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Risk Governance of Algorithmic Recommendation in Education for Fostering a Strong Sense of Community for the Chinese Nation: A Conceptual Analysis in Chinese Higher Education

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Abstract

Algorithmic recommendation increasingly shapes how educational platforms organize learning resources, distribute attention, and mediate students' encounters with knowledge, values, and cultural narratives. This article offers a conceptual analysis of algorithmic recommendation in education for fostering a strong sense of community for the Chinese nation in Chinese higher education. It develops the concept of educational visibility mediation to explain how recommendation systems shape what educational content becomes visible, what is repeatedly encountered, and how content is interpreted. Unlike general accounts of algorithmic curation or information filtering, this concept foregrounds the pedagogical conditions through which algorithmic systems influence meaning-making and identity formation. The article links three theoretical tensions—personalization versus common identity formation, platform visibility versus educational meaning-making, and data-driven optimization versus value-oriented formation—to five risk dimensions: subjectivity, content diversity, pedagogical mediation, experiential embodiment, and evaluative distortion. It then proposes a governance framework connecting these risks with value-oriented regulation, diversity-sensitive design, teacher-led mediation, student algorithmic literacy, online–offline integration, and multidimensional evaluation. The article contributes to AI-in-education and algorithmic governance debates by showing that recommendation systems should be assessed not only by technical performance, but also by their capacity to sustain educational purpose, cultural breadth, reflective agency, and collective belonging.

Keywords: Algorithmic Recommendation; Educational Visibility Mediation; Risk Governance; National Community Education; Identity-Oriented Education; AI Ethics in Education

1. Introduction

Educational platforms increasingly rely on algorithmic recommendation to organize learning resources, tailor content exposure, and guide students' learning trajectories. In educational recommender systems, personalization is often justified by its capacity to filter large volumes of resources and match learners with relevant content (da Silva et al., 2023). Research on artificial intelligence in higher education has also examined applications such as learner profiling, prediction, assessment, adaptive systems, personalization, and intelligent tutoring (Zawacki-Richter et al., 2019). These developments indicate that algorithmic recommendation is no longer a peripheral technical function. It has become part of the infrastructure through which educational knowledge, attention, and learning opportunities are organized.

The educational significance of algorithmic recommendation cannot be assessed only through efficiency, accuracy, or personalization. Ethical research on AI in education has cautioned that good intentions alone do not ensure ethical outcomes, particularly when fairness, transparency, bias, agency, and inclusion are involved (Holmes et al., 2022). Studies of algorithmic bias further show that educational algorithms may reproduce or amplify inequalities when their assumptions, data sources, or deployment contexts are insufficiently examined (Baker and Hawn, 2022). These concerns become more complex when recommendation systems are used not simply to support learning performance, but to mediate students' exposure to values, histories, cultural meanings, and forms of collective belonging.

A clearer research gap emerges at the intersection of three bodies of literature. First, AI-in-education research has focused largely on personalization, learning optimization, prediction, and adaptive support. Second, AI ethics and algorithmic governance studies have emphasized privacy, fairness, transparency, accountability, explainability, and bias (Mittelstadt et al., 2016; Milano et al., 2020) Third, Chinese scholarship on education for fostering a strong sense of community for the Chinese nation has mainly examined conceptual foundations, curriculum integration, pedagogical pathways, teacher roles, and institutional mechanisms. Less attention has been paid to how algorithmic recommendation may reorganize educational visibility in identity-oriented and value-oriented education.

Critical algorithm studies provide a useful basis for addressing this gap. Algorithms do not merely process information; they participate in classifying, ranking, filtering, and structuring social experience (Beer, 2017; Kitchin, 2017). In educational contexts, this means that recommendation systems influence which contents students repeatedly encounter, what becomes easy to access, what remains peripheral, and how particular forms of knowledge appear meaningful. For this reason, algorithmic recommendation should be examined not only as a tool for personalized resource matching, but also as a mechanism that shapes the conditions under which educational encounters are organized.

The issue is especially significant in Chinese higher education. Education for fostering a strong sense of community for the Chinese nation—hereafter referred to as national community education—is a historically, institutionally, and culturally situated educational practice. It is connected with ideological and political education, national identity formation, ethnic unity,

cultural belonging, and the cultivation of a shared understanding of history and collective future. The concept is China-specific, but the theoretical question it raises is broader: when algorithmic recommendation enters education aimed at identity formation and value cultivation, how should its risks be conceptualized and governed?

Research on filter bubbles, exposure diversity, and recommender-system ethics suggests that personalization may narrow users' informational horizons when relevance is defined mainly through similarity, previous behavior, or engagement signals (Bozdag and van den Hoven, 2015; Helberger et al., 2018; Areeb et al., 2023). In national community education, this is not only a problem of content quantity. It also concerns educational sequencing, cultural breadth, teacher-guided interpretation, and students' reflective engagement. A system may recommend more content while still failing to provide the range, structure, and context needed for meaningful identity formation.

Recent national policy has emphasized strengthening education for fostering a strong sense of community for the Chinese nation within the broader construction of a strong education system (Central Committee of the Communist Party of China and State Council, 2025). This policy context makes Chinese higher education a valuable site for conceptual analysis. The purpose of this article is not to treat China as an isolated case, nor to present a policy explanation for international readers. Rather, it uses the Chinese higher education context to examine a wider educational technology problem: recommendation systems increasingly mediate not only access to learning resources, but also the visibility, repetition, and interpretation of value-laden educational content.

This article develops the concept of educational visibility mediation to capture this process. The concept differs from general accounts of algorithmic curation and information filtering because it focuses not only on how content is selected or filtered, but also on how recommendation systems shape pedagogical sequencing, teacher mediation, student interpretation, and identity formation. It also differs from broader visibility governance by foregrounding educational purpose: what becomes visible matters because it affects what students can understand, compare, question, and internalize within a structured educational process.

The article presents a conceptual analysis rather than an empirical evaluation. It draws on interdisciplinary literature on AI in education, algorithmic ethics, recommender systems, learning analytics, and Chinese scholarship on national community education. The framework is developed through a conceptual synthesis of two analytical lines. The first concerns algorithmic mechanisms, including prediction, ranking, filtering, engagement optimization, feedback loops, and datafication. The second concerns the educational process of national community education, including agency, content, pedagogy, experience, and evaluation. Their intersection provides the basis for identifying five risk dimensions: subjectivity, content diversity, pedagogical mediation, experiential embodiment, and evaluative distortion.

The argument proceeds in five steps. Section 2 clarifies national community education as a form of identity-oriented and value-oriented education in Chinese higher education. Section 3 defines educational visibility mediation and distinguishes it from related concepts. Section 4

identifies three theoretical tensions generated by algorithmic recommendation: personalization versus common identity formation, platform visibility versus educational meaning-making, and data-driven optimization versus value-oriented formation. Section 5 explains how these tensions generate five risk dimensions. Section 6 develops a governance framework that links each risk dimension to governance principles, responsible actors, and practical measures. The discussion then clarifies the contribution, boundary conditions, and future research agenda.

The article makes three contributions. First, it reframes algorithmic recommendation as educational visibility mediation, shifting attention from personalized delivery to the organization of value-laden educational encounters. Second, it clarifies the conceptual pathway from algorithmic mechanisms to theoretical tensions, risk dimensions, and governance principles. Third, it develops a risk-governance framework for algorithmic recommendation in national community education. By doing so, the article contributes to international debates on AI in education and algorithmic governance while remaining grounded in the specific educational mission of Chinese higher education.

2. Conceptualizing National Community Education

National community education (NCE) refers in this article to education for fostering a strong sense of community for the Chinese nation. It is a China-specific form of identity-oriented and value-oriented education, situated within the historical, institutional, and cultural context of Chinese higher education. Rather than treating identity formation as a purely cognitive process, NCE connects knowledge, emotion, value reflection, and responsible action. Its educational purpose is to help students understand shared history, cultural diversity, national unity, and a common future within the broader development of Chinese society.

Chinese scholarship has emphasized that NCE is closely related to ideological and political education, but it should not be reduced to a single course, slogan, or policy requirement. She and Liu (2026) argue that education and publicity for fostering a strong sense of community for the Chinese nation have become important for the disciplinary development of ideological and political education. In university settings, this means that NCE is not simply an additional topic inserted into the curriculum. It functions as a cross-cutting educational orientation that connects curriculum design, campus culture, teacher mediation, student experience, and institutional governance.

This conceptualization also helps make NCE intelligible to international readers. Zhang and Fagan (2016) show that ideological and political education in mainland Chinese universities shapes students' civic perceptions and participation. Yuan and Li (2019) further examine the relationships among ethnic identity, national identity, and perceived social mobility among students in China. These studies suggest that identity formation in Chinese higher education involves both personal development and collective belonging. NCE can therefore be understood as a form of identity-oriented education, while retaining its specific meaning within China's historical and institutional context.

Curriculum is one of the main channels through which NCE is organized. Course content, teaching materials, and learning activities provide students with structured access to historical narratives, cultural resources, and social values. Li and Li (2019) emphasize curriculum mechanisms for fostering national community consciousness in higher education. Fan and Zhang (2020) also draw attention to the use and optimization of textbooks and teaching materials in national community education. These studies indicate that NCE depends not only on the presence of relevant content, but also on how that content is selected, sequenced, interpreted, and connected to students' understanding.

Teachers play a central role in this process. They do more than transmit information. They interpret complex materials, guide discussion, connect curriculum with students' lived experience, and help students move from knowing to understanding, identification, and action. Li (2020) highlights the challenges and optimization mechanisms related to teachers' roles in national community education. From this perspective, teacher mediation is not supplementary. It is part of the educational structure through which content becomes meaningful.

NCE also requires institutional coordination. It is implemented through courses, co-curricular activities, campus culture, student affairs, public communication, and practical education. Ren and Li (2020) argue from a systems perspective that fostering national community awareness among university students requires coordinated educational mechanisms. This system-level view is important because NCE cannot be achieved through isolated content delivery. It depends on the alignment of curriculum, institutional resources, teacher participation, student experience, and evaluation.

These features clarify why algorithmic recommendation raises a distinctive problem for NCE. If NCE depends on agency, content, pedagogy, experience, and evaluation, then digital recommendation systems may influence each of these educational conditions. Intelligent algorithms may support NCE by improving resource aggregation, expanding audience reach, and enhancing the precision of content delivery, as Ding and Cheng (2023) suggest. Yet the same systems may also change which materials become visible, how often they are repeated, and whether they are interpreted within a pedagogically meaningful sequence. For this reason, the next section examines algorithmic recommendation as a mechanism of educational visibility mediation.

3. Algorithmic Recommendation as Educational Visibility Mediation

Algorithmic recommendation is often described as a technical process for matching users with relevant resources. In education, however, recommendation systems do more than improve access to content. They influence which materials become visible, how often students encounter them, and under what interpretive conditions these materials are understood. This article conceptualizes this process as educational visibility mediation. The term refers to the process through which algorithmic systems shape the visibility, repetition, and interpretation of educational content in students' digital learning environments.

This concept needs to be distinguished from related terms. Algorithmic curation usually refers to how platforms select, rank, and present content to users. Information filtering emphasizes how systems remove, prioritize, or personalize information according to user profiles or behavioral traces. Visibility governance focuses more broadly on how institutions, platforms, and technical systems regulate what becomes visible or invisible. Educational visibility mediation overlaps with these concepts, but it has a more specific focus. It asks how algorithmic recommendation shapes the pedagogical conditions under which educational content is encountered, sequenced, interpreted, and connected to identity formation. Its concern is therefore not only what content appears on a platform, but how that visibility affects educational meaning-making.

Educational visibility mediation operates through three related mechanisms. The first is visibility allocation: recommendation systems influence which content becomes accessible, salient, or prominent. Materials placed at the top of an interface, pushed through recommendation labels, or linked to trending lists are more likely to enter students' attention, while other materials remain peripheral. The second is visibility repetition: algorithms repeatedly present certain materials through feedback loops based on clicks, viewing time, completion behavior, search history, or interaction frequency. Repetition can normalize particular narratives, themes, or representations. The third is visibility interpretation: recommendation systems affect the context in which students encounter content. A historical narrative, cultural symbol, or policy-related text may have different educational meanings when it appears in a structured course, a teacher-guided discussion, a short-video feed, or a platform-generated recommendation sequence.

Critical algorithm studies help explain why these mechanisms matter. Algorithms participate in classifying, ranking, filtering, and organizing social experience (Beer, 2017; Kitchin, 2017). Recommender-system ethics similarly shows that recommendation technologies raise ethical issues because they mediate autonomy, preference formation, and exposure to information (Milano et al., 2020). In educational contexts, these concerns become pedagogical. A technically accurate system may successfully predict what students are likely to click, but it may not identify what students need to encounter for deeper historical understanding, cultural breadth, or reflective judgment.

National community education makes this distinction especially important. Its educational purpose is not limited to increasing content exposure. It requires structured encounters with shared history, cultural diversity, social responsibility, and collective belonging. If recommendation systems organize content mainly through similarity, popularity, or engagement, students may receive abundant materials while still lacking coherent educational sequencing. For example, a student who watches short videos related to ethnic culture may be recommended more visually attractive materials about festivals, clothing, food, or tourism. Such content can increase interest, but it may leave less visible more complex materials on historical interaction, social integration, institutional development, or shared national narratives. This example is not empirical evidence; it is a conceptual illustration of how visibility allocation and repetition can produce content abundance without educational depth.

Educational visibility mediation also clarifies why teachers and curricula remain central. In a structured course, teachers can connect particular materials to broader concepts, clarify historical

background, compare sources, and guide students from exposure to understanding. A recommendation sequence may instead organize materials according to similarity, popularity, or predicted engagement. The issue is not simply whether students see enough content, but whether recommended content is placed within an educational sequence that supports interpretation and reflection.

Chinese scholarship has recognized that intelligent algorithms can support national community education by aggregating information, expanding audience reach, and improving precision in content delivery (Ding and Cheng, 2023). The concept of educational visibility mediation adds a further layer to this discussion. It shows that algorithmic recommendation should be evaluated not only by relevance, efficiency, or reach, but also by its capacity to support educational sequencing, teacher mediation, cultural breadth, and reflective identity formation. This concept provides the analytical bridge from algorithmic mechanisms to the theoretical tensions discussed in the next section.

4. Theoretical Tensions

Educational visibility mediation helps explain why algorithmic recommendation creates tensions in national community education. These tensions do not arise simply because digital technology enters education. They emerge when recommendation systems reorganize the ways in which students encounter knowledge, values, and collective narratives. Three tensions are central to the argument: personalization versus common identity formation, platform visibility versus educational meaning-making, and data-driven optimization versus value-oriented formation.

The first tension concerns personalization and common identity formation. Recommendation systems usually begin with behavioral traces, such as clicks, viewing time, search history, completion records, comments, and interaction patterns. These traces allow platforms to infer preferences and recommend materials likely to sustain engagement. In many learning contexts, personalization can reduce information overload and improve access to relevant resources. National community education, however, cannot depend only on learners' existing preferences. Students also need to encounter unfamiliar histories, diverse cultural materials, and broader narratives that connect personal identity with collective belonging. Research on filter bubbles and exposure diversity has shown that recommendation systems may restrict informational horizons when relevance is defined mainly through similarity or past behavior (Bozdag and van den Hoven, 2015; Helberger et al., 2018; Areeb et al., 2023). In NCE, this tension points to a risk that students may receive personally engaging content while missing materials that are educationally necessary for common identity formation.

The second tension lies between platform visibility and educational meaning-making. Platform visibility is produced through ranking, recommendation labels, trending lists, similarity models, and feedback loops. These mechanisms make some content prominent and leave other content peripheral. Educational meaning-making follows a different logic. It depends on curriculum sequencing, teacher interpretation, classroom discussion, comparison of perspectives, and students' reflective engagement. A historical story, cultural symbol, or policy-related text does

not become educationally meaningful simply because it is frequently recommended. It becomes meaningful when placed within a pedagogical sequence and connected to broader questions of history, culture, identity, and responsibility. Critical research on the datafication of teaching in higher education has shown that digital infrastructures can reshape educational relations when pedagogical processes are reorganized through data systems (Williamson, Bayne, and Shay, 2020). This tension helps explain why platform visibility may support educational attention while still weakening pedagogical mediation if it is detached from curricular interpretation.

The third tension concerns data-driven optimization and value-oriented formation. Recommendation systems commonly optimize measurable indicators, including clicks, dwell time, completion rates, likes, shares, comments, or repeated visits. These indicators can help platforms identify attention and participation, but they do not necessarily capture understanding, reflection, identification, or value internalization. A student may spend substantial time watching recommended content without developing deeper historical understanding. Another student may interact less frequently online but participate more meaningfully in classroom dialogue, field learning, or collective cultural activities. Learning analytics research has long emphasized that educational data require careful interpretation because they raise ethical questions about responsibility, student agency, and institutional action (Slade and Prinsloo, 2013). For NCE, the key issue is not whether data are useful, but whether the chosen indicators correspond to the educational goal. Metrics may inform educational judgment; they should not define educational formation.

These three tensions provide the conceptual basis for the five risk dimensions developed in the next section. Personalization versus common identity formation helps explain subjectivity risk and content diversity risk. Platform visibility versus educational meaning-making helps explain pedagogical mediation risk and experiential embodiment risk. Data-driven optimization versus value-oriented formation helps explain evaluative distortion risk. The purpose of this section is therefore not to present another risk framework, but to clarify how algorithmic mechanisms generate tensions that later become risks when they enter the educational process of NCE.

Table 1. Three Theoretical Tensions

Algorithmic mechanism	Educational tension	Risk implication
Preference prediction and similarity-based recommendation	Personalization versus common identity formation	Students may encounter content that confirms existing interests while missing unfamiliar but educationally necessary materials.
Ranking, filtering, trending lists, and recommendation labels	Platform visibility versus educational meaning-making	Highly visible content may not support systematic interpretation or curricular sequencing.
Measurement of clicks, viewing time, completion, and interaction frequency	Data-driven optimization versus value-oriented formation	Platform metrics may inform participation but cannot define identity formation, emotional belonging, or value internalization.

5. From Theoretical Tensions to Five Risk Dimensions

The previous section identified three tensions generated by algorithmic recommendation in national community education. This section develops those tensions into five risk dimensions. The five dimensions are not proposed as a loose list. They are derived from the intersection between algorithmic mechanisms and the educational process of NCE. On the algorithmic side, recommendation systems operate through prediction, ranking, filtering, repetition, feedback loops, and datafication. On the educational side, NCE depends on agency, content, pedagogy, experience, and evaluation. When these two lines intersect, risks emerge around who guides education, what content students encounter, how meaning is mediated, where educational experience takes place, and how educational outcomes are judged.

This derivation also explains the relationship between the three theoretical tensions and the five risk dimensions. Personalization versus common identity formation mainly produces subjectivity risk and content diversity risk. Platform visibility versus educational meaning-making mainly produces pedagogical mediation risk and experiential embodiment risk. Data-driven optimization versus value-oriented formation mainly produces evaluative distortion risk. Table 2 summarizes this conceptual pathway.

Table 2. Conceptual Pathway from Tensions to Risk Dimensions

Theoretical tension	Educational process affected	Risk dimension	Core risk question
Personalization versus common identity formation	Agency	Subjectivity risk	Who guides students' encounters with identity-related content: educators, students, or platform algorithms?
Personalization versus common identity formation	Content	Content diversity risk	Do recommendation systems expose students to sufficiently broad and balanced historical, cultural, and social materials?
Platform visibility versus educational meaning-making	Pedagogy	Pedagogical mediation risk	Is recommended content integrated into curricular sequencing, teacher explanation, and reflective learning?
Platform visibility versus educational meaning-making	Experience	Experiential embodiment risk	Does digital exposure remain connected to embodied, social, and participatory educational experience?
Data-driven optimization versus value-oriented formation	Evaluation	Evaluative distortion risk	Do platform metrics correspond to educational goals such as understanding, belonging, and reflection?

5.1. Subjectivity Risk

Subjectivity risk concerns the allocation of educational agency. In NCE, teachers and students are not passive channels through which content passes. Teachers interpret historical narratives, organize classroom dialogue, connect materials to lived experience, and guide students from

knowledge exposure toward reflection and identification. Students also need space to compare sources, question representations, and form reflective judgments. Recommendation systems may disturb this structure when algorithmic sequencing begins to guide students' encounters before teachers or students recognize those encounters as educational choices.

This risk is linked to concerns about agency in AI-in-education ethics and algorithmic bias. Educational algorithms may shape learning opportunities unevenly when their assumptions and deployment contexts are not carefully examined (Baker and Hawn, 2022). In NCE, the issue is not only unequal access, but the possible displacement of educational judgment. A student may receive a sequence of recommended videos on national history because the platform predicts emotional engagement. The student may watch actively but reflect passively if the materials are detached from teacher explanation, comparative inquiry, or curricular purpose. Subjectivity risk therefore concerns both teacher agency and student reflective agency.

5.2. Content Diversity Risk

Content diversity risk arises when personalization narrows students' exposure to educationally significant materials. Recommender systems often infer relevance through similarity, previous behavior, popularity, or engagement signals. These mechanisms may increase the amount of content students receive, but abundance does not guarantee breadth. Research on filter bubbles and exposure diversity has shown that recommendation systems can restrict informational horizons when they repeatedly present similar materials or reinforce existing preferences (Bozdag and van den Hoven, 2015; Helberger et al., 2018; Areeb et al., 2023).

For NCE, content diversity is an educational condition rather than a decorative addition. Students need to understand the unity of the Chinese nation through diverse histories, cultures, regions, and forms of interethnic interaction. A platform may repeatedly recommend short videos about festivals, costumes, food, or scenic landscapes because these materials attract attention. Such content may stimulate interest, yet it may leave less visible materials on historical interaction, social integration, institutional development, and shared national narratives. The risk is therefore not a shortage of content, but a narrowing of educationally necessary exposure.

5.3. Pedagogical Mediation Risk

Pedagogical mediation risk concerns how educational meaning is organized. It differs from subjectivity risk in emphasis. Subjectivity risk asks who holds educational agency; pedagogical mediation risk asks how content becomes meaningful within an educational process. Recommended materials may be attractive, accurate, or abundant, but they do not automatically form a coherent learning sequence. Meaning depends on curricular structure, teacher explanation, classroom dialogue, comparison of perspectives, and opportunities for reflection.

This risk is intensified when recommendation systems organize materials according to similarity, popularity, or predicted engagement rather than pedagogical sequence. Research on the datafication of teaching in higher education warns that digital infrastructures can reshape educational relations when pedagogical processes are reorganized through data systems (Williamson, Bayne, and Shay, 2020). In NCE, a series of short videos, news fragments, or cultural stories may remain lively but educationally thin if students are not guided to understand

historical context, conceptual relationships, or value implications. Pedagogical mediation risk therefore concerns the loss of educational sequencing and interpretive depth.

5.4. Experiential Embodiment Risk

Experiential embodiment risk concerns where and how identity-related education takes place. NCE involves more than exposure to digital materials. It also depends on dialogue, collective activities, campus culture, field learning, community interaction, and embodied participation. Digital recommendation may expand access to resources, but it cannot fully replace social and experiential forms of learning.

The risk emerges when platform-mediated exposure becomes detached from embodied educational practice. A student may frequently encounter recommended content about cultural diversity or national history, yet rarely participate in seminar discussions, campus activities, field visits, or collaborative projects that allow such content to become lived experience. In this case, algorithmic recommendation increases visibility but weakens experiential depth. The issue is not whether digital platforms should be used, but whether digital encounters remain connected to social, spatial, and participatory forms of education.

5.5. Evaluative Distortion Risk

Evaluative distortion risk arises when platform metrics become substitutes for educational judgment. Recommendation systems and learning platforms commonly record clicks, viewing time, completion rates, likes, comments, shares, or repeated visits. These indicators can provide useful information about attention and participation. Yet learning analytics research has emphasized that educational data require careful interpretation because they raise questions about responsibility, agency, institutional action, privacy, and meaning (Slade and Prinsloo, 2013).

For NCE, the central question is correspondence: do the chosen metrics correspond to the educational goals being pursued? A dashboard may show high engagement with recommended materials, but high engagement does not necessarily indicate historical understanding, cultural breadth, emotional belonging, or reflective judgment. Conversely, meaningful learning may occur through slower activities such as classroom discussion, reflective writing, field observation, or collective practice, which are less easily captured by platform metrics. Evaluative distortion risk therefore appears when measurable engagement is mistaken for educational formation.

Together, the five risk dimensions clarify how algorithmic recommendation may affect the educational process of NCE. Subjectivity risk concerns who guides learning; content diversity risk concerns what students encounter; pedagogical mediation risk concerns how meaning is organized; experiential embodiment risk concerns where education is experienced; and evaluative distortion risk concerns how outcomes are judged. This structure prepares the governance framework developed in the next section.

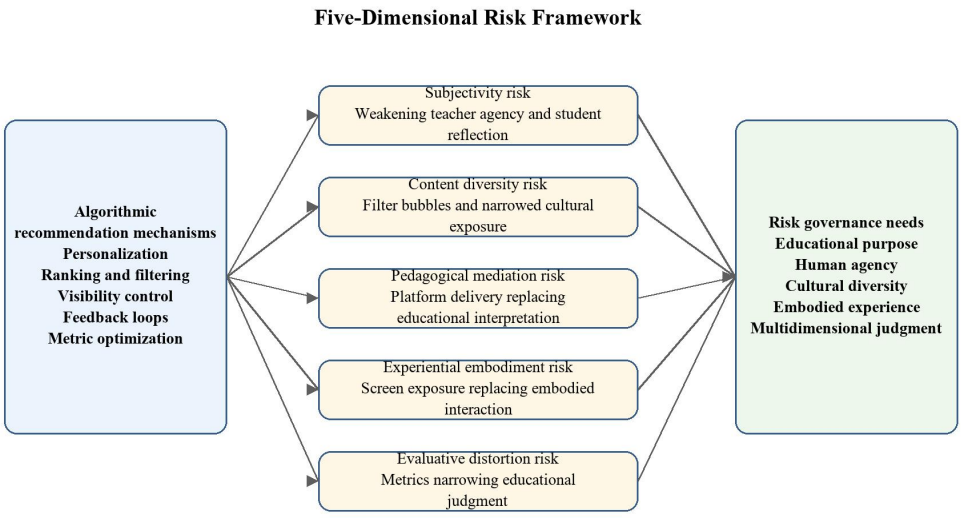

Figure 1. A five-dimensional risk framework of algorithmic recommendation in identity-oriented education

6. Risk Governance Framework

The previous section identified five risk dimensions generated when algorithmic recommendation enters the educational process of NCE. This section develops a governance framework that responds to those risks. Risk governance refers here to the institutional, pedagogical, and technical processes through which universities identify, prevent, mitigate, and evaluate the risks associated with algorithmic recommendation. In NCE, governance cannot be reduced to technical optimization. Platform governance always involves both technical design and social responsibility, especially when automated systems shape the visibility of cultural, historical, and value-laden content (Gorwa, Binns, and Katzenbach, 2020). The purpose of governance is therefore to align recommendation systems with educational aims rather than allow platform-centered optimization to define educational value.

The governance framework follows the logic developed in the previous sections. The three theoretical tensions identified in Section 4 generate the five risk dimensions developed in Section 5. Each risk dimension then requires a corresponding governance principle and a set of practical measures. The five principles proposed here are value-oriented algorithmic regulation, diversity-sensitive recommendation design, teacher-led pedagogical mediation with student algorithmic literacy, online–offline educational integration, and multidimensional educational evaluation.

Value-oriented algorithmic regulation responds primarily to subjectivity risk. It requires universities to define the educational purposes, content boundaries, and review procedures that guide the use of recommendation systems in NCE. This does not mean replacing educational dialogue with one-way messaging. Rather, it means that algorithmic recommendation should operate within a clearly articulated educational framework. Universities and curriculum committees can establish review mechanisms for recommended content, clarify which types of materials are appropriate for NCE, and create correction procedures when algorithmic outputs

conflict with curricular aims. Platform providers should also be required to explain the basic logic of recommendation rules used in educational settings, especially when those rules affect the visibility of value-laden content.

Diversity-sensitive recommendation design responds to content diversity risk. In NCE, diversity is not only a matter of including more content. It concerns whether students encounter a sufficiently broad range of historical narratives, cultural materials, regional experiences, and forms of interethnic interaction. Platform designers and curriculum teams can introduce diversity requirements into recommendation pools, such as balancing materials across regions, historical periods, ethnic cultures, genres, and levels of complexity. They can also set mechanisms to reduce excessive repetition of similar content and introduce unfamiliar but educationally necessary materials. A recommendation system designed for NCE should not only ask what a student is likely to click; it should also ask what a student needs to encounter in order to understand unity through diversity.

Teacher-led pedagogical mediation responds to pedagogical mediation risk. Algorithms may recommend resources, but teachers organize educational meaning. Teachers can connect recommended materials with course concepts, historical background, classroom discussion, comparative reading, and reflective writing. This principle also includes student algorithmic literacy. Students should learn how recommendation systems shape what they see, why certain materials are repeatedly suggested, and how to compare platform-generated content with curricular resources. The learner-centered orientation of AI in education is relevant here because students should not remain passive recipients of algorithmic decisions; they should develop the capacity to work critically with AI-supported learning environments (Ouyang and Jiao, 2021). Teacher mediation and student algorithmic literacy together help transform recommended content from platform exposure into educational interpretation.

Online–offline educational integration responds to experiential embodiment risk. Digital recommendation can expand access to resources, but NCE also depends on embodied interaction, campus culture, field learning, group discussion, and collective practice. Universities can connect recommended digital materials with offline seminars, cultural activities, visits to museums or community sites, student projects, and dialogue-based learning. A recommended video or article should not be treated as a complete educational experience. Its educational value increases when students discuss it, compare it with other sources, relate it to lived experience, and connect it with social participation. In this sense, online recommendation should become an entry point for educational experience rather than a substitute for it.

Multidimensional educational evaluation responds to evaluative distortion risk. Platform metrics such as clicks, viewing time, completion rates, likes, and comments can provide useful information about attention and participation. Yet these indicators cannot fully represent historical understanding, cultural breadth, emotional belonging, reflective judgment, or value internalization. Ethical research on learning analytics has emphasized that educational data require careful attention to interpretation, privacy, consent, responsibility, and institutional action (Pardo and Siemens, 2014) . Universities should therefore combine platform data with teacher observation,

classroom dialogue, reflective writing, student feedback, portfolio assessment, and qualitative evaluation. Metrics should support educational judgment rather than replace it.

Table 3 summarizes the practical governance framework. It links each risk dimension with a governance principle, responsible actors, and operational measures. The table is not intended as a fixed administrative checklist. Rather, it clarifies how different actors can share responsibility for governing algorithmic recommendation in NCE.

Table 3. Risk Dimensions, Governance Principles, Responsible Actors, and Operational Measures

Risk dimension	Governance principle	Responsible actors	Operational measures
Subjectivity risk	Value-oriented algorithmic regulation	University administrators; curriculum committees; platform providers	Define educational aims; establish content review procedures; examine recommendation rules; create correction mechanisms for inappropriate or misleading outputs.
Content diversity risk	Diversity-sensitive recommendation design	Platform designers; curriculum teams; teaching-resource reviewers	Build diverse content pools; balance regions, historical periods, cultural themes, and media genres; reduce excessive repetition; introduce unfamiliar but educationally necessary materials.
Pedagogical mediation risk	Teacher-led mediation and student algorithmic literacy	Teachers; teaching teams; students; academic support units	Connect recommended materials with course concepts; organize comparative reading and classroom discussion; design reflective tasks; teach students how recommendation systems shape exposure.
Experiential embodiment risk	Online–offline educational integration	Universities; teachers; student affairs offices; practice bases	Link digital resources with seminars, campus culture, field visits, community interaction, group projects, and collective practice.
Evaluative distortion risk	Multidimensional educational evaluation	Teachers; quality assurance units; platform analysts; students	Combine platform metrics with reflective writing, teacher observation, classroom dialogue, portfolio assessment, qualitative feedback, and student self-reflection.

This framework treats algorithmic recommendation as governable rather than inherently harmful. Recommendation systems can support NCE when they improve resource access, broaden educational reach, and assist teachers in organizing learning materials. Their value, however, depends on whether technical systems are aligned with educational purpose, teacher agency, student reflection, content diversity, embodied experience, and meaningful evaluation. The central governance question is therefore not whether recommendation systems should be used, but how they can be made educationally accountable.

7. Discussion

The framework developed in this article contributes to AI-in-education research by shifting attention from algorithmic personalization to educational visibility mediation. Existing research often evaluates recommendation systems according to relevance, accuracy, efficiency, learner engagement, or adaptive support. These criteria remain important, but they are insufficient when recommendation systems enter identity-oriented and value-oriented education. In such contexts, the central question is not only whether a system recommends relevant content, but whether it supports the educational conditions through which students encounter, interpret, and reflect on value-laden knowledge.

The first theoretical contribution lies in reframing algorithmic recommendation as a problem of educational visibility. Recommendation systems do not simply deliver content after learners express preferences. They help organize what becomes visible, what is repeatedly encountered, and how content is positioned within students' learning environments. This reframing differs from general discussions of algorithmic curation or information filtering because it foregrounds educational purpose. A recommendation may be technically accurate and engaging while still being educationally insufficient if it weakens curricular sequencing, narrows cultural breadth, bypasses teacher mediation, or turns complex educational formation into measurable engagement.

The second contribution concerns the relationship between personalization and collective identity formation. Personalization is often treated as an educational benefit because it can reduce information overload and provide learners with materials aligned with their interests. However, identity-oriented education cannot be based only on existing preferences. Students may need to encounter unfamiliar, complex, or less immediately attractive materials in order to develop broader understanding. International scholarship on citizenship education and collective identity supports this point. Banks (2008) emphasizes that diversity and group identity remain central to citizenship education in a global age. Ashmore, Deaux, and McLaughlin-Volpe (2004) conceptualize collective identity as multidimensional, involving self-categorization, evaluation, emotional significance, and social embeddedness. Dovidio, Gaertner, and Saguy (2007) further show that common ingroup identity involves both shared belonging and the management of difference. These studies do not replace the Chinese concept of NCE, but they help clarify why identity formation cannot be reduced to content exposure or information delivery.

The third contribution is an extension of AI ethics in education. Existing AI ethics frameworks have emphasized fairness, transparency, accountability, privacy, explainability, bias, and human agency. These concerns are necessary, but they do not fully capture the ethical challenges of algorithmic recommendation in NCE. A system may be transparent, privacy-protective, and technically efficient, yet still fail to support educational sequencing, cultural breadth, teacher-guided interpretation, embodied participation, or multidimensional evaluation. Educational purpose should therefore be treated as a central ethical category. From this perspective, the ethical question is not only whether recommendation systems make fair or explainable decisions, but whether they sustain the educational conditions necessary for reflective identity formation.

This discussion also clarifies the boundary conditions of the proposed framework. The framework is designed primarily for value-oriented and identity-oriented education. It should not be directly generalized to all forms of online learning. In a mathematics practice platform, for example, recommendation may reasonably prioritize error diagnosis, adaptive sequencing, and performance improvement. In NCE, however, recommendation must be judged against broader educational goals, including historical understanding, cultural breadth, reflective judgment, emotional belonging, and responsible participation. The framework is therefore most useful in educational contexts where technologies mediate identity, values, belonging, citizenship, moral judgment, or collective responsibility.

A second boundary condition concerns institutional capacity. The governance framework proposed in this article assumes that universities retain meaningful authority over curriculum design, platform selection, content review, teacher training, and educational evaluation. If educational platforms operate as closed commercial infrastructures with limited transparency or weak institutional oversight, risk governance becomes more difficult. Value-oriented regulation, diversity-sensitive design, teacher-led mediation, online–offline integration, and multidimensional evaluation all require institutional responsibility. Without such responsibility, recommendation systems may remain governed mainly by platform incentives rather than educational purposes.

A third boundary condition concerns student agency. Students should not be understood as passive objects of algorithmic influence. They may compare sources, question recommendation patterns, seek alternative materials, and resist platform-driven attention. However, such agency does not appear automatically. It depends on algorithmic literacy, teacher guidance, and educational environments that encourage reflection. For this reason, student algorithmic literacy should be regarded as part of governance rather than as a supplementary digital skill. Students need to understand not only how to use platforms, but also how platforms use data to shape visibility, repetition, and attention.

The conceptual framework developed here also suggests a future empirical research agenda. Subjectivity risk could be examined through interviews with teachers and students, classroom observation, and analysis of how platform recommendations influence learning choices. Content diversity risk could be studied through recommendation audits that compare the themes, sources, regions, cultural representations, and difficulty levels of recommended materials. Pedagogical mediation risk could be investigated by examining how teachers integrate platform-recommended resources into curriculum design, discussion, and reflective tasks. Experiential embodiment risk could be studied by comparing students' online exposure with their participation in seminars, field learning, campus activities, and community-based projects. Evaluative distortion risk could be examined by comparing platform metrics with qualitative evidence such as reflective writing, teacher assessment, dialogue records, and student feedback.

These empirical directions would help validate, refine, or challenge the framework proposed in this article. They would also make it possible to examine whether the five risk dimensions appear differently across platforms, universities, disciplines, student groups, and teaching contexts. Such research should not simply ask whether algorithmic recommendation improves engagement. It should ask whether recommendation environments support educational purpose, broaden students'

horizons, sustain teacher agency, strengthen student reflection, and connect digital exposure with embodied educational experience.

Overall, the discussion shows that algorithmic recommendation in NCE should be neither rejected as inherently harmful nor accepted as automatically beneficial. Its educational value depends on governance. The key issue is whether universities can align technical systems with curriculum, teacher mediation, student agency, cultural diversity, embodied experience, and meaningful evaluation. In this sense, the Chinese higher education context offers more than a local case. It provides a theoretically productive setting for examining how educational technologies should be governed when they mediate identity, value, and collective belonging.

8. Conclusion

This article has developed a conceptual framework for understanding and governing algorithmic recommendation in national community education within Chinese higher education. Its central argument is that algorithmic recommendation should not be evaluated only as content delivery, personalization, or information filtering. It should also be understood as educational visibility mediation: a process through which recommendation systems shape what educational content becomes visible, what is repeatedly encountered, and how such content is interpreted within students' learning environments.

The article has shown that educational visibility mediation generates three theoretical tensions: personalization versus common identity formation, platform visibility versus educational meaning-making, and data-driven optimization versus value-oriented formation. These tensions are then translated into five risk dimensions derived from the intersection of algorithmic mechanisms and the educational process of NCE: subjectivity, content diversity, pedagogical mediation, experiential embodiment, and evaluative distortion. On this basis, the article proposes a governance framework that connects each risk dimension with corresponding governance principles, responsible actors, and operational measures.

The main implication is that algorithmic recommendation should be governed rather than rejected. Recommendation systems may support NCE by improving access to resources, expanding educational reach, and assisting teachers in organizing learning materials. Their educational value, however, depends on whether they are aligned with curricular purpose, teacher mediation, student reflection, cultural breadth, embodied experience, and multidimensional evaluation. A technically efficient recommendation system may still be educationally inadequate if it narrows students' horizons, weakens interpretive guidance, or substitutes platform metrics for educational judgment.

As a conceptual study, this article does not provide empirical evidence about a specific recommendation system, platform, university, or student group. Its contribution lies in theory-building and framework development. Future research can test and refine the proposed framework through several empirical strategies. Recommendation audits can examine whether platform outputs provide sufficient diversity in themes, regions, cultural representations, sources, and levels of complexity. Teacher and student interviews can explore how algorithmic

recommendation affects agency, interpretation, and reflective learning. Classroom observation can investigate how teachers integrate recommended materials into curricular sequencing and discussion. Comparative studies can examine differences across platforms, courses, universities, and student groups. Design-based research can further test whether diversity-sensitive recommendation, student algorithmic literacy, and multidimensional evaluation improve the educational use of recommendation systems.

By foregrounding the Chinese higher education context, this article contributes to international debates on AI in education, algorithmic governance, and identity-oriented education. National community education is a China-specific educational field, but the broader question it raises is internationally relevant: when educational technologies mediate identity, values, and collective belonging, governance must begin with educational purpose. Algorithmic systems should therefore be assessed not only by technical performance, but also by their capacity to sustain cultural breadth, teacher agency, student reflection, embodied experience, and meaningful educational formation.

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The author declares no conflict of interest.

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