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AI-Based Personalized Learning in Smart Education: A Systematic Review, Gap Analysis, and Framework Proposal

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Abstract: Over the past decade, Artificial Intelligence technology has slowly made its way into the education sector, transforming not only teaching but also learning methods for students. However, while making such significant advances, a particular issue is overlooked – all current systems are extremely similar when it comes to personalization of lessons for students because no two learners have identical ways of thinking, pacing, or retaining information. Therefore, this paper examines ten studies published by IEEE during 2020-2025 on the topic of AI-driven personalized learning to determine the gaps within this industry. Upon analysis of the reviewed articles, common issues were discovered – poor or imbalanced datasets, recommendation engines that cannot be justified, lack of privacy measures, non-real-time adaptivity, as well as preference shown for some students over others. Based on the findings mentioned above, a proper problem statement was formulated along with a framework aimed at addressing the identified issues. The designed model is called UEPPAI-SE, and it includes a combination of multi-source student data collection, reinforcement learning engine for real-time adaptation, explanations for all recommendations, and federation of data to keep personal information from being stored on central servers.
Index Terms: Artificial Intelligence, Personalized Learning, Smart Education, Adaptive Learning, Explainable AI, Federated Learning, Reinforcement Learning, Educational Technology, Learning Analytics.

I. INTRODUCTION

If you walk into any university classroom today, you'll see students who differ drastically in terms of their academic background, the speed at which they learn, and their objectives sitting together in a single class. Some of these students have trouble following the lesson, while others have completed the assigned readings before attending. It is one of the oldest challenges facing educational institutions and has remained unsolved for many years due to the absence of scalable solutions. AI provides a possible solution to this challenge in principle since it makes it feasible to monitor the performance of individual students on specific tasks, detect drops in comprehension, and recommend alternative learning materials or slower pacing, among other actions. However, in reality, deployed AI systems fail to meet this goal by a wide margin. As we examined some of the latest studies on this topic, it became increasingly clear that they would present impressive results on the accuracy of their models in controlled settings. In each of these studies, though, it became apparent that their datasets were too small, the models failed to provide useful insights into their decision-making processes, and deploying them in other universities would require considerable effort. The objective of the present research is to determine how far the existing knowledge has advanced in this area. Ten studies that were indexed in the IEEE database and conducted from 2020 to 2025 have been examined within the framework of personalized learning using AI. Instead of just presenting information about each study, we tried to make an analysis of all the papers considered and find the common ground, weak points, and issues left unsolved by any researcher. On the basis of the conducted analysis, we have formulated the problem statement and developed a framework addressing every gap. The rest of the work is organized as follows. In Section II, each one of the ten analyzed articles is discussed. The research gaps are highlighted in Section III. The research problem is presented in Section IV. Our research approach and framework are described in Section V. Section VI covers the expected impact of our proposal. The discussion is covered in Section VII. Possible future research directions are identified in Section VIII.

II. LITERATURE REVIEW

The search was conducted via IEEE Xplore, Scopus, and Google Scholar, with search terms "AI-based Personalized Learning" AND "Smart Education" AND "Adaptive Systems", and limiting the search to open-access papers between the years of 2020 to 2026.

Out of the total 523 hits initially obtained, ten papers were selected based on the number of citations and diversity of approaches adopted in research such as research that dealt with language learning, implementation in rural environments, decentralized systems, or even specialized tutoring systems. The papers chosen have been highlighted in Table I.

A. AI-Based Personalized E-Learning Systems (2022)

One such citation leader among surveys is that by Mir Murtaza et al. [4]. In the journal IEEE Access, it examined the architectural framework for e-learning using artificial intelligence through an exploration of the various systems' capabilities regarding recommendations, learning style identification, and monitoring performance. From these components, the authors crafted a model using collaborative filtering and knowledge tracing as its basis. What makes the survey effective is its comprehensive coverage. Unlike many papers, which tend to concentrate on one area alone, this particular study attempts to tackle the issue in its entirety. Its one true admission, however, is the difficulty of designing an integrated system that works, given how challenging it is even now to achieve such scale.

B. AI-Based Learning Style Prediction in Online Learning (2022)

The ongoing problem with adaptive learning lies in the fact that most of these systems have learners fill out surveys on their preferred learning style before creating recommendations based on that information – as if we asked patients to diagnose their illnesses themselves. Instead, Pardamean et al. [2] chose a novel way of proceeding. They created an unsupervised recommendation system based on collaborative filtering techniques and managed to identify the learning styles of the participants without requiring their prior knowledge. The results were impressive: a low root mean squared error of 0.9035 and significant changes from pre-test to post-test. What does it say about the future of educational platforms? Perhaps, behavior tracking may prove even more effective than questionnaires when it comes to identifying personal learning preferences.

C. Smart Learning Environment for Business English (2025)

What is unusual about Chuang and Hung [1] is that they conducted their experiment not in a lab setting with artificial subjects and artificially simulated software, but in a real-life classroom environment with actual students and commercially available AI software, such as ChatGPT and Canva AI. While most research on this topic describes systems that have been tried out under experimental laboratory conditions, Chuang and Hung [1] had to cope with the complexity of a real-life lesson. The proposed system, known as the Smart Learning Environment, resulted in tangible improvements in students' abilities to write coherently, speak fluently, and give presentations confidently. This is a small-scale study, but it is important due to its practical implementation during an entire semester.

D. Personalised Learning Platform Using AI-Based Adaptive Systems (2025)

The dynamic learning tracks model suggested by Shashi S B et al. [3] consisted of ML algorithms and NLP components, which were used to create a constantly changing path depending on the results received from the student. In contrast to allocating students to a particular learning track and remaining within it throughout the whole course, this platform constantly assessed their performance and redirected the path accordingly.

Students who worked with the platform achieved better grades and demonstrated greater confidence than those who were using the static curricula. The incorporation of NLP component into the process is significant because it allows parsing responses in open-ended questions as well as the answers to closed questions.

E. AI-Powered Smart Learning Platform with Adaptive Assessments (2025)

Pavan Kumar Kollipara et al. [5] developed a framework that integrates the three concepts of adaptive testing, which varies the difficulty of items according to the learner's responses, personalized paths generated through traversing the knowledge graph, and prediction analytics that identify at-risk students.

While each of these concepts may not be novel by themselves, what is noteworthy about the framework proposed by the authors is the integration between these technologies. In essence, if a learner is found to have poor performance through the adaptive test, this directly influences the learning path, and vice versa, thus affecting the predictive analysis as well. The results were positive with increased engagement and tracking outcomes. The drawback that is subtly mentioned by the authors is that implementing such technology requires more effort due to the coupling between the components.

F. Personalized Learning in Automation: A 3D AI-Based Approach (2023)

The majority of investigations in personalized learning have been dedicated to texts and videos. Asmar Ali et al. [6] questioned the effects of transitioning into 3D virtual environments with regards to an area where practice plays as prominent a role as does theoretical study – the field of automation engineering.

An Artificial Intelligence-driven Intelligent Tutoring System helped students perform various 3D industrial simulations and provided them with constructive feedback based on procedural knowledge modeling. The results revealed much higher levels of conceptual understanding and skill acquisition in students working in the 3D environment than in those using standard two-dimensional textbooks.

G. AI-Based Self-Learning Platform for College English Listening (2020)

Zhou Junping's study [7], the earliest one in our group of papers, is also the most down-to-earth. The system applied speech recognition and learner modeling technologies in order to find out what level of listening skill each particular student had, and then to assign him/her appropriate practice tasks. As a result, not only did students improve their listening performance, but also they began doing this independently. It is a very practical advantage which an intelligently designed system of AI-based tutoring provides. When learners know what their current standing is and how to improve, they will naturally make more efforts to do so. While the system in question is concerned with only one skill, that of listening in English, the concept behind it has a broader application.

H. AI Recommendation System for Language Learning Using k-NN (2025)

While other modern recommendation engines tend to rely heavily on deep learning by default, Zhu Feng and Jing Zhang [8] opted for k-Nearest Neighbours. This choice is critical, as the method is explainable. It would even be possible for either a teacher or a learner themselves to understand the logic behind a certain resource being recommended to a learner since learners with similar interaction patterns found it useful. They demonstrated substantial gains in regard to the rate of content retention and recommendation accuracy. Their point about interpretability being a crucial feature to account for at the design stage is well-taken. In a school environment where one needs to trust the AI-powered recommendation of content, explainability comes first.

I. Effectiveness of AI Learning Tools in Rural Primary Schools (2025)

Verma et al. [9] did not do their research in places where other AI education scholars typically conduct their studies; rather, they did their research in rural Indian primary schools, which lack proper technology resources and teacher knowledge about AI. The authors used a mixed methodological approach to examine whether personalized AI could positively impact literacy and numeracy. The results showed that personalized AI instruction was beneficial to learners in terms of improving their literacy and numeracy skills, provided there was proper infrastructure and support from the teachers. However, if students had to share tablets, lacked internet connectivity, or the teachers did not have sufficient training on AI, then there were no positive outcomes of using AI.

J. AI-EduAgent: Decentralized Adaptive Learning (2025)

On the other hand, the design of the AI-EduAgent system proposed by Yannam Bharath Bhushan et al. [10] made a different choice with respect to its architecture. Rather than uploading the information about the students to a central server to perform the computations there, the adaptive process takes place locally on the device via the use of autonomous agents that adopt reinforcement learning policies. This makes it clear why the system enjoys benefits with respect to data privacy since the raw information is never uploaded. It also provides potential advantages in terms of performance since the local adaptation was shown to enhance knowledge retention during the experiments.

K. EduTrack: AI Personalized Learning Through Secure Analytics (2025)

This paper by K. Thamarai Selvi et al. [11] combines recommendation and security into one system dubbed EduTrack. The system was able to combine collaborative and content-based recommendation algorithms in a hybrid system which was then embedded in analytics channels that were encrypted to fit regulatory requirements while still being effective. Students who used EduTrack fared better compared to others, and the system showed that it is possible to have analytics channels and protect students' privacy at the same time. The technical challenge involved here is a valuable achievement in itself because privacy is often an add-on feature in systems.

TABLE I
Summary of Reviewed Research Papers on AI-Based Personalized Learning

Ref.	Title (Short)	Author(s)	Year	Core Method	Key Finding / Limitation
[4]	AI-Based Personalized E-Learning Systems	Mir Murtaza et al.	2022	Multi-module AI + collaborative filtering	Good architecture; scalability is unsolved
[2]	AI Learning Style Prediction	Pardamean et al.	2022	Unsupervised collaborative filtering	RMSE=0.9035; removes self-report bias
[1]	Smart Learning Env. for Business English	Chuang & Hung	2025	SLE with ChatGPT and Canva AI	Real classroom gains in communication
[3]	Personalised Learning Platform Using AI	Shashi S B et al.	2025	ML + NLP adaptive paths	Better performance; needs larger corpora
[5]	AI-Powered Smart Learning Platform	Kollipara et al.	2025	Knowledge graphs + predictive analytics	Tightly coupled; hard to port
[6]	Personalized Learning in Automation	Asmar Ali et al.	2023	3D AI-based ITS	Better procedural skill transfer
[7]	AI Self-Learning for English Listening	Junping Zhou	2020	Speech recognition + learner modeling	Improved autonomy; narrow scope
[8]	AI k-NN Recommender for Languages	Zhu Feng, Jing Zhang	2025	k-Nearest Neighbours	Interpretable; strong retention gains
[9]	AI Tools in Rural Primary Schools	Durgesh Verma et al.	2025	Mixed-methods field study	Gains only where infrastructure holds
[10]	AI-EduAgent Decentralized Learning	Yannam et al.	2025	On-device reinforcement learning	Privacy-friendly; convergence slower
[11]	EduTrack Secure Analytics	K. Thamarai Selvi et al.	2025	Hybrid recommendation + encryption	Privacy and quality both achieved

III. RESEARCH GAPS

Reading all ten articles together brought some repeating problems to light. These five gaps were identified.

1) Too Few Samples or Skewed Datasets: Almost all the studies analyzed acknowledged their datasets' limitations in one way or another. There have been training sets of several hundred students' data, and datasets of just one institution or subject matter. A machine learning algorithm can be taught to detect a pattern within a particular part of the sample, but that pattern will be misleading for all other samples. Such a concern has been highlighted by Murtaza et al. [4]. Likewise, Verma et al. [9] observed the same problem in the more difficult to collect rural data.
2) Models that Are Unable to Justify Their Recommendations: Only one of the studied works that use k-NN models by Zhu and Zhang [8] identified interpretation of recommendations as the first design principle. All other models – neural classification architectures, tutoring systems based on neural networks, and hybrid recommender systems – provided recommendations but did not offer any justification of them. In medicine, it would be classified as a safety problem. In education, at least, it means that it creates a trust problem since teachers cannot verify recommendation and students have no chance to understand why they were recommended.
3) Privacy Issues Addressed After the Fact: Student personal data is highly sensitive information since it can contain information about their failures and struggles. Out of ten works discussed in the paper, only two – AI-EduAgent [10] and EduTrack [11] – included measures related to ensuring the privacy of student personal information into the main architecture of their projects.

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4) Adaptive Change That Occurs Too Infrequently: Almost all of the systems under review adjusted their model only at the end of a session, or when the data needed was sufficiently collected to warrant a retraining process. Real change happens far more rapidly. A student struggling to understand a particular topic during a 40-minute session must be supported while the session is going on, not a week later. The discrepancy between the adaptive change that can occur and what actually does is evident in most of the reviewed literature.
5) Tilt Toward Amplifying Preexisting Inequalities: Verma et al. [9] address this issue best: recommendation engines designed using a dataset comprised mainly of data from well-equipped students in urban environments will design recommendations tailored for such students. These recommendation engines may function poorly, or worse, actively discriminate against students who do not belong to such groups. None of the papers considered in this assignment contain a thorough examination of the fairness of their recommendations.

IV. PROBLEM STATEMENT

With all that in mind, here was the result of our discussion on the problems related to personalized AI-powered education:
The current AI-based personalized learning systems are not able to ensure reliable individualization, real-time processing, and fairness. However, this is not due to a lack of viability of the concept per se, but due to the lack of consideration of various aspects of its implementation altogether: the scope of data for model training is limited, lack of explainability of the algorithmic decisions, protection of student information is insufficient, slow adaptation rate that renders the process useless during the learning session, and absence of evaluation of fairness.

V. PROPOSED SOLUTION FRAMEWORK

UEPPAI-SE is the name of our framework, which aims at filling gaps in Explainable and Privacy-preserving AI research in the context of Smart Education. Instead of addressing each identified gap separately, our framework is devised such that all six components support each other and limit each other in their functioning.

A. Combining Data from Various Sources

One's learning process is not just a series of quiz results. The proposed framework integrates data coming from academic transcripts, in-session activities tracking logs, collaborative interactions with peers, self-assessments, as well as available physiological indicators like task completion time and revisit rate. Combining these sources results in an understanding of a person's knowledge and preferred learning style much deeper and less prone to being affected by bias introduced through individual sources. This solves the problem mentioned in [4], [5].

B. Adaptive Engine with Real-Time Reinforcement Learning

The central component of UEPPAI-SE's personalized learning approach involves designing an adaptive engine based on reinforcement learning theory. Here, the learning system itself becomes the agent, while the current state of the learner represents the environment, and the objective is selecting actions to maximize future learning gains. Our approach relies on the concept of Markov Decision Processes:

$$\pi^* = \arg\max\pi\ E[\Sigma(t=0 \text{ to } T)\ \gamma^t r_t \mid s_0, \pi] \quad (1)$$

In this case, π represents the content-selection policy being learned, s_0 represents the initial state of the student, r_t is a reward signal generated based on engagement and performance at each step t, and γ is a discount factor weighing immediate versus future rewards. More important, the learning engine does not update until after the session is over; instead, it is updated continually during the session, differentiating real-time adaptation from post-session batch processing typical of most current systems.

C. A Transparency Layer to Build Teacher Trust

Each piece of advice comes with an explanation. In a teacher's dashboard view, this will be a visualization of SHAP values for the most impactful features used in forming the recommendation. From the student's perspective, it takes the form of brief natural language statements such as "The reason why we are recommending you watch a more slowly paced video about this topic is that the last three questions you answered were answered more slowly than usual." Techniques such as LIME allow for local, sample-specific explanations, whereas SHAP gives global visualizations across an entire class.

D. *Federated Learning with On-site Data Integrity*

Unlike other approaches that need institutions to send their students' data out of their network borders, UEPPAI-SE uses federated learning wherein the local model update, which is trained using the students' data from each institution, is sent to a central aggregator together with differential privacy noise. The communication channel between the institutions and the aggregator is encrypted end-to-end and the UEPPAI-SE framework complies with GDPR, FERPA, and the Digital Personal Data Protection Act of India. This tackles the architectural problem highlighted by Yannam et al. [10] with respect to federated learning.

E. *On-Site Fairness Monitor in the Recommendation Engine*

After the recommendation engine ranks the suggested resources to users based on certain criteria, the fairness monitor evaluates whether the ranking algorithm is biased against some groups of people with respect to demographic parity and so on. In case of any bias in the resource recommendation process, the system will perform fairness-aware re-ranking. Weekly reports about the fairness of the recommended resources are provided to institutional administrators to detect any drifts in the fairness metric values. Hence, this strategy solves the problem presented by Verma et al. [9].

F. *Educational Knowledge Graph Connecting Everything*

As has been mentioned before, the system itself works through the educational knowledge graph that connects learning objectives, prerequisites, curriculum contents, and assessment methods. When the RL system suggests an action to be taken by a certain learner in the course of his learning process, it makes sure that this action is not out of the way of what the graph prescribes and does not skip the prerequisites stage. The knowledge graph is also the basis of the predictive analytics dashboard where teachers not only can see the current progress of their students but also understand the reasons behind potential difficulties in conceptual connections.

VI. EXPECTED OUTCOMES

1) For Students: The first and most obvious result would be that studying becomes more meaningful. If the student comprehends the reason for revisiting an idea, and that reasoning is presented clearly without using technical language, then there is a higher chance that he will become interested in it. Dynamic adaptability will ensure that the program makes changes to its approach based on the student's struggles before he loses hope. Privacy-friendly technology will guarantee that the learner does not need to worry about having his academic weaknesses exposed.
2) For Educators: Educators waste many hours identifying who needs extra help and figuring out why. The UEPPAI-SE analytics dashboard helps streamline and sharpen this process, but it does not attempt to automate educator decision-making – it merely provides a better starting point. If an educator can instantly determine which concept is causing the greatest difficulties in class, they can alter their subsequent lecture to address this issue. It is also critical to remember the significance of the XAI layer; a suggestion made by the algorithm that an educator cannot comprehend is unlikely to be followed.
3) For Academia and Educational Organizations: The fact that the architecture is modular means that each piece may be changed and contrasted. For example, a team of researchers interested solely in federated learning for educational purposes could implement just the federated learning module and use basic alternatives elsewhere. Regulatory frameworks vary by organization, so different organizations would want to change the privacy constraints without having to recreate the entire infrastructure from scratch.

TABLE II
Proposed Framework vs. Representative Existing Approaches

Capability	[4]	[10]	[5]	Proposed
Real-Time Adaptation	×	✓	×	✓
Explainability (XAI)	×	×	×	✓
Privacy Preservation	×	✓	×	✓
Fairness Monitoring	×	×	×	✓
Knowledge Graph	×	×	✓	✓
Multi-Source Data	×	×	✓	✓
Integrated Platform	×	×	×	✓

VII. DISCUSSION

A. *The Engineering is Harder Than It Appears*

Indeed, it is quite hard to build a combined approach of reinforcement learning and federated learning in order to apply it to practice in education, and one has to recognize that. Within federated learning, RL agents are capable of learning good policies with respect to the particular student group that is being trained by the agent, since the local policy update rate, noise rate, and gradient compression level are all interwoven in complex ways. Empirical analysis of these interconnections requires much more work than we are capable of now.

Moreover, running SHAP explanation on each recommendation takes significant computation effort, particularly when an educational institution does not have the capacity to conduct high-level computing in terms of its servers. This will result in lagging, thus failing to meet the objective of building an adaptive mechanism. Distilled models can be considered as an alternative approach, although at the expense of some accuracy levels.

B. *Ethics and Compliance Aren't Options*

The mere gathering of data about the behavior of students through several sources entails significant risk, especially when these students are minors. In such cases, there ought to be the proper procedure for seeking their informed consent prior to the gathering of data rather than just having vague terms and conditions nobody knows. Also, the students deserve to have access to their data, allowing them to update any inaccurate information, as well as un-subscribe from selected data streams without having their accounts suspended entirely.

Compliance also can't be a tacked-on part of software development. As the GDPR, FERPA, and Indian data protection laws show, there are technological matters such as data minimization, purpose limitation, breach notification, and more that need to be taken into consideration from the very beginning of the software development process. Our federated learning approach has helped solve quite a lot of problems; nevertheless, a legal review of the entire matter by an expert knowledgeable in both the regulation and technology is necessary.

C. *Technology Alone Will Not Change a Classroom*

The research literature abounds with examples of technologies which showed promising results during the pilot phase only to disappear quietly soon after. It has very little to do with any error in the algorithm used; instead, the primary cause is an insufficient effort in preparing the teachers to use the system, the technology being an additional burden for the administration instead of a help in managing it, or simply not enough time and opportunity for the teachers to get accustomed to the new system. Every implementation of UEPPAI-SE will have to go hand-in-hand with extensive teacher training and realistic assessments of time investment.

VIII. FUTURE RESEARCH DIRECTIONS

1) Multilingual and Multilingual Adaptation: In fact, almost everything we read had been carried out using English and/or Mandarin. India alone has many languages used in schools, including Hindi, Marathi, Tamil, and Telugu. Clearly, an LLM that cannot support any of these languages will never be able to help Indian learners learn better. While multilingual pretrained models such as mBERT already exist, it still requires additional effort for training them using regional datasets which is yet to be done in the research community. Language learning works by Chuang and Hung [1] offer some insights into how this could be done.
2) Tracking Learners' Progress over Many Semesters, not Just One: All of the papers we analyzed used a maximum of one semester for assessing outcomes. However, learning is a lengthy process which lasts for many semesters, and it takes several semesters to see results of personalized learning such as true understanding of concepts and improvement in study habits. Building longitudinal learner models which would allow tracking learners' progress over many semesters is an ambitious goal indeed, but also one which is worth pursuing.
3) How to Define Success?: Another issue related to comparing the performance of the analyzed systems is that all of them use different criteria for measuring success. Some papers use RMSE, while others measure accuracy or engagement times or levels of user satisfaction. It makes sense to have some benchmarks, which would allow evaluating whether one system is superior to another. For example, establishing the dataset and evaluation protocols that would be analogous to ImageNet in computer vision could be very useful in advancing research.

4) What about the Teacher's Role?: The question of how to separate tasks of the AI system and the teacher has not been properly addressed by any of the ten papers. The common assumption, however, is that AI is responsible for personalization, whereas teachers should do the rest. In reality, however, the division between these two components can be rather ambiguous. Thus, studies that would address collaboration between human beings and AI systems could be helpful in this case.
5) Working Offline: The lessons learned by Verma et al. [9] from rural schools suggest one of the limitations of AI education technology that will persist regardless of future advances: many people do not have reliable internet connections or even affordable ones. To create an AI learning system dependent on a permanent server connection is not feasible for many learners. The challenge of designing an effective learning tool that can gracefully degrade without network access is an important technical problem.

IX. CONCLUSION

Our goal was to examine critically the state of AI-based personalized learning without focusing on how far from reality the most hopeful papers suggest this field can go. In the end, based on ten selected papers from IEEE journal publications, what we saw was a technology with significant potential but also a series of persistent problems to solve. The progress made is indeed impressive: the successful implementation of personalized and adaptive e-learning technologies, which contribute to improving students' academic success, increased privacy protection, advanced language teaching, which is impossible to achieve by only one instructor. However, there are still some issues to tackle: the limited scope of data used to train models, lack of explanation from models, privacy preservation measures added at a later stage, insufficiently dynamic adaptability, and preference to design technologies for convenient users.

That is why the UEPPAI-SE framework that we suggest incorporates several components of personalized education technology into one integrated model, such as reinforcement learning, federated privacy preservation, knowledge graph backbone, explainability based on XAI, and fairness monitor. We consider this to be essential since solving one of the mentioned problems while others remain untouched is not enough to make any changes to the situation.

There are many challenges to be addressed on the road from a framework proposal to implementation, and we have been very straightforward about those parts that have proven to be truly challenging technically, and those areas where we do not feel ethical questions have yet to be adequately addressed. It is our sincere hope that this paper will provide some clarity around what must be developed next based on a careful consideration of what has already been developed.

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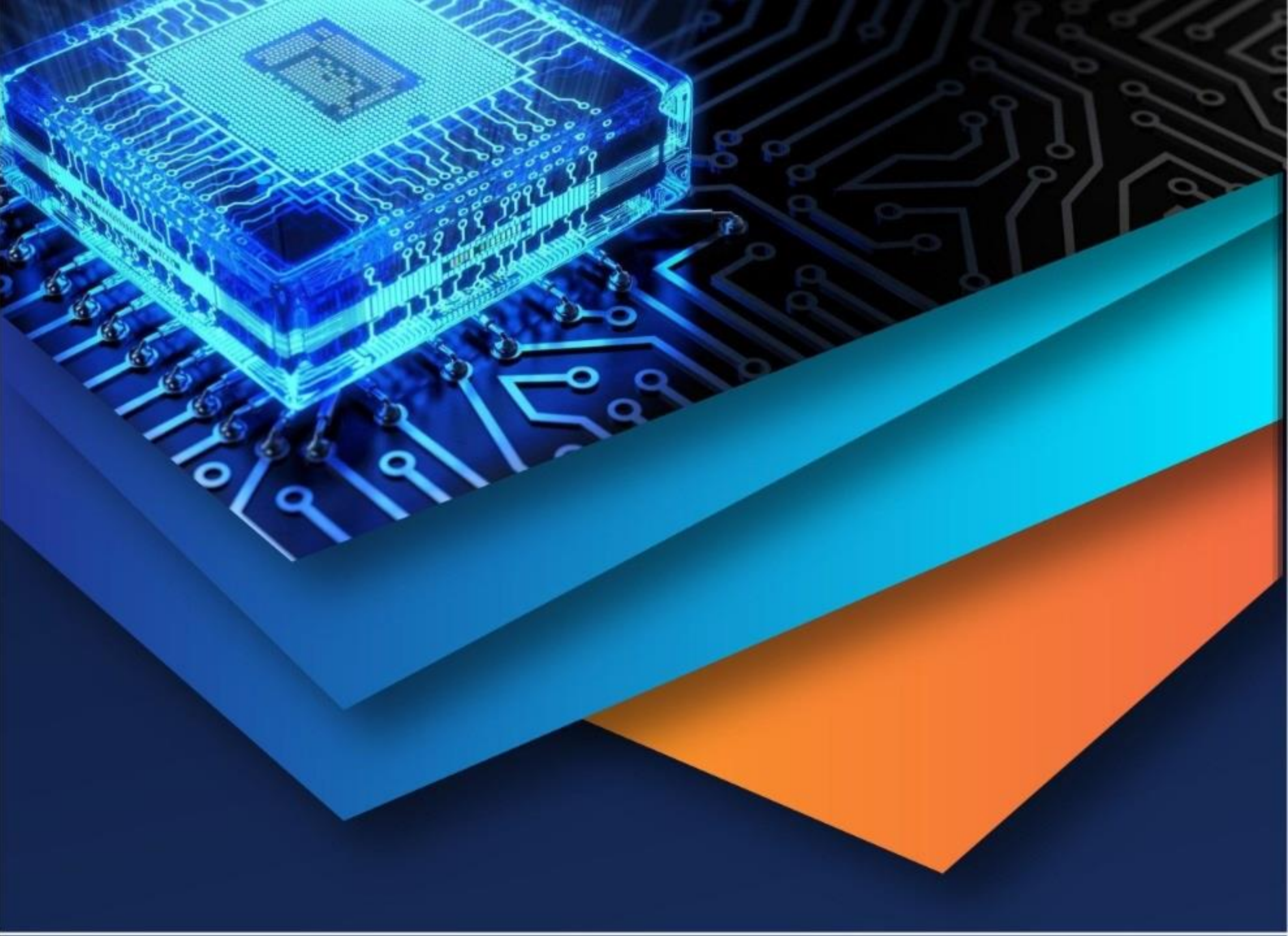

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