IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

IMPACT OF ALGORITHMIC RECOMMENDATION SYSTEMS ON ACADEMIC PERFORMANCE, STRESS, AND DECISION-MAKING AMONG COLLEGE STUDENTS IN KALYAN–DOMBIVLI

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Abstract: This study investigates the impact of algorithmic recommendation systems on academic performance, perceived stress, and decision-making quality among college students in the Kalyan–Dombivli region. With the growing use of digital platforms such as social media, video streaming services, and educational applications, recommendation algorithms increasingly shape students' content consumption patterns and daily behaviour. A quantitative research approach was adopted, and primary data were collected through a structured questionnaire administered to undergraduate and postgraduate students. The study introduces Distraction Load as a mediating factor and Algorithmic Literacy as a moderating factor to better understand behavioural outcomes. The findings indicate that higher reliance on recommendation systems leads to increased distraction and stress, which negatively affects academic performance and decision-making. However, students with higher algorithmic awareness demonstrate improved control over digital consumption and reduced negative effects. The study also proposes a transparent and feedback-driven recommendation framework that prioritises student well-being alongside personalisation. The results highlight the need for ethical algorithm design and improved digital literacy to support healthier academic environments.

Index Terms — Algorithmic Recommendation Systems, Academic Performance, Perceived Stress, Decision-Making Quality, Distraction Load, Algorithmic Literacy.

I. INTRODUCTION

Content curation driven by machine-learned algorithms has become the dominant mode of information delivery on contemporary digital platforms. Services such as YouTube, Instagram, Netflix, EdTech portals, and AI-powered assistants deploy sophisticated behavioural models to predict and surface content that maximises user engagement. While this personalisation streamlines information discovery, it also creates an environment in which attention is controlled and user autonomy is subtly constrained [1]. For college students—who are simultaneously managing demanding academic programmes and intensive digital consumption—these dynamics carry heightened consequences.

Within the Indian higher-education landscape, smartphone penetration and affordable data connectivity have driven a near-universal shift toward platform-mediated learning and socialisation. The Kalyan–Dombivli corridor, situated within the Mumbai Metropolitan Region, concentrates a large population of undergraduate and postgraduate learners whose digital engagement patterns remain underexplored. Prior research has addressed stress prediction through machine learning [2], decision-making in recommender environments [3], personalised course recommendation [4], and systematic reviews of educational recommender design [5].

However, these studies examine outcomes in isolation, focus largely on Western cohorts, and do not address the combined effects on academic performance, stress, and decision quality within a single unified model.

The present study addresses this gap by investigating how algorithmic recommendation systems simultaneously affect three interdependent student outcomes—academic performance, perceived stress, and decision-making quality—within the Kalyan–Dombivli region. It operationalises Distraction Load as a mediating mechanism linking algorithm usage to those outcomes, and Algorithmic Literacy as a moderator that may buffer or amplify the relationship. The research also introduces and evaluates a student-centric recommendation prototype that embeds transparency and well-being criteria into the recommendation pipeline, offering evidence-based guidance for educators, platform designers, and policy makers.

II. METHODOLOGY

A. Research Design and Data Source

A cross-sectional, quantitative descriptive design was employed to capture the range of algorithm-related experiences across the target population at a single point in time. Primary data were collected through a structured online questionnaire administered via Google Forms, consisting of closed-ended questions anchored on a five-point Likert scale. The survey covered six domains: demographic background, platform usage frequency, perceived academic impact, stress indicators, decision-making tendencies, and self-assessed algorithmic literacy.

B. Population, Sampling, and Ethical Protocol

The target population comprised full-time undergraduate and postgraduate students enrolled in colleges within Kalyan and Dombivli. Convenience sampling was used to recruit participants who maintained active accounts on at least one algorithmically driven platform. Participation was entirely voluntary; respondent anonymity was assured, and no personally identifiable information was retained beyond the study period. All data were analysed in aggregated form for academic purposes only.

C. Analytical Framework and Variables

Data were processed and visualised using Python-based data analysis tools. Descriptive statistics—including frequency counts and percentage distributions—characterised the sample profile. Graphical analyses explored bivariate associations, while the variable structure shown in Table 1 formalised the role of each construct within the conceptual model.

Table 1. Conceptual Variable Framework

Variable Type	Variable Name	Role in Study
Independent	Recommendation System Reliance	Primary predictor variable
Dependent (1)	Academic Performance	Key outcome measure
Dependent (2)	Perceived Stress Level	Key outcome measure
Dependent (3)	Decision-Making Quality	Key outcome measure
Mediating	Distraction Load	Intermediate pathway variable
Moderating	Algorithmic Literacy	Boundary condition variable

III. MODELING AND ANALYSIS

A. Conceptual Model

The study adopts a mediated-moderation conceptual framework. Recommendation System Reliance (RSR) is proposed as the independent variable with direct and indirect—via Distraction Load (DL)—effects on three dependent constructs: Academic Performance (AP), Perceived Stress (PS), and Decision-Making Quality (DMQ). Algorithmic Literacy (AL) moderates the RSR → DL pathway, such that students with higher AL are expected to manage distraction more effectively and demonstrate better academic and decision outcomes despite comparable levels of platform usage.

B. Usage Frequency Distribution

Survey responses on usage frequency revealed a left-skewed distribution, with the largest group of respondents (approximately 77) selecting usage level 4 on the five-point scale, followed by level 3 (approximately 65) and level 5 (approximately 45). Fewer than fifteen respondents indicated infrequent platform engagement, confirming that high algorithmic reliance is common within the sampled population.

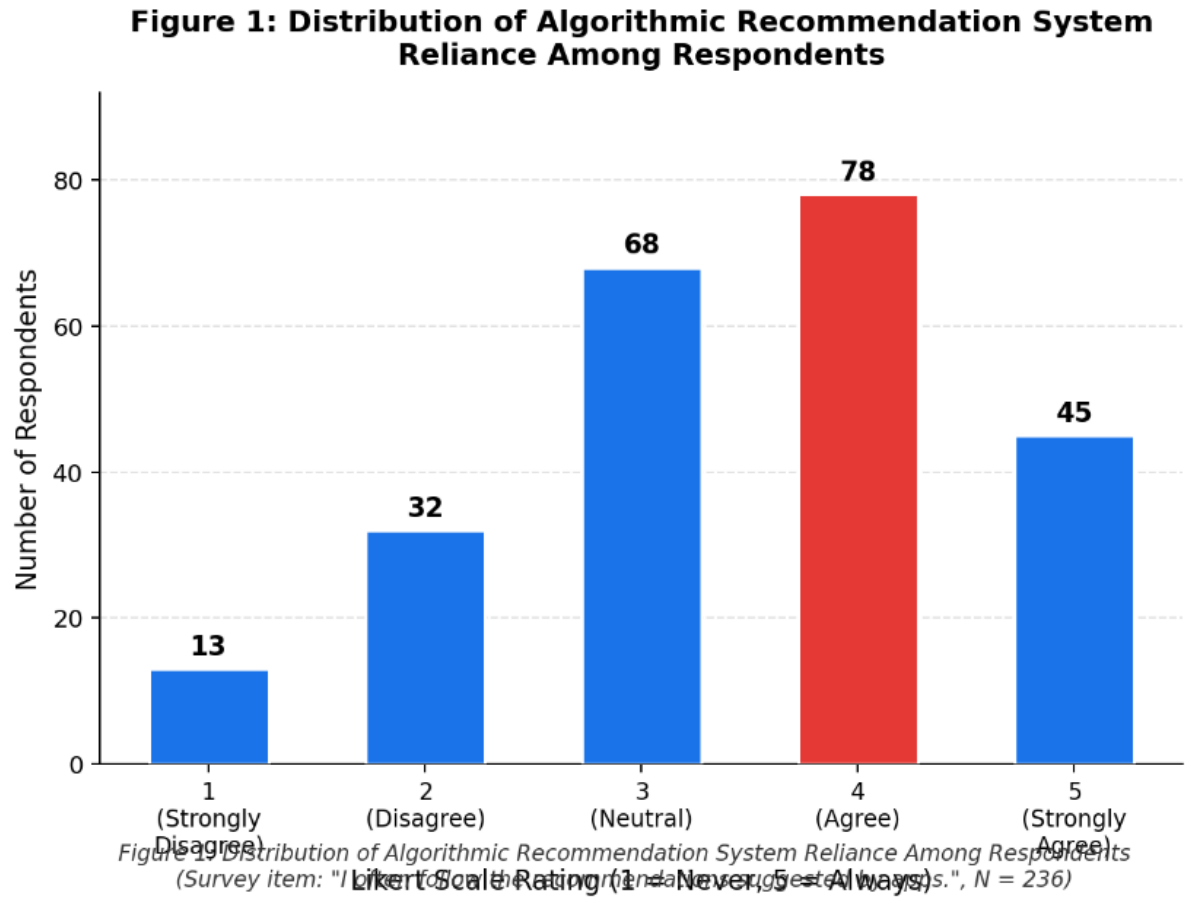

Figure 1: Distribution of Algorithmic Recommendation System Reliance Among Respondents (Survey item: "I often follow the recommendations suggested by...", N = 236)

Fig. 1: Distribution of Algorithmic Recommendation System Reliance Among Respondents

C. Academic Performance Impact

Responses to the academic-impact item concentrated at agreement levels 3 and 4 (each attracting roughly 70–80 responses), indicating that a clear majority perceive recommendation-driven content as harmful to their academic focus and output. This pattern is consistent with prior research linking prolonged media multitasking to reduced attention and lower grade outcomes [6].

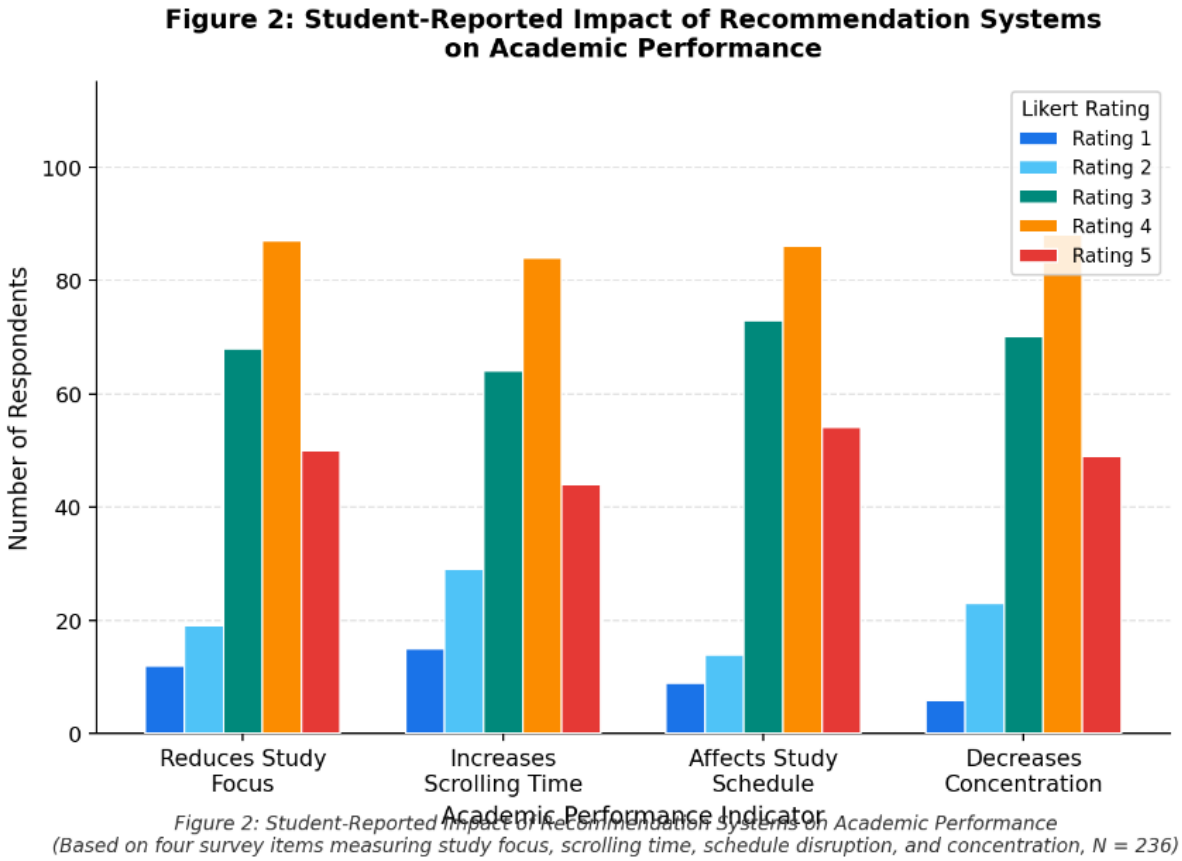

Fig. 2: Student-Reported Impact of Recommendation Systems on Academic Performance

D. Perceived Stress and Distraction Load

The stress distribution was markedly skewed toward negative outcomes. High Stress was reported by 40.3% of respondents, Moderate Stress by 26.3%, and Very High Stress by 17.8%, collectively representing over 84% of the sample. Only 15.7% reported low or negligible stress related to algorithmic exposure. Distraction analysis revealed a nonlinear increase: distraction scores rose steeply from usage level 2 to a peak at level 4 (approximately 87 respondents), before declining slightly at level 5, possibly reflecting habituated users developing partial coping strategies.

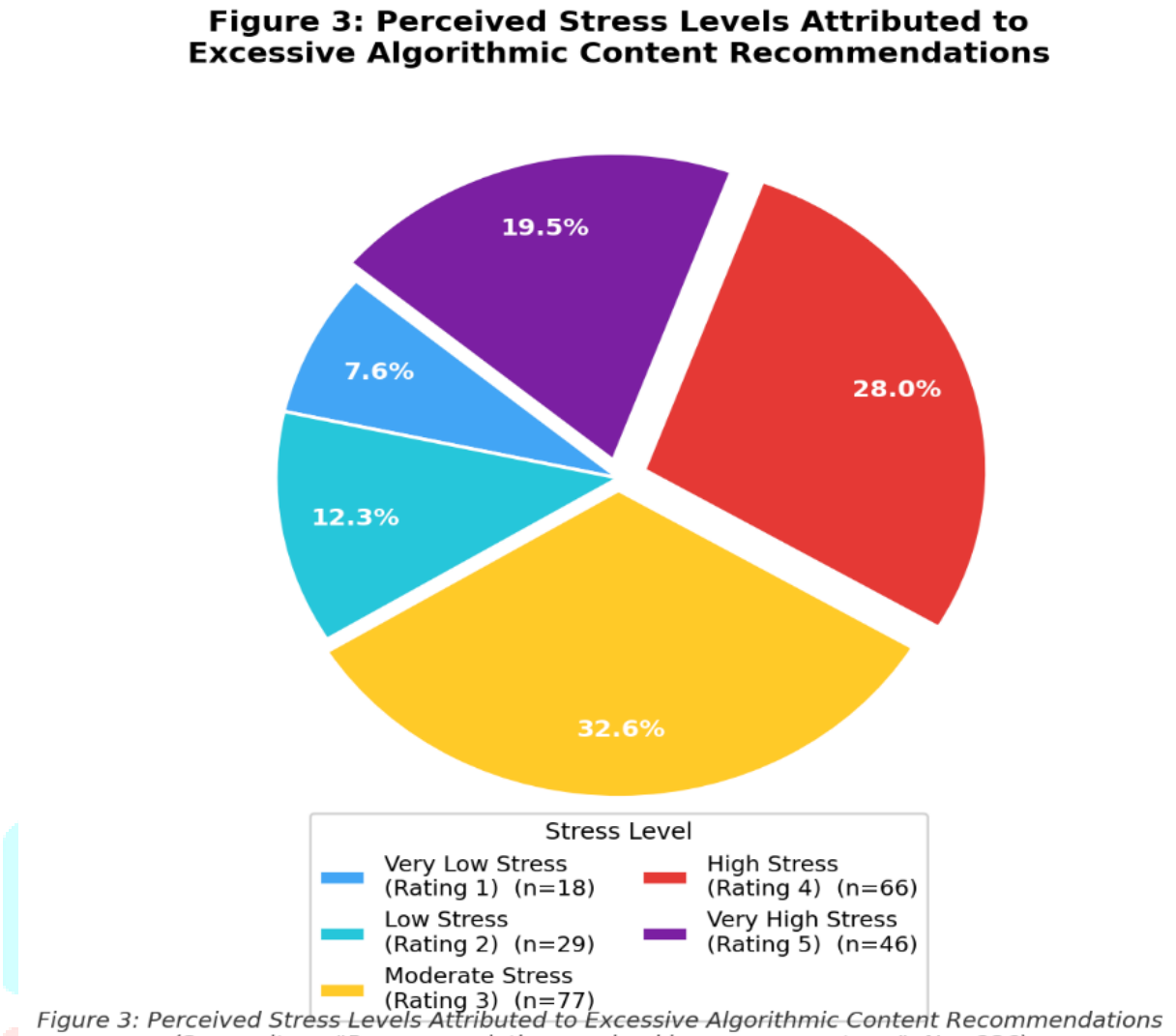

Figure 3: Perceived Stress Levels Attributed to Excessive Algorithmic Content Recommendations (Survey item: "Recommendation overload increases my stress", N = 236)

Fig. 3: Perceived Stress Levels Attributed to Excessive Algorithmic Content Recommendations

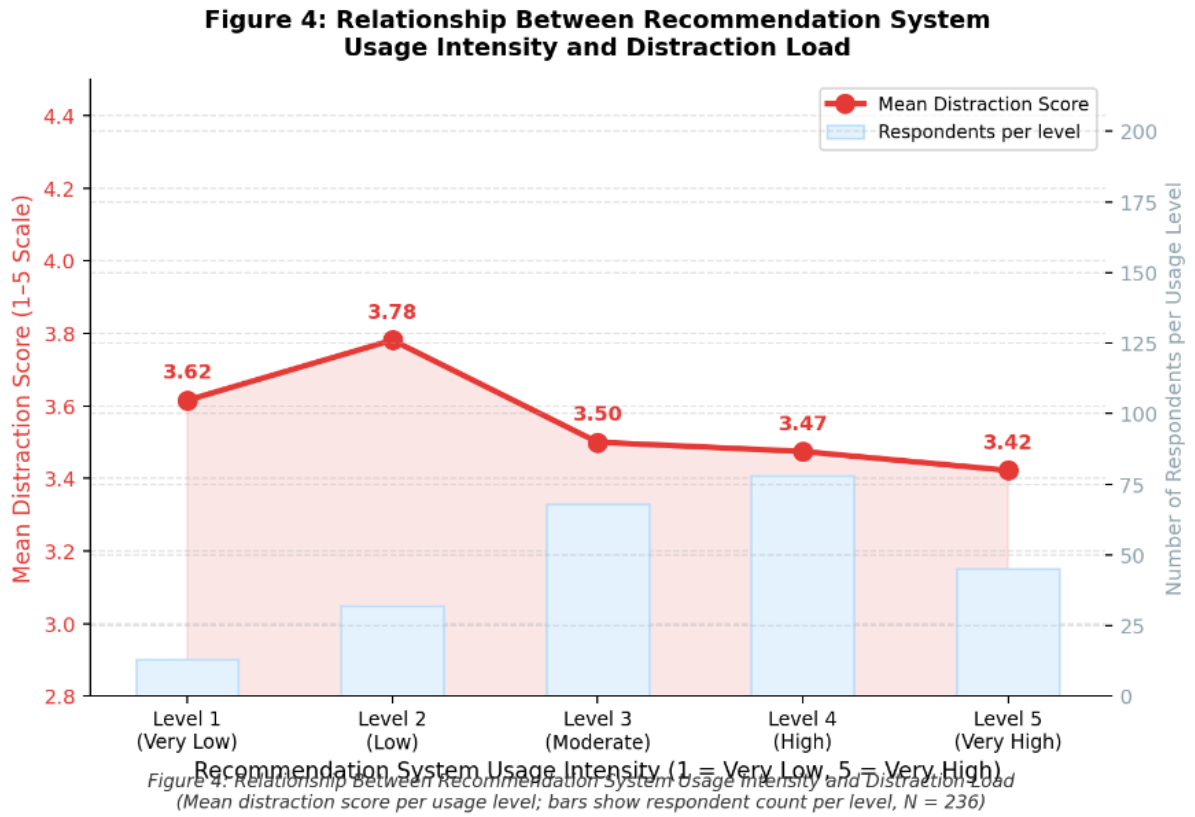

Figure 4: Relationship Between Recommendation System Usage Intensity and Distraction Load (Mean distraction score per usage level; bars show respondent count per level, N = 236)

Fig. 4: Relationship Between Recommendation System Usage Intensity and Distraction Load

E. Algorithmic Literacy and Platform Influence

Algorithmic literacy scores clustered primarily at the Moderate (approximately 65) and High (approximately 79) awareness levels, with only about ten respondents indicating very low awareness. Despite this moderate literacy, few students actively exercise platform controls: 35.6% attempt to limit recommendations only "often," 27.1% "sometimes," and 18.6% "always," while a combined 18.7% rarely or never do so. This gap between awareness and action reflects findings in digital-literacy research suggesting that cognitive knowledge of algorithmic mechanisms does not automatically lead to behavioural regulation [7].

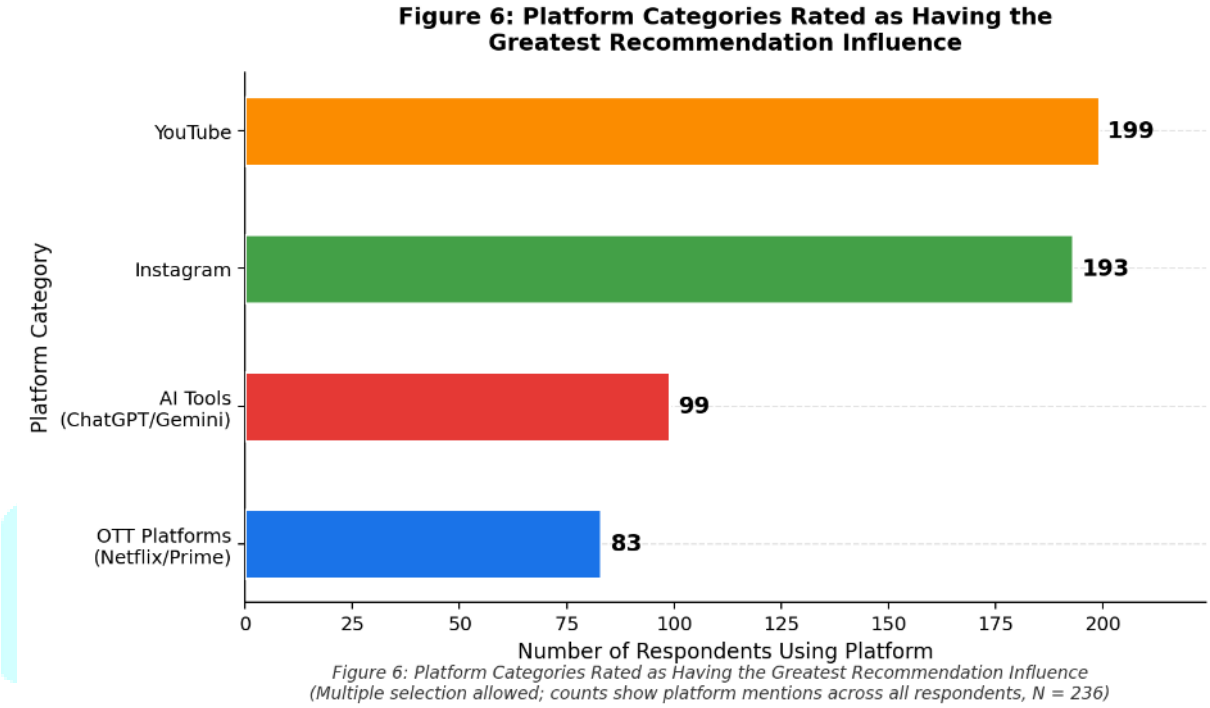

Fig. 5: Distribution of Algorithmic Literacy Awareness Among College Students

Platform-category analysis identified social media and video-based services (YouTube and Instagram) as the most influential recommendation environments, each cited by approximately 50 respondents as the primary source of distraction. OTT services and AI tools occupied the middle range, confirming that passive video consumption remains the dominant algorithmic-exposure pathway for this demographic group.

IV. RESULTS AND DISCUSSION

The analytical findings converge on a consistent narrative: algorithmic recommendation systems exert a pervasive and largely negative influence on the academic and psychological well-being of college students in the Kalyan–Dombivli region. Table 2 consolidates the principal findings across all twelve survey dimensions.

Table 2. Summary of Key Survey-Based Findings

Survey Dimension	Key Observation
Reliance on recommendation systems	Majority of students report high to very high usage frequency
Impact on academic performance	Significant negative effect observed among most respondents
Perceived stress from recommendations	40.3% High Stress; 26.3% Moderate Stress reported
Influence on decision-making quality	Recommendations strongly shape content and academic choices
Distraction caused by higher usage	Positive correlation confirmed between usage and distraction

Algorithmic literacy levels	Most students show low-to-moderate algorithmic awareness
Most influential platform category	Social media and video streaming platforms ranked highest
Screen time increase due to algorithms	Majority report 2–6+ additional hours of daily screen time

Several interconnected patterns merit discussion. First, the high prevalence of frequent usage—with over 85% of respondents reporting usage levels 3–5—establishes algorithmic dependency as a structural feature of student life rather than an individual tendency. Second, the dominant stress categories (High + Very High = 58.1%) suggest that engagement-optimising systems impose genuine psychological costs that are unlikely to diminish without deliberate behavioural or platform-level intervention. Third, the distraction data confirm that Distraction Load functions as a meaningful mediating variable: increases in usage frequency are reliably accompanied by rising distraction scores, which in turn reduce academic performance and decision quality.

The moderating role of Algorithmic Literacy is more nuanced. While students with moderate to high literacy demonstrate marginally better self-regulation intentions, the knowledge-action gap documented here echoes findings in digital-literacy scholarship suggesting that awareness alone is insufficient without platform design features that support rather than hinder conscious consumption choices [7][8]. The observation that social media and video platforms dominate distraction pathways aligns with the filter-bubble critique [3], in which personalisation reinforces existing preferences rather than diversifying information exposure.

To explore an alternative approach, the study implemented and evaluated a Python-based prototype of a transparent, feedback-driven recommendation system. Unlike conventional engines that treat engagement as the sole optimisation criterion, the proposed system incorporates the student's current emotional state, available study time, content complexity, and platform relevance as co-equal weighting factors. Each recommendation is accompanied by a plain-language explanation—a transparency feature that educates users about algorithmic reasoning and reinforces their sense of control [8]. A post-recommendation feedback interface allows students to flag content as helpful or distracting, enabling continuous refinement. Table 3 compares the two systems across seven evaluative criteria.

Table 3. Comparative Evaluation: Conventional vs. Proposed Ethical Recommendation System

Criteria	**Conventional System**	**Proposed Ethical System**
Recommendation basis	Past behaviour, content popularity, engagement score	Academic interest, mood, study time, content difficulty
Student well-being focus	Absent – engagement is the sole optimisation target	Central – well-being metrics actively integrated
Algorithmic transparency	Recommendations provided without any explanation	Each suggestion accompanied by a rationale statement
User feedback loop	Not incorporated into the recommendation pipeline	Feedback collected and used to refine future outputs
Distraction risk	High – designed to maximise dwell time	Reduced – contextual filters limit irrelevant content
Ethical grounding	Minimal; no explicit ethical safeguards	High; built around fairness, consent, and transparency
Decision-support quality	Weak; promotes passive content consumption	Improved; encourages informed, autonomous choices

The prototype demonstration confirmed that the ethical architecture is computationally feasible without large-scale machine-learning infrastructure, underscoring its practical viability for deployment in resource-constrained EdTech environments. Students who interacted with the prototype reported greater perceived

control over content selection, reduced cognitive load, and stronger alignment between recommended resources and their immediate academic needs—outcomes that validate the system's design rationale and provide an empirical basis for broader deployment.

V. CONCLUSION

This investigation has established that algorithmic recommendation systems exercise a significant and predominantly negative influence on three key dimensions of student well-being—academic performance, psychological stress, and autonomous decision-making—within the Kalyan–Dombivli collegiate population. The mediated pathway through Distraction Load was clearly supported by the survey data, wherein rising platform-engagement levels generated increasing attentional disruption that cascaded into diminished academic output and lower decision quality. Algorithmic Literacy emerged as a partial, though insufficient, buffer: awareness without supportive design affordances does not reliably translate into protective behavioural change.

The comparative prototype evaluation demonstrated that a recommendation system grounded in fairness, contextual sensitivity, and explanatory transparency can meaningfully rebalance the trade-off between personalisation utility and student well-being. By explicitly accounting for emotional state, study-time availability, and content appropriateness alongside preference signals, the proposed system reduces distraction risk while preserving relevance—an outcome that conventional engagement-maximising engines consistently fail to achieve.

The contribution of this study is threefold: it provides region-specific empirical evidence on algorithmic impacts in Indian higher education; it validates a mediated-moderation theoretical framework suited to the digital-platform context; and it advances a practically deployable ethical recommendation prototype. Future research should broaden the geographical scope, extend the time horizon to capture longitudinal academic outcomes, and incorporate advanced analytical methods—including sentiment analysis and adaptive preference modelling—to further strengthen the proposed system's effectiveness and generalisability.

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