 0, & i = j, \\ \max\{0, s_{ij}\}, & i \neq j. \end{cases} \quad (19)$$

The boundary operation changes only negative scores that cannot represent an admissible influence intensity. Positive scores retain their original values. All subsequent calculations are conducted with the real matrix A .

Step 4. Normalize the real direct-relation matrix.

The real direct-relation matrix is normalized to place the influence values on a comparable scale. The normalization coefficient is determined from the maximum row sum and maximum column sum:

$$\eta = \max \left\{ \max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n a_{ij} \right\} \quad (20)$$

The normalized direct-relation matrix is obtained as

$$X = \frac{A}{\eta} = [x_{ij}]_{n \times n} \quad (21)$$

The spectral radius of X should satisfy $\rho(X) < 1$.

This condition ensures that the infinite matrix series used to calculate the total effects is convergent.

Step 5. Calculate the total-relation matrix.

The normalized matrix X represents the direct influences among the factors. Indirect effects arise when one factor affects another through one or more intermediate factors. The total-relation matrix combines the direct and indirect influence paths:

$$T = X + X^2 + X^3 + \dots = X(I - X)^{-1}, \quad (22)$$

where I is the $n \times n$ identity matrix. The total-relation matrix is expressed as

$$T = [t_{ij}]_{n \times n} \quad (23)$$

Each element t_{ij} measures the total influence transmitted from C_i to C_j . It contains the original direct influence and the indirect influences transmitted through other factors.

Step 6. Determine the influence and dependence values.

The total influence exerted by factor C_i is obtained from the sum of row i in matrix T :

$$r_i = \sum_{j=1}^n t_{ij}, \quad i = 1, 2, \dots, n. \quad (24)$$

The value r_i represents the combined direct and indirect influence of C_i on the remaining factors. The total influence received by C_i is calculated from the sum of column i :

$$c_i = \sum_{j=1}^n t_{ji}, \quad i = 1, 2, \dots, n. \quad (25)$$

A larger c_i indicates that the corresponding factor is more strongly affected by the surrounding system.

Step 7. Calculate prominence and relation

Prominence is defined as the sum of the influence and dependence values:

$$P_i = r_i + c_i \quad (26)$$

The value P_i reflects the overall involvement of factor C_i in the system. Factors with larger prominence values occupy more central positions. The factors are ranked in descending order of P_i .

Relation is calculated as

$$Q_i = r_i - c_i \quad (27)$$

The sign of Q_i determines the causal role of each factor. A positive value indicates that C_i exerts more influence than it receives and therefore belongs to the cause group. A negative value places the factor in the effect group. When $Q_i = 0$, the exerted and received influences are balanced.

4. Data Analysis

4.1 Construction of the Initial Direct-Relation Matrix

To obtain judgments grounded in school practice, six teachers were invited to evaluate the relationships among the twelve factors. The expert panel covered primary, junior secondary, and senior high school education, while the participants' teaching experience ranged from 3 to 15 years. Such a composition introduced perspectives from different stages of school education and reduced the likelihood that the assessment would reflect the circumstances of a single educational level.

The experts assessed the extent to which each factor directly influenced every other factor using the four linguistic terms established in Section 3: no influence (NI), weak influence (W), medium influence (M), and strong influence (S). All diagonal entries were assigned a value of zero, since a factor was not assumed to exert a direct influence on itself. No sufficiently reliable evidence was available to distinguish the relative importance of the six participants. Each expert was therefore assigned an equal weight of $\frac{1}{6}$.

The calculation followed the procedure specified in the methodology section. Linguistic judgments were first converted into their corresponding spherical fuzzy numbers. For each directional relationship, the six individual evaluations were integrated through the spherical weighted arithmetic mean (SWAM) operator. The aggregated result remained a spherical fuzzy number containing membership, non-membership, and hesitancy information. It was subsequently transformed into a crisp influence value using the score function introduced in Section 3.

The relationship between AI education in schools (C_1) and critical reasoning and thinking (C_2) illustrates how an entry in Table 3 was obtained. The six experts evaluated the influence of (C_1) on (C_2) as M, M, S, W, M, and M. According to the linguistic scale used in this study, NI was represented by (0.00,0.30,0.15), W by (0.35,0.25,0.25), M by (0.60,0.20,0.35), and S by (0.85,0.15,0.45).

Assigning each teacher a weight of $1/6$ and applying Equations (15)–(17) gives

$$\bar{\mu}_{12} = \sqrt{1 - (1 - 0.60^2)^{4/6}(1 - 0.85^2)^{1/6}(1 - 0.35^2)^{1/6}} = 0.642756,$$

$$\bar{\nu}_{12} = 0.20^{4/6}0.15^{1/6}0.25^{1/6} = 0.197860,$$

$$\bar{\pi}_{12} = [(1 - 0.60^2)^{4/6}(1 - 0.85^2)^{1/6}(1 - 0.35^2)^{1/6} - (1 - 0.60^2 - 0.35^2)^{4/6}(1 - 0.85^2 - 0.45^2)^{1/6}(1 - 0.35^2 - 0.25^2)^{1/6}]^{1/2} = 0.426979.$$

After the six evaluations were incorporated, the SWAM operator generated an aggregated spherical fuzzy number of (0.642756,0.197860,0.426979). The score function converted this three-component result into a crisp influence value of 0.684583. Rounded to three decimal places, the value became 0.685 and was entered in row (C_1) and column (C_2) of Table 3.

Every other directional relationship was processed in the same manner. The resulting matrix therefore represents neither the raw questionnaire scores nor a simple arithmetic average. Instead, it contains the crisp values obtained after linguistic transformation, SWAM aggregation, and defuzzification. Table 3 reports the completed initial direct-relation matrix.

Table 3
Aggregated and Defuzzified Initial Direct-Relation Matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
C_1	0.000	0.685	0.793	0.713	0.599	0.970	1.080	1.313	0.849	1.007	1.007	0.523
C_2	0.873	0.000	0.685	0.685	1.156	0.849	1.156	0.588	0.490	0.652	0.817	0.929
C_3	0.764	0.685	0.000	0.929	0.490	0.817	0.817	0.970	0.929	1.007	1.007	0.461
C_4	0.873	1.007	0.929	0.000	0.873	0.764	0.873	1.080	0.713	0.929	0.929	0.713
C_5	0.873	0.793	0.873	1.007	0.000	1.007	0.929	0.873	1.080	1.007	1.239	0.523
C_6	0.929	0.873	0.929	1.007	0.929	0.000	1.473	1.313	0.793	0.929	0.929	0.793
C_7	1.007	0.793	1.313	0.793	1.001	1.156	0.000	1.156	0.713	0.929	0.685	0.713
C_8	0.632	0.713	0.599	0.897	0.873	0.604	0.929	0.000	0.849	0.793	0.793	0.713
C_9	0.929	0.736	0.604	0.604	0.523	0.929	0.793	0.685	0.000	0.604	0.523	0.377
C_{10}	0.817	0.849	0.523	1.007	0.793	0.685	0.793	1.080	0.929	0.000	0.604	0.713
C_{11}	1.156	0.929	0.764	0.713	0.929	0.873	1.156	0.761	0.523	0.632	0.000	1.001
C_{12}	1.313	0.713	0.685	0.685	1.001	0.929	1.080	1.007	0.929	1.007	1.156	0.000

4.2 Determination of the Total-Relation Matrix

Before the direct and indirect influences could be combined, the initial direct-relation matrix was normalized in accordance with the procedure outlined in Section 3. Comparison of the row sums and column sums yielded a maximum value of 11.077439, which served as the normalization coefficient.

Using the relationship $C_1 \rightarrow C_2$ as an example, the unrounded direct influence value of 0.684583 was converted into a normalized value of 0.061800. At this stage, the result described only the immediate influence of AI education in schools on critical reasoning and thinking.

The total-relation matrix was subsequently derived from the normalized matrix. This operation incorporated the influence transmitted through the other factors, thereby extending the analysis beyond direct judgments alone. Once these indirect paths were included, the total influence of (C_1) on (C_2) reached 0.437094. The difference between the normalized direct value and the total value reflects the cumulative contribution of indirect connections within the system.

Table 4 presents the total-relation matrix used in the remaining analysis.

Table 4
Total-Relation Matrix

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂
C ₁	0.430	0.437	0.445	0.452	0.446	0.491	0.559	0.571	0.449	0.490	0.494	0.372
C ₂	0.486	0.362	0.422	0.432	0.474	0.466	0.545	0.494	0.405	0.446	0.464	0.390
C ₃	0.465	0.412	0.352	0.441	0.410	0.450	0.506	0.512	0.429	0.462	0.466	0.345
C ₄	0.510	0.469	0.462	0.397	0.475	0.482	0.551	0.559	0.445	0.491	0.496	0.393
C ₅	0.532	0.471	0.477	0.500	0.420	0.521	0.578	0.566	0.492	0.517	0.540	0.394
C ₆	0.568	0.505	0.510	0.529	0.528	0.468	0.654	0.635	0.498	0.542	0.546	0.439
C ₇	0.546	0.474	0.515	0.489	0.507	0.537	0.506	0.595	0.469	0.517	0.503	0.411
C ₈	0.439	0.399	0.389	0.423	0.425	0.419	0.496	0.412	0.409	0.430	0.434	0.351
C ₉	0.415	0.359	0.350	0.358	0.355	0.400	0.436	0.423	0.297	0.371	0.368	0.289
C ₁₀	0.467	0.422	0.396	0.445	0.433	0.439	0.502	0.518	0.428	0.377	0.433	0.362
C ₁₁	0.530	0.459	0.448	0.454	0.476	0.488	0.570	0.532	0.427	0.466	0.417	0.412
C ₁₂	0.582	0.478	0.476	0.489	0.517	0.531	0.607	0.594	0.495	0.532	0.549	0.359

4.3 Determination of Prominence and Relation

The total-relation matrix provided the basis for measuring the position of each factor within the system. Summing a row produced the influence degree R_i , which represents the combined direct and indirect influence exerted by factor C_i . Summing a column yielded the received-influence degree C_i , indicating the total influence received from the other factors.

The prominence value $R_i + C_i$ captures the overall extent to which a factor participates in the system of relationships. A high value may arise because the factor strongly affects other elements, because it is strongly affected by them, or because both conditions are present. The relation value $R_i - C_i$ distinguishes between net drivers and net receivers. Positive values identify the cause group, while negative values indicate the effect group.

Teacher AI literacy (C_6) illustrates the interpretation of these indicators. Its influence degree was 6.422, and its received-influence degree was 5.692. The two values produced a prominence score of 12.114 and a positive relation score of 0.730. Teacher AI literacy was therefore both highly connected and causally influential.

A different pattern appeared for interdisciplinary teaching (C_8). Its influence degree was 5.025, whereas its received-influence degree reached 6.411. Although the prominence score remained relatively high at 11.436, the relation value was -1.386 . Interdisciplinary teaching was accordingly identified as a highly connected effect factor rather than an upstream driver.

The results for all twelve factors are summarized in Table 5.

Table 5
Prominence and Relation Values of the Factors

Code	Factor	R_i	C_i	$R_i + C_i$	Rank	$R_i - C_i$
C ₁	AI education in schools	5.636	5.970	11.607	3	-0.334
C ₂	Critical reasoning and thinking	5.386	5.245	10.631	10	0.140
C ₃	Digital, media and information literacies	5.249	5.242	10.491	11	0.008
C ₄	Generic skills development	5.729	5.409	11.138	7	0.320
C ₅	Teacher curriculum leadership	6.008	5.465	11.473	4	0.542
C ₆	Teacher AI literacy	6.422	5.692	12.114	2	0.730
C ₇	Teacher facilitating skills	6.068	6.510	12.578	1	-0.442
C ₈	Interdisciplinary teaching	5.025	6.411	11.436	5	-1.386
C ₉	Assessment approaches	4.421	5.243	9.664	12	-0.822
C ₁₀	Dimensions of assessment	5.223	5.640	10.862	8	-0.417
C ₁₁	Effective work with evidence	5.679	5.711	11.390	6	-0.032
C ₁₂	Administrative attitude toward GenAI	6.209	4.517	10.726	9	1.692

4.4 Analysis of the SF-DEMATEL Results

4.4.1 Prominence analysis

Prominence indicates the extent to which a factor is embedded in the overall network of influence. Teacher facilitating skills (C_7) occupied the most central position, with a prominence value of 12.578. Teacher AI literacy (C_6) followed at 12.114, while AI education in schools (C_1) ranked third at 11.607. The leading positions of these factors point to the close connection between teacher competence, classroom facilitation, and the wider development of AI education in schools.

Teacher curriculum leadership (C_5) ranked fourth, with a prominence value of 11.473. Its position suggests that teachers' involvement in curriculum planning is closely linked to changes occurring elsewhere in the system. Interdisciplinary teaching (C_8) ranked fifth at 11.436, demonstrating that GenAI-related change may extend beyond individual subjects and reshape the connections among different areas of learning.

Effective work with evidence (C_{11}) occupied sixth place, followed by generic skills development (C_4) and dimensions of assessment (C_{10}). Administrative attitude toward GenAI (C_{12}) ranked ninth. The remaining positions were held by critical reasoning and thinking (C_2), digital, media and information literacies (C_3), and assessment approaches (C_9).

The complete prominence order was $C_7, C_6, C_1, C_5, C_8, C_{11}, C_4, C_{10}, C_{12}, C_2, C_3$, and C_9 .

Assessment approaches (C_9) received the lowest prominence score. This position should not be interpreted as evidence that assessment is unimportant. Within the influence structure identified by the six experts, C_9 was simply less extensively connected with the remaining factors than the higher-ranked elements.

4.4.2 Cause–Effect analysis

Six factors formed the cause group: critical reasoning and thinking (C_2), digital, media and information literacies (C_3), generic skills development (C_4), teacher curriculum leadership (C_5), teacher AI literacy (C_6), and administrative attitude toward GenAI (C_{12}).

Administrative attitude toward GenAI (C_{12}) recorded the highest positive relation value of 1.692. Its influence degree reached 6.209, compared with a received-influence degree of 4.517. The substantial difference between these values identifies administrative attitude as the strongest upstream driver. Decisions concerning school policy, resource allocation, institutional support, and acceptable uses of GenAI may shape a broad range of subsequent educational practices.

Teacher AI literacy (C_6) recorded the second-highest positive relation value of 0.730 and the second-highest prominence score. This combination distinguishes it from a peripheral cause factor. Teachers' knowledge of how GenAI operates, what its outputs can and cannot provide, and how it may be used responsibly in instruction can influence curriculum design, classroom facilitation, interdisciplinary activities, and assessment.

Teacher curriculum leadership (C_5) also held a notable causal position, with a relation value of 0.542. Curriculum leadership enables teachers to connect emerging technological opportunities with learning objectives, subject content, and classroom conditions. Generic skills development (C_4) followed with a positive value of 0.320.

Critical reasoning and thinking (C_2) had a smaller positive relation value of 0.140. Digital, media and information literacies (C_3) produced a value of only 0.008. Although the sign of the latter result placed C_3 in the cause group, its influence and received-influence degrees were almost balanced. Its causal role should consequently be interpreted as weak rather than decisive.

The effect group comprised AI education in schools (C_1), teacher facilitating skills (C_7), interdisciplinary teaching (C_8), assessment approaches (C_9), dimensions of assessment (C_{10}), and effective work with evidence (C_{11}).

Interdisciplinary teaching (C_8) recorded the most negative relation value at -1.386 , indicating the strongest net receiving role in the model. Developing interdisciplinary teaching may require prior progress in administrative support, teacher AI literacy, curriculum leadership, and the cultivation of relevant student capabilities.

Assessment approaches (C_9) had the second-lowest relation value of -0.822 . Its location in the effect group suggests that assessment reform is more likely to emerge in response to changes in teaching practice, curriculum expectations, learning activities, and school policy.

Teacher facilitating skills (C_7) combined the highest prominence score with a negative relation value. It therefore represents a central outcome rather than a dominant initiating factor. The effectiveness with which teachers guide inquiry, discussion, collaboration, and responsible technology use appears to depend on several conditions elsewhere in the system.

Effective work with evidence (C_{11}) had a relation value of -0.032 . Its influence and received-influence degrees were nearly equal. C_{11} was classified as an effect factor according to the sign of the result, though its position was close to neutral.

4.4.3 Identification of the key factors

Prominence and relation reveal complementary aspects of the results. A factor with high prominence occupies a central position in the network, while a positive relation value indicates that it exerts more influence than it receives.

Teacher AI literacy (C_6) combined a high prominence rank with a strong positive relation value. It may therefore be regarded as the principal central cause factor. Improvements in teacher AI literacy are likely to extend beyond individual tool use and affect curriculum decisions, classroom facilitation, interdisciplinary practice, and assessment design.

Administrative attitude toward GenAI (C_{12}) was the strongest net cause, despite ranking ninth in prominence. This pattern is consistent with an upstream governance factor whose influence reaches several parts of the system, while the factor itself remains comparatively less dependent on changes elsewhere.

Teacher curriculum leadership (C_5) ranked fourth in prominence and third among the positive relation values. Its dual position indicates that curriculum leadership is both closely connected to the system and capable of initiating change. Involvement by teachers in curriculum decisions can help convert school-level policy and professional knowledge into feasible classroom practices.

Teacher facilitating skills (C_7) emerged as the most central effect factor. AI education in schools (C_1) and interdisciplinary teaching (C_8) also represented important system outcomes. Taken together, the findings suggest that administrative commitment, teacher AI literacy, and curriculum leadership establish the conditions under which changes in teaching and learning are more likely to occur.

5. Research Conclusions and Suggestions

5.1 Research Conclusions

This study used an adapted SF-DEMATEL procedure to examine twelve factors associated with GenAI-induced changes in school education. Judgments from six teachers were aggregated using the SWAM operator and converted into real-valued scores before the DEMATEL analysis. The resulting prominence and relation values describe the influence structure identified from these teachers' assessments.

Teacher facilitating skills (C_7), teacher AI literacy (C_6), and AI education in schools (C_1) achieved the highest prominence values. Their positions show that changes in classroom facilitation, teachers' professional understanding of AI, and school-level AI education are closely connected with the wider

factor system. Teacher curriculum leadership (C_5) and interdisciplinary teaching (C_8) also formed part of the system's highly connected core.

Administrative attitude toward GenAI (C_{12}) was the strongest cause factor. Teacher AI literacy (C_6) and teacher curriculum leadership (C_5) also exerted substantial net influence. These factors constitute important starting points because changes in governance, professional competence, and curriculum leadership may spread to several areas of educational practice.

Teacher facilitating skills (C_7), interdisciplinary teaching (C_8), and assessment approaches (C_9) belonged to the effect group. Their development appears to depend on conditions established by school administration, teacher competence, curriculum organization, and related factors. Interdisciplinary teaching had the most negative relation value among the twelve factors, indicating the strongest net receiving role.

The findings portray GenAI-induced educational change as an interconnected process rather than the isolated introduction of a new technology. Institutional direction, teacher development, curriculum work, and classroom practice influence one another. Policies aimed at the upstream cause factors may therefore generate broader effects than interventions directed only at individual outcomes.

5.2 Countermeasures and Suggestions

A clear institutional position on the educational use of GenAI should be established at the school level. Since administrative attitude was identified as the strongest upstream factor, school leaders need to clarify acceptable uses, responsibilities, and boundaries. Rules concerning data protection, academic integrity, tool selection, and teaching management can provide teachers and students with a more stable basis for responsible use.

Teacher AI literacy requires sustained professional development rather than one-time technical training. Relevant programs may address the principles and limitations of GenAI, the evaluation of generated information, instructional applications, ethical risks, and classroom management. Practical activities should allow teachers to examine outputs, identify inaccuracies, and redesign tasks for different student groups.

Curriculum leadership offers another point of intervention. Teachers can be involved in selecting appropriate AI-supported resources, revising learning activities, and evaluating whether technological applications contribute to curriculum objectives. Participation in these processes may prevent a gap from emerging between school policy and classroom implementation.

Support for teacher facilitating skills should focus on the changing role of teachers in AI-supported learning environments. GenAI can assist inquiry, discussion, collaboration, and knowledge integration, yet students still require guidance in evaluating evidence, questioning generated answers, and explaining their reasoning. The teacher's facilitating role remains essential to ensuring that technology use contributes to meaningful learning.

Interdisciplinary teaching needs coordinated planning across subjects. Schools may create opportunities for teachers from different disciplines to design shared projects or inquiry tasks involving GenAI. Such cooperation can help students connect knowledge from multiple fields while learning to evaluate the strengths and limitations of generated content.

Assessment practices should evolve alongside changes in teaching and learning. Process-based assessment, evidence-supported tasks, oral explanations, project work, and the evaluation of reasoning may provide a fuller account of student learning than final answers alone. These approaches are also better suited to contexts in which students can readily access generated information.

5.3 Limitations and Future Research Directions

Several limitations remain. The expert group consisted of six teachers, which limited the breadth of the evaluation. The participants represented primary, junior secondary, and senior high school education, but their judgments cannot capture every regional, institutional, or disciplinary context.

Spherical fuzzy sets enabled uncertainty in the expert evaluations to be represented more explicitly. The results nevertheless retained a subjective component because the influence relationships were derived from professional judgments. A differently constituted expert group might assess some relationships in another way.

The model also provides a static representation of the factor system. GenAI technologies, school policies, and teacher practices continue to develop, meaning that the strength and direction of particular relationships may change over time.

Future research may involve a larger and more diverse panel that includes teachers, administrators, curriculum specialists, and educational technology researchers. Combining expert evaluation with interviews, classroom observation, policy documents, or school cases could provide additional evidence for interpreting the relationships. Longitudinal studies may further examine whether the prominence and causal roles of the factors shift as the educational use of GenAI becomes more established.

Acknowledgement

This research was not funded by any grant.

Conflicts of Interest

The author declares no conflicts of interest.

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