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Algorithm Recommendation and the Shaping of Youth Values: Mechanisms, Risks, and Governance Pathways—An Empirical Study Based on a Survey of University Students

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Abstract: ***In the context of rapid advancements in artificial intelligence, algorithm recommendation technology has become deeply embedded in the information acquisition and cognitive construction processes of young people, emerging as a significant technological force shaping their value perceptions, identifications, and choices. This study, grounded in Social Construction of Technology (SCOT) theory and Selective Exposure Theory, constructs an analytical framework of "technological logic—influence mechanisms—governance pathways," and employs a questionnaire survey method to empirically examine the current status of algorithm recommendation's influence on youth values among 230 university students across four grade levels. The findings reveal that: (1) algorithm recommendation creates a significant "filter bubble" effect, with students generally perceiving content homogenization and limited exposure to diverse viewpoints; (2) algorithmic influences demonstrate dual effects—promoting knowledge acquisition while reinforcing cognitive biases, with notable grade-level variations; (3) the level of algorithmic literacy remains generally moderate, with insufficient critical awareness; (4) students exhibit a significant "awareness-behavior gap" in algorithmic coping strategies. The study further identifies value orientation drift, echo chamber formation, critical thinking erosion, and superficial value internalization as primary risks. Accordingly, governance pathways are proposed encompassing three dimensions: technological optimization, institutional regulation, and literacy enhancement.***

Keywords: Algorithm Recommendation, Youth Values, Filter Bubble, Dual Effects, Collaborative Governance.

1. Introduction

The rapid development of artificial intelligence has fundamentally transformed the modes of information production, dissemination, and acquisition. Algorithm recommendation technology, by collecting and analyzing users' behavioral data and constructing precise user profiles to achieve personalized content delivery, has become the core operational logic of mainstream internet platforms. According to data from the 53rd Statistical Report on Internet Development in China, as of December 2023, the number of short video users in China reached 1.053 billion, with an utilization rate of 96.4%, among whom the youth demographic constitutes a significant proportion [1]. In this context, algorithm recommendation not only determines the information content to which young people are exposed but also subtly shapes their cognitive frameworks and value orientations.

The academic community has progressively recognized that algorithm recommendation is not a value-neutral tool. Some scholars have noted that the development of algorithm recommendation technology is a value-led process, reflecting a complex interplay between technological logic and value logic [2]. Wang Junying and Wang Hongmi pointed out that algorithm recommendation creates risks including "algorithmic black boxes," "algorithmic divides," and "algorithmic illusions" that exert unidirectional shaping effects on youth values [3]. Shi Xuwen and Li Rui analyzed the risks of algorithmic recommendation on the cultivation of mainstream values among youth from three dimensions: "filter bubbles," "decentralization," and "traffic supremacy" [4]. Zeng Qanyu, drawing on cultivation theory and value rational choice theory, expounded the inherent logic of algorithmic recommendation's influence on youth value formation [5]. However, existing research exhibits three deficiencies: firstly, most studies remain at the macro-level of risk analysis, lacking in-depth exploration of the mechanisms by which algorithms act upon youth value formation; secondly, theoretical analysis predominates while empirical support remains relatively weak; thirdly, policy recommendations tend toward homogenization without differentiated designs for different demographic groups.

This study proposes three core research questions: RQ1: Through what mechanisms does algorithmic recommendation influence the formation and evolution of youth values? RQ2: What dual effects does algorithmic influence present across different demographic groups? RQ3: How can the transformation of recommendation mechanisms from "content catering" to "value-led" be achieved? The research, grounded in Social Construction of Technology (SCOT) theory and Selective Exposure Theory, constructs an analytical framework of "technological logic—influence mechanisms—governance pathways," and employs a questionnaire survey method among 230 university students across four grade levels to empirically examine the current status of algorithmic recommendation's influence on youth values. The aim is to reveal intrinsic mechanisms and propose operational governance pathways with differentiated strategies.

2. Literature Review and Theoretical Framework

2.1 Research on the Impact of Algorithmic Recommendation on Youth Values

In recent years, domestic and international scholars have explored the relationship between algorithmic recommendation and youth values from multiple perspectives. Research in the technological orientation camp argues that technical defects such as algorithmic black boxes, algorithmic divides, and algorithmic illusions exert unidirectional shaping effects on youth value formation. The algorithmic black box manifests as youth being unable to determine the authenticity of information and the intent behind its push; the algorithmic divide reflects the differentiation in algorithmic cognition and coping capabilities among different youth groups; the algorithmic illusion refers to the deviation between the simulated environment constructed by algorithms and the real world [3]. Research in the cultural orientation camp has found that under algorithmic influence, youth have formed new cultural forms such as “algorithmic collusion” and “algorithmic dependence,” which have given rise to information cocoons characterized by cultural stratification and isolation, plunging youth into emotional contradictions of instant gratification and deep anxiety [6]. Research in the governance orientation camp focuses on how to resolve algorithmic risks, forming a three-dimensional “technology-institution-literacy” response framework [7].

International research, represented by Mukhtar Ahmmad’s systematic review based on the PRISMA 2020 framework, analyzed 30 peer-reviewed studies published between 2015 and 2025, covering multiple platforms including Facebook, YouTube, Twitter/X, Instagram, TikTok, and Weibo, revealing three consistent findings: first, algorithmic systems structurally amplify ideological homogeneity; second, youth agency in algorithmic environments is constrained; third, echo chambers produce dual effects [8]. Jylhä et al. found that the “algorithmic imaginaries” of youth are characterized by constant comparison between algorithmic and non-algorithmically mediated social contexts [9].

2.2 Theoretical Foundations

Social Construction of Technology (SCOT) holds that the design, development, and application of technology are not governed purely by technological logic but are jointly shaped by the cognitive frameworks, interests, and value preferences of relevant social groups [10]. Algorithmic recommendation technology, from data collection and feature extraction to weight setting and ranking output, reflects the value judgments of designers and institutional power dynamics. Its technological logic is itself the material expression of specific value orientations.

Selective Exposure Theory posits that individuals tend to seek out information consistent with their existing beliefs while avoiding inconsistent information [11]. Algorithmic recommendation precisely captures and reinforces this preference through user profiling, filtering out heterogeneous information and leading to a solidification of cognitive structures among youth.

Cognitive Dissonance Theory suggests that when individuals face information conflicting with existing beliefs, they experience psychological discomfort and tend to avoid such information [12]. Algorithmic recommendation reduces opportunities for youth to experience cognitive dissonance through continuous “agreeable” content delivery, causing their value judgments to gradually deviate from pluralistic, objective tracks.

2.3 Analytical Framework

Based on the above theories, this study constructs an analytical framework of “technological logic—influence mechanisms—governance pathways.” Technological logic reveals the “value-loaded” nature of algorithms, the influence mechanism explains the specific pathways of algorithmic effects through a four-stage model of “cognition-selection-identification-internalization,” and governance pathways propose a three-dimensional collaborative framework of “technology-institution-literacy” to facilitate the transformation from content-catering to value-led recommendation.

3. Research Design

3.1 Questionnaire Design

This study employed a self-administered questionnaire survey with a questionnaire consisting of 45 items across eight dimensions: (1) basic information (5 items), (2) algorithmic contact and usage behavior (8 items), (3) algorithmic perception and cognition (6 items), (4) cognitive processing dimension (6 items), (5) value selection and judgment (5 items), (6) value identification and internalization (6 items), (7) value evolution and self-reflection (4 items), and (8) media literacy and critical awareness (5 items). Dimensions 4 through 8 employed a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). Items 25, 28, and 36 were reverse-scored.

The questionnaire design drew upon existing research. The algorithmic awareness section referenced Zhao Longxuan and Lin Cong’s measure of algorithmic awareness, which asked respondents to indicate “the extent to which they are aware that algorithms are being used by internet platforms to recommend entertainment, news, and advertising content” [13]. The cognitive processing dimension incorporated items from related studies on cognitive bias [14], while the media literacy dimension integrated relevant research findings [15].

3.2 Sample and Data Collection

Using stratified convenience sampling, a questionnaire survey was conducted among university students across four grade levels, yielding 230 valid responses (effective response rate: 98.3%). The sample distribution was as follows: freshmen (first-year undergraduates): 62 respondents (26.96%), sophomores: 58 respondents (25.22%), juniors: 60 respondents (26.09%), and seniors: 50 respondents (21.74%). In terms of gender: 92 males (40.0%) and 138 females (60.0%). Regarding college affiliation: 78 respondents from humanities and social sciences (33.91%), 78 from science and engineering (33.91%), 42 from economics and management (18.26%), and 32 from other disciplines (13.91%). The age range was 18 to 24 years (mean age: 20.8 years, SD=1.6).

Data analysis was conducted using SPSS 26.0 and Excel, employing descriptive statistics, frequency analysis, cross-tabulation analysis, and one-way ANOVA to examine between-group differences across grade levels.

4. Empirical Findings

4.1 Overview of Algorithm Usage Behavior and Platform Preferences

The survey reveals that algorithmic recommendation platforms have become an indispensable component of university students' daily lives. Regarding daily usage duration, 4.78% of respondents (11 students) reported using these platforms for less than 2 hours per day, 28.26% (65 students) for 2-4 hours, 44.35% (102 students) for 4-6 hours, and 22.61% (52 students) for more than 6 hours. Cumulatively, 67.0% of students use algorithmic platforms for more than 4 hours daily, indicating that these platforms have become the predominant channel for information acquisition and leisure activities among youth. Significant grade-level differences were observed ($F=8.42$, $p<.001$): upperclassmen (juniors and seniors) reported longer average usage durations ($M=4.7$ hours, $SD=1.4$) compared to underclassmen (freshmen and sophomores: $M=3.9$ hours, $SD=1.5$), reflecting progressive platform integration throughout the college experience.

In terms of platform preference, short video platforms dominate, led by Douyin (ranked first by 73.9% of respondents), followed by Xiaohongshu (48.3% ranking it second), and Bilibili (with higher usage among underclassmen at 56.5%). Cross-grade analysis reveals an interesting pattern: freshmen and sophomores demonstrate a stronger preference for content platforms emphasizing knowledge-sharing and community interaction (Bilibili and Xiaohongshu), while juniors and seniors exhibit greater reliance on short-video entertainment platforms (Douyin and Kuaishou). This suggests a potential transition from "exploratory" to "entertainment-oriented" platform usage as college education progresses.

4.2 Content Exposure Characteristics

Multiple-response analysis of content type preferences reveals a structure of concentrated yet diversified content consumption. Entertainment and humor content was selected by 91.3% of respondents (210 students), ranking first; lifestyle/fashion/beauty content by 79.1% (182 students); knowledge/science popularization by 73.0% (168 students); news information by 68.7% (158 students); and current affairs/hot topics by 63.5% (146 students). Other content categories show notable grade-level variation: upperclassmen (juniors and seniors) demonstrate significantly higher engagement with news/current affairs content compared to underclassmen ($\chi^2=12.34$, $p<.01$), suggesting that academic maturation fosters greater attention to social issues. Conversely, freshmen exhibit higher interest in entertainment/gaming content ($\chi^2=9.87$, $p<.05$), consistent with developmental patterns of information-seeking behavior.

4.3 Algorithmic Perception and Awareness: A Generational Divide

Awareness of algorithmic recommendation mechanisms is nearly universal among respondents, with 90.4% (208 students) indicating they "have always known" that platforms recommend content based on browsing behavior, while an additional 6.1% (14 students) only recently became aware of this mechanism. This near-universal awareness suggests that algorithm recognition has become foundational digital literacy among contemporary university students. However, self-rated understanding of algorithmic operational logic reveals a more nuanced picture: only 28.7% (66 students) reported a clear understanding of "how algorithms analyze my behaviors and preferences," 43.0% (99 students) indicated moderate understanding, and 28.3% (65 students) reported limited understanding. Significant grade-level differences emerged ($F=5.73$, $p<.01$): seniors demonstrated the highest understanding levels ($M=3.52$ on 5-point scale, $SD=0.82$), followed by juniors ($M=3.28$, $SD=0.91$), sophomores ($M=3.05$, $SD=0.89$), and freshmen ($M=2.84$, $SD=0.94$). This gradient suggests that algorithmic literacy develops progressively through experiential learning and academic exposure.

Regarding perception of algorithmic influence, a substantial majority (87.0%) of respondents agreed that "the longer I use the platforms, the better the algorithms seem to understand me," with no significant grade-level differences. This finding indicates that all student cohorts experience high algorithmic precision. However, perceptions of algorithmic intentionality — "I sometimes feel algorithms are deliberately guiding me toward certain topics or viewpoints"—showed moderate agreement (mean score 3.42, $SD=0.95$), with 61.3% (141 students) expressing agreement. Senior students exhibited the highest scores ($M=3.62$, $SD=0.88$), suggesting that prolonged exposure heightens awareness of algorithmic agency.

4.4 The Filter Bubble Effect and Cognitive Narrowing

One of the most robust findings concerns the pervasiveness of the "filter bubble" effect. When asked whether they "feel algorithmically recommended content is sometimes overly homogenized, lacking novelty," 85.2% (196 students) expressed agreement (choosing "agree" or "strongly agree"), with only 6.5% (15 students) disagreeing. This perception was relatively uniform across grade levels ($F=1.24$, $p>.05$), suggesting that the homogenization effect is a universal experience independent of usage duration or demographic factors.

Regarding restricted information exposure, 52.2% (120 students) agreed that algorithmic recommendations "allow me to see mostly what interests me, rarely exposing me to different viewpoints," with freshmen exhibiting the highest agreement rate (58.1%) and seniors the lowest (44.0%), indicating that prolonged academic experience may somewhat moderate cognitive narrowing ($F=3.56$, $p<.05$). Correspondingly, 43.0% (99 students) of respondents "rarely encounter viewpoints completely opposite to their own through algorithmic recommendation platforms," with upperclassmen reporting slightly more frequent exposure to divergent views (juniors 38.3%, seniors 40.0%) compared to underclassmen (freshmen 48.4%, sophomores 44.8%). This grade-level gradient suggests that cognitive development and educational experiences partially counteract algorithmic homogenization.

In terms of cognitive consequences, 48.7% (112 students) agreed that algorithmically recommended content "reinforces my existing views on certain issues," with the highest agreement among juniors (56.7%) and lowest among freshmen (40.3%). Additionally, 46.5% (107 students) perceived that platform content "makes the world seem more extreme or simplified than it actually is," with no significant grade-level variation. These findings collectively indicate that while the filter bubble effect is universally perceived, its intensity and manifestation vary across developmental stages, with academic progression potentially offering protective mechanisms against some aspects of algorithmic cognitive narrowing.

4.5 Algorithmic Influence on Value Selection and Judgment

The survey reveals that algorithmic recommendation exerts a measurable but subtle influence on youth value judgments. When asked whether "algorithmic recommendations have influenced my judgments and views on social issues," 48.3% (111 students) expressed agreement, 39.1% (90 students) remained neutral, and 12.6% (29 students) disagreed. This pattern suggests that while many students acknowledge algorithmic influence, a substantial proportion remain either uncertain or disinclined to attribute value changes to algorithmic factors. Grade-level differences were significant ($\chi^2=11.27$, $p<.05$), with seniors demonstrating the lowest agreement rate (40.0%) and freshmen the highest (54.8%). This inverse relationship suggests that critical thinking development and curriculum exposure may reduce vulnerability to algorithmic influence.

Regarding content evaluation, 51.7% (119 students) agreed that "some views in algorithmically recommended content are attractive but may lack objectivity," with upperclassmen demonstrating sharper critical awareness (juniors 58.3%, seniors 56.0%) compared to underclassmen (freshmen 43.5%, sophomores 48.3%). This grade-level divergence ($F=4.31$, $p<.01$) provides compelling evidence for the developmental trajectory of critical evaluation skills.

However, concerning active resistance, only 41.7% (96 students) reported that they "actively search for and follow perspectives from different angles to compensate for algorithmic cognitive bias" (the reverse-scored item), while 51.3% (118 students) remained neutral and 7.0% (16 students) indicated passive acceptance. This pattern reveals a significant "awareness-behavior gap": students recognize algorithmic risks but fail to translate this awareness into effective coping behavior, a phenomenon observed across all grade levels without significant variation ($F=1.86$, $p>.05$). This gap represents a critical intervention opportunity.

4.6 Value Identification and Internalization: Surface vs. Deep Processing

The data reveal that value identification with algorithmically recommended content operates primarily at a superficial level. A majority of 53.0% (122 students) expressed neutral responses regarding agreement with mainstream values conveyed through algorithmic content, while 37.8% (87 students) expressed agreement and 9.1% (21 students) expressed disagreement. This neutral majority suggests that youth maintain a cautious, non-committal stance toward algorithmically mediated values, without embracing or rejecting them definitively.

Regarding value change, 27.8% (64 students) acknowledged that they "change their attitudes toward certain matters due to algorithmically recommended content," while a majority of 56.1% (129 students) remained neutral. This distribution indicates that while overt value change is not widely reported, subtle attitudinal shifts may be occurring beneath the surface of conscious recognition. The limited grade-level variation ($F=1.52$, $p>.05$) suggests that this pattern is developmental stable.

More concerning is the finding regarding value stability: only 13.5% (31 students) agreed that "even when faced with opposing information, I still adhere to viewpoints formed under algorithmic influence," with 65.2% (150 students) neutral and 21.3% (49 students) disagreeing. This suggests that algorithmically influenced views have not yet solidified into stable value commitments. Similarly, regarding behavioral internalization, only 27.0% (62 students) reported that "in real life, I act in ways advocated by algorithmically recommended content," while 45.2% (104 students) disagreed or strongly disagreed. These findings collectively indicate a significant disconnect between cognitive exposure and value internalization: algorithmic content shapes what youth know and think about, but has not deeply penetrated their belief systems or behavioral patterns.

4.7 Algorithmic Literacy and Critical Awareness

Assessment of algorithmic literacy dimensions reveals moderate but insufficient levels of critical engagement. While 51.3% (118 students) agreed that they "actively judge the authenticity and credibility of algorithmically recommended content," a substantial 41.7% (96 students) remained neutral, and 7.0% (16 students) did not engage in such critical evaluation. Grade-level comparisons reveal that seniors demonstrated the highest critical evaluation engagement (60.0%), followed by juniors (55.0%), sophomores (48.3%), and freshmen (43.5%), indicating a clear developmental progression ($F=5.82$, $p<.01$).

Regarding active behavioral adjustment to influence algorithm outcomes, only 43.9% (101 students) reported consciously adjusting their browsing behaviors (such as clicking "not interested," deliberately searching specific topics, or using multiple accounts). A substantial portion (51.3%, 118 students) remained neutral, indicating awareness of this possibility but uncertain implementation. This pattern aligns with the awareness-behavior gap identified earlier.

Belief in algorithmic literacy as a protective factor was relatively high: 59.1% (136 students) agreed that "improving algorithmic literacy can effectively resist negative effects of algorithmic recommendations," with no significant grade-level differences. Similarly, 61.7% (142 students) expressed willingness to "systematically learn how to identify and respond to the value impacts of algorithmic recommendations." This strong endorsement of algorithmic education, combined with moderate current literacy levels, suggests high potential receptivity for educational interventions.

4.8 Self-Perceived Value Evolution

In terms of self-perceived value changes, 37.4% (86 students) agreed that "compared to before using these platforms, my values have changed," while 50.4% (116 students) remained neutral, and 12.2% (28 students) disagreed. The relatively high neutral rate suggests that students either perceive value change as gradual and difficult to assess, or that they are not fully conscious of algorithmic effects.

Consistent with earlier findings, 53.9% (124 students) reported that they "reflect on whether algorithmically recommended content is influencing my value judgments," with seniors showing the highest reflection rates (62.0%) and freshmen the lowest (46.8%). This reflective capacity likely serves as a critical protective factor against undue algorithmic influence.

Regarding positive perceptions, 54.8% (126 students) agreed that algorithmic recommendations "have helped broaden my horizons and enrich my value cognition," acknowledging the positive dimensions of algorithmic exposure. At the same time, 40.9% (94 students) agreed that algorithmic recommendations "have made my value judgments more narrow and rigid," with juniors reporting the highest agreement (46.7%) and freshmen the lowest (35.5%). This dual perception confirms the "double-edged sword" nature of algorithmic influence, with both positive knowledge-broadening and negative cognitive-narrowing effects operating simultaneously.

5. Analysis of Risks and Underlying Causes

5.1 Primary Risks Identified

5.1.1 Value Orientation Drift and Mainstream Value Erosion

While the survey indicates that overt value change remains limited, the finding that 48.3% of students acknowledge algorithmic influence on social issue judgments—with freshmen demonstrating the highest vulnerability (54.8%) — signals a concerning trend. Freshmen, in their initial adaptation to the digital ecosystem, appear least equipped to resist algorithmic value shaping. The high agreement rates regarding content homogenization (85.2%) and reinforcement of existing views (48.7%) suggest that algorithm recommendation's "alternative agenda-setting" function is gradually weakening youth's capacity for independent, multi-perspective value evaluation [16].

5.1.2 Echo Chamber Formation and Impaired Intergroup Dialogue

The finding that 52.2% of students agree algorithms rarely expose them to different viewpoints, with the rate reaching 58.1% among freshmen, confirms the formation of "echo chambers" in youth information environments. Within these structurally isolated digital spaces, homogeneous information undergoes continuous reinforcement, while heterogeneous perspectives are systematically filtered out [17]. This process has two concerning implications: first, it inhibits the development of perspective-taking and empathetic understanding; second, potential value conflicts among differently "echo-chambered" groups may threaten social cohesion [18].

5.1.3 Critical Thinking Erosion and Declining Information Discernment

Although 51.3% of students report actively judging content authenticity, this leaves nearly half either passively consuming or uncertain about evaluation. The grade-level progression in critical evaluation (from 43.5% among freshmen to 60.0% among seniors) suggests that without intentional educational intervention, algorithmic influence may impair cognitive development during the critical freshman and sophomore years. The finding that only 41.7% actively compensate for algorithmic bias through diverse information seeking—with no significant grade-level improvement—suggests a persistent cognitive habit that may become entrenched.

5.1.4 Superficial Value Internalization and the Knowledge-Action Disconnect

The consistent finding that value internalization operates at the surface level—with over 70% not reporting behavioral changes consistent with algorithmically mediated values — indicates that algorithmic recommendation primarily shapes what youth know and think about, without penetrating belief systems or behavioral patterns. This "knowledge-action disconnect" [19] reflects the inherent superficiality of algorithm-facilitated information exposure: youth consume content without engaging in the reflective, sustained cognitive processing necessary for deep value internalization.

5.2 Causal Analysis

5.2.1 Technological Predicament: Structural Limitations of Algorithmic Architecture

First, "user profiling" technology, designed to maximize engagement, inevitably reinforces cognitive biases through a continuous positive feedback loop. Second, algorithm optimization objectives center on user engagement metrics (click-through rates, completion rates, interaction rates), structurally conflicting with mainstream value guidance goals [20]. Third, current algorithmic recommendation systems lack explicit value-discrimination mechanisms, making them incapable of identifying content inconsistent with mainstream values. Low-quality and even harmful content reaches youth through algorithmic amplification, particularly affecting first-year students.

5.2.2 Capital Logic: Platform Incentives Prioritizing Traffic Maximization

Commercial platforms treat algorithmic recommendation primarily as a traffic-maximization tool. Under capital logic, algorithms are incentivized to recommend high-emotional-arousal content, prioritizing immediate attention metrics over content value and social responsibility. This capital-driven logic maintains youth in cycles of "sensory stimulation—

superficial satisfaction—continued consumption," sacrificing critical thinking and value reflection for instant gratification [3]. This effect is particularly pronounced among freshmen (54.8% acknowledging algorithmic influence), suggesting that entering university — a period of identity exploration — coincides with maximum algorithmic vulnerability.

5.2.3 Institutional Lag: Incomplete Regulatory Frameworks

Although China has established foundational regulations, implementation gaps persist. First, the technical complexity of algorithms exceeds regulatory capabilities. Second, heterogeneous recommendation mechanisms across platforms render uniform regulation difficult. Third, current governance emphasizes ex-post punishment rather than establishing a full-cycle governance system spanning algorithm design, operational supervision, and impact evaluation [21]. Institutional deficiencies provide room for algorithmic risks to persist unaddressed.

5.2.4 Individual Agency Deficits: Insufficient Critical Awareness and Coping Skills

The survey reveals significant individual-level vulnerabilities. First, algorithmic systems operate largely as "black boxes" for most users, with only 28.7% reporting clear understanding of operational mechanisms. Second, youth remain trapped between "cannot live without" and "cannot resist" these platforms. Third, systematic algorithmic literacy education is absent from most curricula. The grade-level differences observed—with seniors demonstrating higher critical awareness and lower algorithmic vulnerability—suggest that educational interventions could be effective, yet the current absence of targeted instruction means students must develop these skills incidentally.

6. Governance Pathways and Recommendations

6.1 Technological Optimization: Value-Led Algorithm Design

Promoting algorithmic recommendation mechanisms from "content catering" to "value-led" requires source-level technical governance. First, embed mainstream value parameters in algorithm design, incorporating "value similarity index" as a recommendation optimization objective rather than solely pursuing user engagement [4]. Second, implement tiered recommendation strategies: for content with substantial ideological or value implications, impose stricter review and balancing mechanisms to prevent single-perspective dominance [5]. Third, inject random "information diversity factors" into recommendation algorithms, ensuring a threshold proportion of heterogeneous information exposure to disrupt "information cocoon" formation. Fourth, establish comprehensive recommendation evaluation systems that incorporate content quality, value orientation, and information diversity indicators alongside traffic metrics.

6.2 Institutional Regulation: Multi-Stakeholder Algorithmic Governance

First, establish a multi-stakeholder governance structure of "government regulation—platform responsibility—user rights." Government should refine algorithmic recommendation regulatory details, establish mandatory algorithm impact assessment mechanisms, and mandate regular platform risk reporting [21]. Second, platforms should strengthen algorithmic value-oriented review responsibilities, utilizing "human-machine collaboration" for content review before algorithmic push, and exploring "mainstream value weighted recommendation" optimization algorithms [20]. Third, protect user algorithmic rights including algorithmic explanation rights (users' right to understand why content is recommended), recommendation opt-out rights, and information diversity rights. Fourth, encourage independent third-party organizations to conduct periodic algorithmic evaluations.

6.3 Literacy Enhancement: Cultivating Developmental Algorithmic Education

First, systematically integrate algorithmic literacy into higher education curricula with developmental progression. Given the finding that freshmen demonstrate the highest algorithmic vulnerability (54.8% acknowledging influence) and lowest critical evaluation (43.5%), early intervention is imperative. Incorporate algorithmic recommendation mechanisms, risk identification, and coping strategies into first-year orientation and information technology courses [7]. Second, develop practical coping resources tailored to different grade levels. Third, strengthen critical thinking education across all years, with particular emphasis on forming critical evaluation habits during the first two years. Fourth, encourage proactive information consumption planning, reducing passive algorithmic consumption and increasing active information seeking. The grade-level differences observed (seniors demonstrating significantly higher critical awareness) provide empirical support for the efficacy of educational interventions.

6.4 Value Guidance: Enhancing Mainstream Value Communication Effectiveness

First, optimize mainstream media algorithmic recommendation strategies. Mainstream media should study algorithmic mechanisms to enhance mainstream value communication effectiveness through data-driven content delivery [7]. Second, innovate mainstream discourse expression, adapting to youth language habits and aesthetic preferences while reducing preaching tones. Third, actively construct "positive energy" algorithmic ecosystems — collaborating with platforms to produce and promote high-quality, value-rich content in forms appealing to youth (short videos, interactive content). Fourth, establish comprehensive algorithmic recommendation quality evaluation and feedback mechanisms to promptly identify and correct low-quality content and value deviations.

7. Conclusion

Based on survey data from 230 university students spanning all four grade levels, this study empirically examines the current status of algorithmic recommendation's influence on youth values. The findings indicate that algorithmic recommendation has become a dominant force in youth information acquisition, yet its influence manifests dual characteristics: it broadens cognitive horizons while simultaneously creating “filter bubbles” (85.2% perceiving homogenization) and “echo chambers” (52.2% perceiving limited exposure to different views); it facilitates information access while potentially causing value drift and critical thinking erosion. Grade-level variations reveal that freshmen exhibit the highest vulnerability to algorithmic influence (54.8% acknowledging value influence) while seniors demonstrate the greatest critical awareness (60.0% actively evaluating content), suggesting that developmental progression and educational exposure offer protective effects.

This study’s theoretical contributions include: (1) empirically confirming the “filter bubble” and “echo chamber” effects across all four grade levels; (2) revealing the dual nature of algorithmic influence and quantifying positive knowledge-broadening effects (54.8% reporting value cognition enrichment) alongside negative cognitive-narrowing effects (40.9% reporting rigidity); (3) identifying the “awareness-behavior gap” (high recognition of algorithmic risks with low active coping) as a critical intervention point; (4) documenting grade-level developmental trajectories that suggest targeted, progressive educational interventions.

However, this study has limitations. The sample was drawn from a limited geographic region and may not fully represent all university student populations. Future research should extend coverage to multiple regions and institutional types, enhance sample diversity across socioeconomic backgrounds, and incorporate longitudinal designs to trace value development trajectories. Additionally, mixed-methods approaches combining quantitative surveys with qualitative in-depth interviews would further elucidate the mechanisms of algorithmic influence on youth values.

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