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Academic Care: An AI-Powered Early Warning and Intervention System for Student Academic Support

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Abstract: ***Academic institutions generate substantial academic information, but this information is often distributed across different records, stakeholders, and workflows, making it difficult to identify emerging academic difficulties and convert them into timely support. This paper presents Academic Care, a working prototype for academic early warning and student intervention. The system combines a transparent rule-based risk engine with AI-assisted explanation and personalized study planning. A role-based architecture provides separate experiences for students, teachers, and parents, while CSV-based data intake supports prototype data integration. The implemented system includes academic-risk classification and scoring, weak-subject or weak-topic identification, an AI study assistant, personalized study plans, teacher intervention, parent notifications or nudges, JWT authentication, charts and analytics, and feedback/progress tracking. MongoDB is used as the core database technology for the application. The prototype uses synthetic/generated student data and is intended as an engineering and workflow prototype rather than a validated institutional prediction model. Attendance tracking, assignment tracking, and marks/test tracking are not currently available as standalone implemented modules. Therefore, the study does not report fabricated predictive-performance statistics. The contribution of the work is an integrated architecture that connects academic risk detection with explanation, personalized guidance, and stakeholder intervention within a single support loop.***
Keywords: Academic Early Warning; Educational AI; Personalized Learning; Risk Detection; Student Intervention.

I. INTRODUCTION

Higher-education institutions generate a wide range of information related to student academic activity and performance. Such information can potentially support academic decision-making, student advising, and early intervention. Educational data mining and learning analytics have consequently emerged as important areas for analyzing educational data and extracting information that can support learning and institutional practice [1], [2]. Academic analytics has also been proposed as a means of transforming institutional data into actionable information for improving student success and supporting timely intervention [3].

Despite the availability of academic information, a practical challenge remains: identifying an emerging academic problem is only one part of the process. An effective support system should also help stakeholders understand the nature of the problem and determine an appropriate next action. Earlier work on learning-management-system data demonstrated the potential of educational activity data for identifying students who may require additional support and for developing early-warning mechanisms [4]. However, an academic support workflow can become fragmented when risk identification, explanation, intervention, and progress monitoring are implemented as separate activities.

Academic Care was developed to address this gap by connecting academic risk detection with intervention. The central design principle is a closed support loop:

Academic Data → Data Organization → Risk Detection → Weak-Area Identification → Explanation and Planning → Stakeholder Intervention → Progress and Feedback

The system is designed around three major stakeholder groups: students, teachers, and parents. Students receive academic insights and personalized study guidance; teachers receive risk-focused information and intervention capabilities; and parents receive role-specific progress information and notifications or nudges.

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The current implementation is a working prototype under active development. It uses synthetic/generated student data and combines deterministic risk logic with AI-assisted guidance. The prototype therefore demonstrates the engineering architecture and workflow rather than claiming institutionally validated predictive performance.

The main contribution of this work is an integrated academic-support architecture that connects a transparent risk mechanism with weak-area identification and AI-assisted intervention while maintaining role separation between stakeholders.

II. RELATED WORK

A. *Educational Data Mining and Learning Analytics*

Educational Data Mining (EDM) applies computational and analytical techniques to educational data to investigate patterns related to learning and educational processes [1]. Learning analytics similarly focuses on the collection, analysis, and interpretation of learner-related information to improve learning and educational decision-making [2].

These areas establish the technical foundation for systems that analyze student-related information rather than relying exclusively on manually reviewed academic records. However, the usefulness of analytics depends not only on the identification of patterns but also on how those patterns are communicated and acted upon.

B. *Academic Analytics and Early Warning*

Campbell, DeBlois, and Oblinger described academic analytics as an approach for using institutional data and analytical techniques to generate actionable information for higher education [3]. Their work also discussed the potential of analytics for identifying students experiencing academic difficulty and connecting analytical information to intervention processes.

Macfadyen and Dawson demonstrated the potential of learning-management-system activity data for identifying variables associated with student academic achievement and for supporting early-warning reporting [4]. Their work provides an important precedent for the principle used in Academic Care: academic information can be transformed into signals that help educators identify students requiring attention.

The distinction between these approaches and Academic Care is primarily architectural. Academic Care attempts to connect the risk signal directly to weak-area identification, personalized study planning, teacher intervention, and parent-facing communication within one workflow.

C. *Privacy and Ethical Considerations*

Learning analytics introduces important privacy, transparency, accountability, and data-governance considerations because student-related systems may process sensitive educational information [5]. Pardo and Siemens emphasized that learning analytics should consider privacy and ethical principles alongside technical development.

Academic Care currently avoids real student records during development by using synthetic/generated data. JWT authentication and role-based access are implemented to separate student, teacher, and parent experiences. Future deployment with institutional data would require stronger privacy governance, authorization controls, data-retention policies, auditability, and institutional review.

III. PROBLEM STATEMENT AND OBJECTIVES

A. *Problem Statement*

Academic information may be distributed across different records and workflows, making it difficult to continuously identify students who may require academic support. Traditional monitoring approaches may show academic information without providing an integrated mechanism for determining what action should follow.

The problem addressed by Academic Care is therefore defined through three related challenges:

1) Fragmented academic information.
2) Delayed identification of students who may require academic support.
3) Limited conversion of academic insights into concrete and personalized interventions.

The system seeks to address these challenges through an integrated early-warning and intervention workflow.

B. *Objectives*

The primary objectives of Academic Care are:

1) To develop an integrated academic-support platform connecting students, teachers, and parents through role-specific dashboards.

2) To provide students with centralized academic insights and progress information.
3) To provide teachers with risk-focused information and intervention capabilities.
4) To provide parents with accessible information regarding academic progress and notifications or nudges.
5) To implement academic-risk classification and scoring to identify students requiring attention.
6) To identify weak subjects or topics that may require targeted academic support.
7) To generate personalized study guidance through an AI-assisted study assistant.
8) To connect detected academic risk with an actionable intervention workflow.
9) To maintain authentication and role-based access for different stakeholders.
10) To provide feedback and progress tracking for the intervention process.

IV. SYSTEM ARCHITECTURE

Academic Care follows a layered architecture designed around the progression from academic information to intervention.
The major architectural layers are:

1) Data Collection Layer
2) Student Data Layer
3) Analytics and Risk Layer
4) Weak-Area Analysis Layer
5) Intervention Layer
6) Role-Based Presentation Layer

The data collection layer accepts structured academic information, including CSV-based prototype data. The student data layer organizes the available information for subsequent processing. The analytics and risk layer calculates the academic risk signal and classification. The weak-area component identifies subjects or topics requiring attention. The intervention layer converts the resulting information into study plans, recommendations, reminders, and stakeholder actions. Finally, role-based dashboards present relevant information to students, teachers, and parents.

Figure 1. Academic Care System Architecture and Prototype Overview
[INSERT THE EXISTING ACADEMIC CARE ARCHITECTURE DIAGRAM HERE]
The architecture intentionally separates deterministic risk calculation from AI-assisted guidance. This separation is important because the risk signal is generated through defined project logic, while the AI layer is primarily used to provide explanations, conversational guidance, and personalized study planning.
This design prevents the AI component from becoming the sole decision-maker for academic risk classification.

V. METHODOLOGY

A. *Data Handling*

The current prototype uses synthetic/generated student data. Synthetic data were selected during development to avoid exposing real student academic records while allowing the team to implement and demonstrate the complete software workflow.
The prototype also supports CSV-based data intake. Structured CSV information can be imported into the system and subsequently used by the academic-support workflow.
The current data approach is suitable for engineering development and demonstration, but it does not establish whether the system will generalize to real student populations.

B. *Risk Detection*

Academic Care implements a deterministic rule-based risk mechanism for calculating an academic risk score and assigning a corresponding risk classification.
The detailed risk-engine formula is implemented within the project's risk-engine source. The project documentation confirms the presence of risk-score calculation and risk classification. However, unverified feature weights and threshold values are intentionally not reproduced in this paper.
The risk-detection process can be represented conceptually as:
Academic Indicators → Rule-Based Risk Calculation → Risk Score → Risk Classification
The resulting classification is used as an input to the intervention workflow.

The purpose of this architecture is to maintain a transparent and predictable risk mechanism rather than allowing an opaque AI model to independently determine whether a student is at risk.

C. Weak-Area Identification

Risk classification alone does not provide sufficient information for intervention. A student may be identified as requiring support, but teachers and students also need information regarding the academic area that requires attention.

Academic Care therefore includes weak-subject or weak-topic identification.

The workflow is:

Risk Identification → Academic Area Analysis → Weak Subject/Topic → Targeted Guidance

This component shifts the system from simply asking:

Is the student at risk?

toward the more actionable question:

Which academic area requires attention?

The identified weak area can subsequently be used by the intervention and study-planning components.

D. AI-Assisted Study Support

The AI study assistant is integrated into the academic-support workflow. Its role is to interpret the available academic context and provide conversational academic guidance, explanations, and personalized study planning.

The intended workflow is:

Student Context + Risk Information + Weak Areas → AI-Assisted Guidance → Personalized Study Plan

The AI component is therefore positioned as a support mechanism rather than as the sole source of academic-risk decisions.

This distinction improves interpretability because the deterministic layer establishes a consistent risk signal while the AI layer converts the available context into human-readable recommendations.

E. Intervention Workflow

The intervention process is designed as a closed loop:

1) Academic information is collected.
2) The information is organized for analysis.
3) Academic risk is calculated.
4) Risk classification is generated.
5) Weak subjects or topics are identified.
6) Personalized guidance is generated.
7) Teachers can initiate intervention actions.
8) Parents can receive relevant notifications or nudges.
9) Student progress and feedback can be tracked.

The architecture therefore attempts to reduce the gap between analytical output and actual academic support.

VI. IMPLEMENTATION AND TECHNOLOGY

A. Core Database

MongoDB is used as the core database technology of the Academic Care project. The database layer is responsible for supporting the application's structured academic and user-related data requirements.

The choice of a document-oriented database is aligned with the evolving nature of the prototype, where different academic and stakeholder-related data structures may be expanded during development.

B. Authentication and Access Control

JWT-based authentication is implemented within the prototype. Role-based access separates the student, teacher, and parent experiences.

The access model is intended to reduce inappropriate exposure of information between stakeholder groups. A student should receive student-facing information, a teacher should receive teacher-facing academic and intervention information, and a parent should receive parent-facing progress information.

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C. Data Import

CSV import is implemented to support structured prototype data intake. This allows academic information to be transferred into the system without requiring every record to be entered manually through the interface.

D. Dashboard and Analytics

The system provides role-specific dashboards and analytical views. Charts and analytics are used to present academic information in a form that can be interpreted by the respective stakeholder.

The dashboard layer is therefore not treated as a separate analytics product. Instead, it forms the presentation component of the larger risk-to-intervention workflow.

E. Current Implementation Status

Table I summarizes the current implementation status confirmed by the project team.

Table I
Current Implementation Status

Capability	Status
Student Dashboard	Working
Teacher Dashboard	Working
Parent Dashboard	Working
Risk Classification	Working
Risk Score Calculation	Working
Weak-Subject/Topic Identification	Working
AI Study Assistant	Working
Personalized Study Plan	Working
Teacher Intervention	Working
Parent Notifications/Nudges	Working
CSV Import	Working
JWT Authentication	Working
Charts/Analytics	Working
Feedback/Progress Tracking	Working
Attendance Tracking	Not Available
Assignment Tracking	Not Available
Marks/Test Tracking	Not Available

The table deliberately distinguishes implemented functionality from features that remain outside the current prototype scope.

VII. STAKEHOLDER WORKFLOW

A. Student Workflow

The student dashboard provides access to academic information, insights, personalized study guidance, and progress-related information.

When academic risk or a weak area is identified, the student can receive guidance through the intervention workflow. The AI study assistant can further provide conversational academic support and personalized study planning.

The intended student workflow is:

Student → Academic Insights → Risk/Weak Area → Study Guidance → Personalized Plan → Feedback/Progress

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B. Teacher Workflow

Teachers receive a risk-focused view of student academic information. The teacher workflow supports monitoring, analysis, and intervention.

Teachers can use identified academic risks and weak areas as inputs for deciding whether a student requires additional support.

The intended workflow is:

Teacher → Student Risk View → Weak Area → Intervention Action → Progress Monitoring

The system therefore aims to support teacher decision-making rather than replace teacher judgment.

C. Parent Workflow

The parent dashboard provides role-specific academic information, progress visibility, and notifications or nudges.

The parent-facing component is intended to improve communication regarding academic progress while maintaining separation from information intended exclusively for teachers or students.

The workflow is:

Parent → Academic Progress → Notification/Nudge → Awareness → Support

VIII. SECURITY AND ROLE MANAGEMENT

Security is an important consideration for systems that process academic information.

Academic Care currently implements JWT authentication and role-based access. These mechanisms are used to separate student, teacher, and parent experiences.

However, the current authentication mechanism should not be interpreted as complete institutional security.

Deployment with real student information would require additional controls, including:

1) Stronger authorization policies.
2) Institutional identity management.
3) Secure password and credential management.
4) Data-retention policies.
5) Audit logging.
6) Secure API configuration.
7) Privacy governance.
8) Access reviews.
9) Backup and recovery mechanisms.
10) Appropriate institutional consent and data-use policies.

The privacy implications of learning analytics make these controls particularly important when moving from synthetic development data to real student records [5].

IX. PROTOTYPE TESTING AND EXPERIMENTAL BASIS

Academic Care was developed and debugged iteratively. The project team reports that the implemented workflows are functioning after resolving development and integration issues.

Functional development activities included:

1) Integration of role-based application workflows.
2) Authentication and role-specific access stabilization.
3) Dashboard and analytics refinement.
4) CSV-based data intake.
5) Risk classification and scoring.
6) Weak-area identification.
7) AI study assistance.
8) Personalized study planning.
9) Teacher intervention workflows.
10) Parent notification/nudge workflows.
11) Feedback and progress tracking.

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However, the current project evidence does not provide a verified and reproducible benchmark containing model accuracy, precision, recall, F1-score, AUROC, intervention effect size, or statistically validated student outcomes.
The prototype also uses synthetic/generated student data.
Consequently, the current work should be interpreted as a software and workflow prototype, not as an institutionally validated academic-risk prediction model.
This distinction is important. A working application demonstrates that the proposed workflow can be implemented, but it does not by itself establish that the risk mechanism predicts real-world academic outcomes with a particular statistical performance.

X. RESULTS AND DISCUSSION

A. *Prototype-Level Results*

The primary result of the current development is a functioning multi-role prototype that connects academic-risk identification with intervention.
The implementation demonstrates the following workflow:
Data Intake → Risk Classification → Weak-Area Identification → AI Guidance → Personalized Planning → Stakeholder Intervention → Progress Tracking

The prototype therefore extends beyond a conventional academic dashboard that only displays information.
The implemented student, teacher, and parent experiences demonstrate that the same academic context can be presented differently according to stakeholder responsibilities.

B. *Transparent Risk Mechanism*

A major design decision is the separation between deterministic risk logic and AI-assisted guidance.
A completely AI-driven risk decision could be difficult to explain or reproduce. Academic Care instead uses the deterministic risk layer to produce the academic risk signal and uses AI primarily for explanation, guidance, and personalized study planning.
This architecture provides a clearer boundary between:

- Risk calculation
- Academic interpretation
- Intervention planning

Such separation can be beneficial when the system is later evaluated with real institutional data.

C. *From Detection to Intervention*

Academic analytics has historically focused on extracting meaningful information from educational data. Existing work has demonstrated the value of identifying students who may be experiencing academic difficulty [3], [4].
Academic Care builds upon this principle by emphasizing the next step: intervention.
A risk label without an action mechanism can leave the responsibility for interpretation entirely with the stakeholder. Academic Care attempts to reduce this gap by adding weak-area identification, personalized study plans, teacher intervention, and parent-facing notifications.

D. *AI as an Assistance Layer*

The use of AI in Academic Care is intentionally bounded.
The AI component does not replace the deterministic risk mechanism. Instead, it supports:

- Conversational academic guidance.
- Explanation of available academic context.
- Personalized study planning.
- Targeted recommendations based on identified weak areas.

This approach is particularly relevant because AI-generated guidance can be flexible, but its outputs still require appropriate evaluation and human oversight before being relied upon for consequential academic decisions.

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XI. LIMITATIONS

The current prototype has several limitations.

1) Limited Academic Data Modules: Attendance tracking, assignment tracking, and marks/test tracking are not currently available as standalone implemented modules. Therefore, Academic Care should not currently be described as a complete institutional student-information system.
2) Synthetic Data: The prototype uses synthetic/generated student data. Synthetic data are appropriate for development and demonstration, but they cannot establish how the risk mechanism behaves on real student cohorts.
3) Lack of Validated Predictive Metrics: The current project evidence does not contain validated measurements of accuracy, precision, recall, F1-score, AUROC, calibration, or other predictive metrics. Therefore, no numerical predictive-performance claims are made in this paper.
4) Limited Predictive Capability: The current risk mechanism is primarily deterministic and rule-based. More advanced machine-learning-based prediction remains a future development direction.
5) Data Quality Dependency: The reliability of academic risk identification depends on the availability, completeness, consistency, and quality of the academic information supplied to the system. Incomplete or inaccurate information may reduce the usefulness of the resulting risk classification.
6) Real-World Validation: The prototype has not yet undergone institutional deployment or longitudinal evaluation using governed real-world academic data.
7) Security and Scalability: Although JWT authentication and role-based access are implemented, deployment at institutional scale would require additional security, privacy, auditing, scalability, and operational controls.
8) Intervention Dependency: The effectiveness of the intervention workflow depends on stakeholder participation. Students, teachers, and parents must actively engage with the information and respond to identified academic risks.

XII. FUTURE WORK

Several areas can extend the Academic Care system.

A. *Additional Academic Data*

Future development can integrate dedicated modules for:

1) Attendance.
2) Assignment submission.
3) Test and examination marks.
4) Academic activity history.
5) Longitudinal performance trends.

These data sources can provide a more comprehensive basis for academic-risk analysis.

B. *Empirical Risk-Model Evaluation*

The current risk mechanism should be evaluated using appropriately governed and anonymized institutional data.

A future evaluation should define:

1) A representative dataset.
2) Clear inclusion and exclusion criteria.
3) A documented risk-engine formula.
4) Defined risk thresholds.
5) Training, validation, and testing procedures if machine-learning models are introduced.
6) Appropriate baseline comparisons.
7) Reproducible evaluation metrics.

Potential metrics include accuracy, precision, recall, F1-score, AUROC, confusion matrices, calibration measures, and class-specific performance.

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C. Intervention Evaluation

Future research should evaluate whether personalized interventions actually improve academic trajectories.
Possible research designs include:

- Pre-intervention versus post-intervention analysis.
- Controlled comparisons.
- Longitudinal cohort studies.
- Human evaluation of AI-generated study plans.
- Teacher assessment of intervention usefulness.

The evaluation should distinguish between the performance of the risk detector and the effectiveness of the intervention itself.

D. AI Evaluation

AI-generated study plans should be evaluated for:

- Relevance.
- Correctness.
- Consistency.
- Personalization.
- Academic appropriateness.
- Safety.
- Human acceptability.

Teacher or academic-expert review can provide an additional validation layer before AI-generated recommendations are used in high-stakes academic settings.

E. Privacy and Governance

Future deployment with real student data should incorporate stronger privacy and governance mechanisms, including access auditing, data minimization, retention controls, institutional authorization, and appropriate consent or governance processes.

F. Longitudinal Analytics

The system can eventually be extended to track changes in student academic trajectories over time.
Such functionality could support analysis of:
Risk → Intervention → Student Response → New Risk State → Follow-Up Intervention
This would transform Academic Care from a static risk-detection system into a longitudinal academic-support platform.

XIII. CONCLUSION

Academic Care presents a working prototype for AI-assisted academic early warning and student intervention. The system addresses the gap between academic information and actionable support by connecting risk classification, weak-area identification, personalized study planning, teacher intervention, parent notifications, and progress tracking within a single workflow.
The architecture combines a transparent rule-based risk mechanism with AI-assisted explanation and personalization. This separation allows the risk signal to remain deterministic while using AI to support human-readable guidance and study planning.
The current prototype demonstrates the feasibility of the proposed software architecture and stakeholder workflow. Student, teacher, and parent dashboards, risk classification, risk scoring, weak-area identification, AI study assistance, personalized study plans, teacher intervention, parent nudges, CSV import, JWT authentication, analytics, and feedback/progress tracking are implemented.
At the same time, the project has important boundaries. The prototype uses synthetic/generated data, and attendance, assignment, and marks/test tracking are not currently implemented as standalone modules. More importantly, the current evidence does not provide validated predictive or intervention-performance metrics. Therefore, the work should be understood as an engineering prototype rather than a validated institutional prediction system. The next research stage should focus on reproducible evaluation using appropriately governed real-world or anonymized academic data, transparent documentation of the risk engine, measurement of predictive performance, evaluation of AI-generated study plans, and assessment of intervention effectiveness.
The central contribution of Academic Care is consequently not an unsupported claim of predictive accuracy, but an integrated architecture that connects academic risk detection to understandable, personalized, and stakeholder-oriented intervention.

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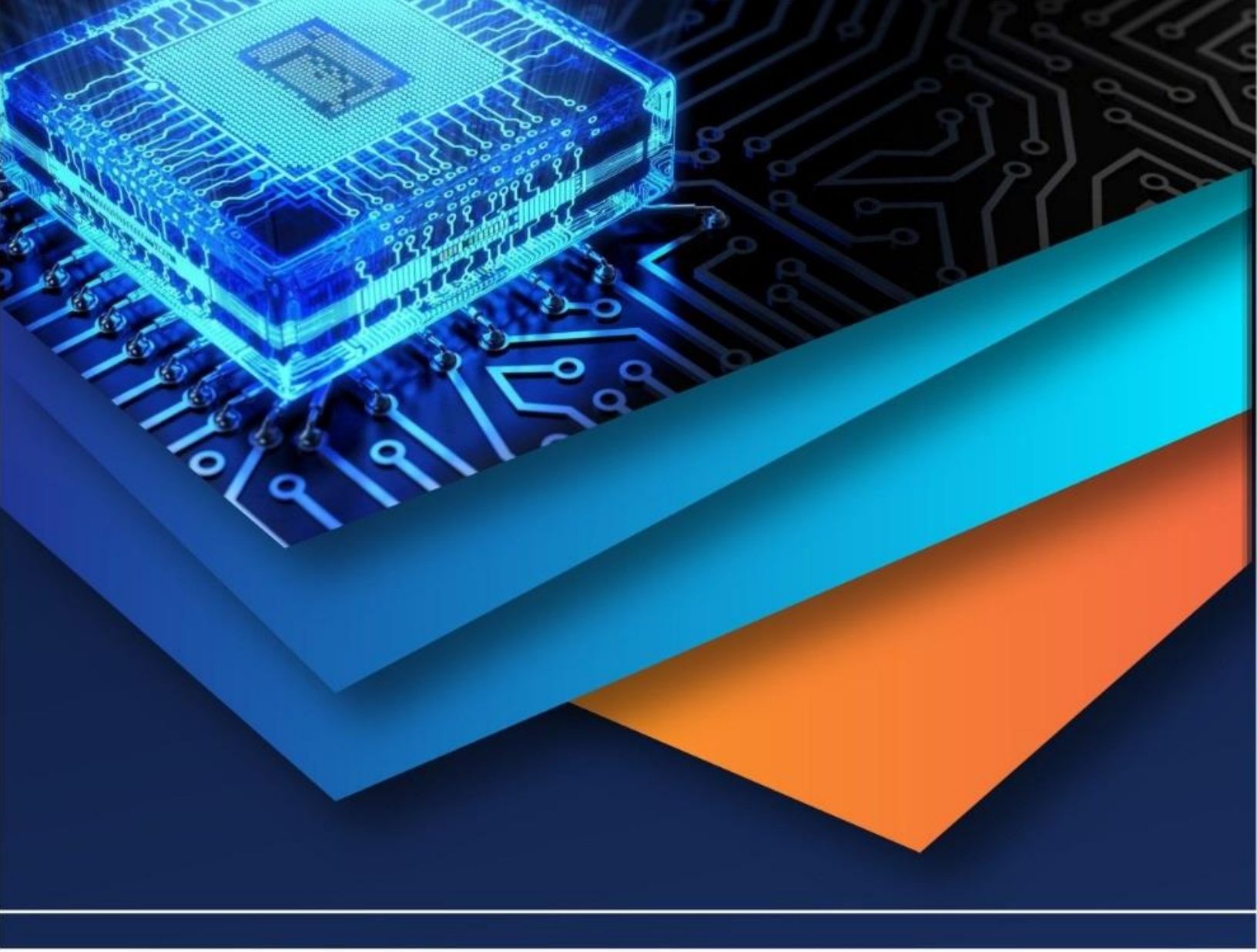
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