

Developing AI Applications for Education: A Design Thinking Approach to Enhance Learning Experiences

Dharmapuri Siri¹; Nagaraju Krishna Chythanya²; Bisthi Geetha Kumari³; Divya Boya⁴; Bhargava Ramu T⁵; Sirasanagandla Bhavyesh⁶

^{1,2,3,4,5,6} Computer Science and Engineering Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Telangana, India

Corresponding Author Email: siri1686@grietcollege.com

Abstract— In the evolving landscape of machine learning (ML), traditional approaches often prioritize technical performance over user needs, leading to solutions that fail to address real-world requirements. To bridge this gap, the integration of design thinking principles into ML development has emerged as a promising approach. This paper explores the application of design thinking to ML, particularly in the educational sector, by focusing on creating user-centered solutions. We outline a methodology that combines empathy, problem definition, ideation, prototyping, and user feedback to ensure that ML solutions are both technically robust and aligned with user needs. Through a case study of an AI-driven personalized learning platform, we demonstrate how this approach can lead to more impactful and widely adopted solutions. We also discuss the benefits of such applications in education, including personalized learning, automated administrative tasks, and enhanced accessibility, while addressing challenges like ethical concerns and integration with existing systems. The paper concludes by highlighting the potential for this methodology to be applied across various industries, its role in advancing AI integration, and future research directions focusing on ethical design and scalability. By merging design thinking with machine learning, organizations can develop solutions that are innovative, user-centric, and effective in real-world applications.

Keywords: Machine Learning (ML), Design Thinking, User-Centered Design, Educational Technology, Personalized Learning, AI-Driven Solutions.

I. INTRODUCTION

In recent years, machine learning (ML) has emerged as a powerful tool for solving a wide range of complex problems across various domains. However, traditional approaches to developing ML solutions often prioritize technical feasibility and algorithmic performance over user needs and preferences[1]. As a result, many ML projects fail to deliver solutions that meet the real-world requirements or expectations of end-users. This gap between technical excellence and user-centric design has led to a growing recognition of the importance of integrating design thinking principles into machine learning projects. Design thinking, a human-centered problem-solving methodology, emphasizes understanding user needs, ideating creative solutions, prototyping iteratively, and testing with users to create impactful solutions[2].

Developing AI Applications for Education

Applying Design Thinking to Educational AI: Integrating design thinking into AI development for educational contexts ensures that the resulting applications are user-centered and address the actual needs of educators and students. The process involves several stages:

Empathy and Understanding Users: Conducting interviews and workshops with educators, students, and administrators to gain insights into their needs, challenges, and preferences.

Defining the Problem: Clearly stating the educational challenges that AI can address, such as personalized learning, automated grading, or adaptive content delivery.

Ideation: Brainstorming potential AI-driven solutions, involving cross-disciplinary teams to ensure diverse perspectives and innovative ideas.

Prototyping: Developing prototypes of AI applications, such as intelligent tutoring systems, recommendation engines for learning resources, or predictive analytics tools for student performance.

User Testing and Feedback: Engaging end-users in testing the prototypes, gathering feedback, and iterating on the design to improve usability and effectiveness.

AI-Driven Personalized Learning Platform

To illustrate the application of design thinking in educational AI, consider the development of a personalized learning platform:

Empathy and Understanding Users: Through interviews and workshops with teachers and students, the development team identified the need for a platform that adapts to individual learning paces and styles.

Defining the Problem: The team defined the problem as the lack of personalized learning experiences that can cater to the diverse needs of students in a typical classroom.

Ideation: The team brainstormed solutions such as AI-driven diagnostic assessments, personalized learning paths, and adaptive quizzes that provide instant feedback.

Prototyping: A prototype platform was developed using machine learning algorithms to analyze student performance data and recommend tailored learning activities.

User Testing and Feedback: Teachers and students tested the platform, providing feedback on its usability and effectiveness. This feedback was used to refine the AI models and user interface.

Benefits of AI Applications in Education

Personalized Learning: AI applications can provide personalized learning experiences, adapting content and pace to meet individual student needs, thereby enhancing engagement and learning outcomes.

Automated Administrative Tasks: AI can automate administrative tasks such as grading and attendance tracking, allowing educators to focus more on teaching and student interaction.

Data-Driven Insights: AI-driven analytics can provide educators with insights into student performance, helping identify at-risk students and informing instructional strategies.

Enhanced Accessibility: AI applications can improve accessibility for students with disabilities by providing customized learning materials and support.

Challenges and Considerations

Ethical Concerns: Ensuring the ethical use of AI in education, including data privacy and avoiding biases in AI algorithms, is crucial.

User Training: Educators and students need training to effectively use AI applications and understand their benefits and limitations.



Fig :1

Highlight of Design thinking and Machine learning

Integration with Existing Systems: Seamlessly integrating AI applications with existing educational technologies and workflows is necessary for widespread adoption.

How does Applied Machine Learning help Design Thinking?

The responsibility of constructing the ML algorithms lies with the Machine Learning Engineer. However, as a Quantitative UX Researcher & Data Scientist, it is your role to utilize these ML algorithms to transform data into actionable insights.

2.1 Machine Learning Use Case in Data Analysis

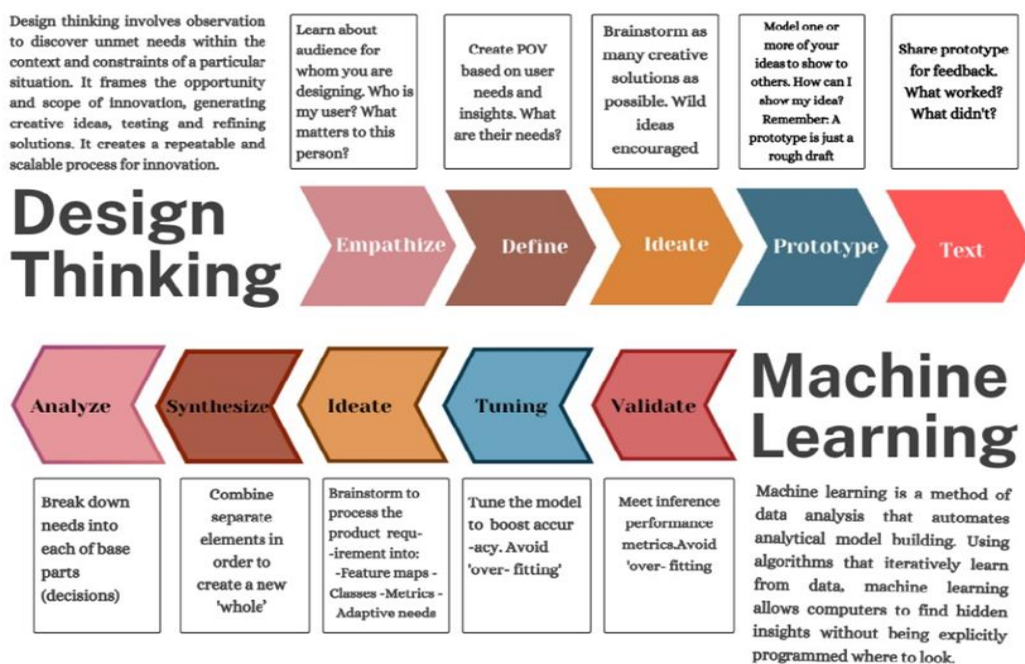
Data clustering plays a crucial role in the Design Thinking process[7,8]. By organizing large datasets into clusters, one can establish connections between these clusters to gain new and deeper insights. This approach aids in problem definition

and the generation of potential solutions. Essentially, it involves transitioning from analysis to synthesis[5]. In Design Thinking, this clustering activity is referred to as Affinity Mapping. Affinity Mapping involves manually labeling various elements, serving as a helpful technique for researchers to make sense of mixed data, including facts, ethnographic research, brainstormed ideas, user opinions, user needs, insights, and design issues. Ideas are grouped into clusters and labeled based on their inherent characteristics by the researcher[6]. While Affinity Mapping is primarily a manual process, it does have limitations when it comes to quantitative data.

The volume of data produced by both machines and humans is staggering and is increasing at an unprecedented rate.

IBM reports that 90% of all data ever generated was created in the past two years. Just think about the immense power contained within this data. If you believe that manually organizing and structuring such vast amounts of data is possible, I commend your confidence. However, if you think it is not feasible, then welcome to the realm of Machine Learning.

Fig 2 : Comparisons of Design thinking and Machine learning



Machine Learning streamlines the data analysis process and enables real-time data-driven predictions without human involvement[9]. An automated Data Model is created and continuously refined to provide accurate predictions on the fly. This is where Machine Learning Algorithms prove to be invaluable in the Design Thinking Cycle[10]. Machine learning is a magic box that is already causing a fundamental leap in human progress. It is the future and the future is here!

II. METHODOLOGY

The methodology presented in this paper outlines a structured approach to integrating design thinking principles into the machine learning (ML) development process. This approach is designed to ensure that ML solutions are not only technically robust but also aligned with user needs, preferences, and real-world contexts.



Fig 3: System Architecture Flow Diagram

1. Empathy and Understanding Users

Objective: Gain a deep understanding of the users, their needs, challenges, and the context in which they will interact with the ML solution.

Activities: Conduct interviews, surveys, and workshops with potential users and stakeholders to gather insights. Observe users in their natural environments to understand their behaviors and pain points. Create user personas and journey maps to represent the diverse needs and experiences of different user groups.

2. Defining the Problem

Objective: Clearly articulate the problem that the ML solution aims to address, ensuring it is grounded in user needs.

Activities:

Synthesize the insights gathered during the empathy phase to define the core problem. Use tools like affinity mapping to cluster related insights and identify key themes. Formulate problem statements that reflect the real challenges faced by users.

3. Ideation

Objective: Generate a wide range of potential solutions to the defined problem, leveraging cross-disciplinary perspectives.

Activities:

Facilitate brainstorming sessions with diverse teams, including data scientists, designers, and domain experts.

Encourage creative thinking and the exploration of unconventional ideas. Prioritize ideas based on feasibility, user impact, and alignment with the problem statement.

4. Prototyping

Objective: Develop low-fidelity prototypes of the ML solutions to quickly test and refine ideas.

Activities:

Build initial prototypes that incorporate ML algorithms, focusing on core functionalities that address user needs. Use rapid prototyping tools to create interactive models that can be tested with users. Iterate on the prototype based on user feedback and technical feasibility.

5. User Testing and Feedback

Objective: Validate the effectiveness and usability of the ML solution by testing it with real users.

Activities:

Conduct user testing sessions where participants interact with the prototype in realistic scenarios. Gather qualitative and quantitative feedback on the solution's usability, effectiveness, and alignment with user needs. Identify areas for improvement and refine the ML models and user interface based on the feedback.

6. Iteration and Refinement

Objective: Continuously improve the ML solution through iterative testing and refinement cycles.

Activities:

Use agile methodologies to incorporate user feedback into subsequent iterations of the solution. Continuously monitor user interactions and performance metrics to identify opportunities for further enhancement. Ensure that the solution remains aligned with evolving user needs and technological advancements.

7. Implementation and Scaling

Objective: Deploy the refined ML solution in real-world settings and scale it to reach a broader user base.

Activities:

Work closely with stakeholders to integrate the solution into existing systems and workflows. Provide training and support to users to ensure successful adoption. Monitor the solution's impact and gather data for ongoing optimization.

Case Study Application: AI-Driven Personalized Learning Platform

1. Empathy and Understanding Users: Interviews with teachers and students revealed the need for a personalized learning platform that adapts to individual learning styles.

2. Defining the Problem: The challenge was identified as the lack of personalized learning experiences in diverse classroom settings.

3. Ideation: Solutions such as AI-driven diagnostic assessments and adaptive learning paths were brainstormed.

Prototyping: A prototype platform was developed, using ML to analyze student data and recommend personalized learning activities.

4. User Testing and Feedback: The prototype was tested with teachers and students, leading to refinements in both the ML algorithms and the user interface.

5. Iteration and Refinement: The platform was continuously improved through user feedback and data-driven insights.

Implementation and Scaling: The platform was deployed in multiple schools, with ongoing support provided to ensure successful integration.

Finally, I would like to conclude that organizations can create ML solutions that are not only technically advanced but also deeply user-centric. The integration of design thinking into the ML development process ensures that solutions are more likely to meet real-world needs, resulting in higher user satisfaction and greater impact.

III. MODELS

1. Empathy Model

Tool: User Personas & Journey Mapping

Steps: Conduct interviews, observations, and research to gather insights. Create detailed user personas representing different user types. Map out the user's journey, highlighting pain points, motivations, and opportunities.

Outcome: A clear understanding of user needs, behaviors, and the context in which they interact with the system.

2. Problem Definition Model

Tool: Affinity Diagramming & Problem Statements

Steps: Use affinity diagramming to cluster related insights from the empathy phase. Identify themes and patterns in user needs and challenges. Formulate specific, user-centric problem statements.

Outcome: A well-defined problem statement that guides the development of ML solutions.

3. Ideation Model

Tool: Brainstorming & Concept Development

Steps: Conduct brainstorming sessions using techniques like "Crazy 8s" or "Mind Mapping." Generate diverse ideas addressing the core problem identified. Develop initial concepts that align with user needs and problem statements.

Outcome: A range of potential solutions emphasizing creativity and diversity of thought.

4. Prototyping Model

Tool: Rapid Prototyping & Wireframing

Steps:

Develop low-fidelity prototypes using tools like Sketch, Figma, or paper prototyping. Incorporate essential ML components to demonstrate core functionalities. Focus on key features and user interactions in the prototype.

Outcome: A tangible prototype that can be tested with users.

5. User Testing and Feedback Model

Tool: Usability Testing & A/B Testing

Steps: Conduct usability testing sessions with real users interacting with the prototype. Use A/B testing to compare different versions of the ML solution.

Gather feedback on usability and effectiveness.

Outcome: Data-driven insights for refining the ML solution.

6. Iteration and Refinement Model

Tool: Agile Iteration & Continuous Integration

Steps: Implement agile practices like sprints and continuous integration. Iterate on the solution based on user feedback and performance metrics.

Continuously refine ML algorithms and user experience.

Outcome: An evolving solution that improves over time.

7. Implementation and Scaling Model

Tool: Change Management & Deployment Strategies

Steps: Develop a change management plan including training and support. Implement deployment strategies for scaling the ML solution. Ensure smooth integration with existing systems and processes.

Outcome: Successful adoption and scaling of the ML solution within the target environment.

Case Study: AI-Driven Personalized Learning Platform

User Persona Development:

Steps: Create personas for different types of teachers and students. Focus on unique challenges and needs in the classroom.

Outcome: Detailed understanding of potential users.

Problem Statement Formulation:

Steps: Define the problem of lack of personalized learning in classrooms. Identify specific gaps that the AI-driven platform will address.

Outcome: A clear, actionable problem statement.

Prototyping AI-Driven Assessments:

Steps: Develop prototypes of AI-driven assessments tailored to individual learning styles. Use mock data to simulate real-world scenarios.

Outcome: Functional prototype demonstrating personalized assessments.

User Testing and Feedback Loop:

Steps: Engage teachers and students in testing the platform. Collect feedback on usability and effectiveness. Iterate on the platform based on user input.

Outcome: Improved platform aligned with user needs.

Fig 4: AI applications can be integrated into education by combining Design Thinking with Machine Learning

This architecture describes how AI applications can be integrated into education by combining Design Thinking with Machine Learning. The process begins with User Needs Assessment (UNA), where the needs and challenges of students, educators, and administrators are understood through interviews and surveys. Based on this, a clear Problem Definition (PD) is established to guide the development of solutions.

Next, during Ideation and Prototyping (I&P), creative brainstorming sessions are conducted, and initial prototypes of AI-driven solutions, like intelligent tutoring systems, are developed. These solutions are then powered by Machine Learning Models (MLM), where data is used to train algorithms that can personalize learning or automate tasks like grading.

The prototypes are tested with real users in the User Testing and Feedback (UTF) phase, gathering insights to refine the AI application. After making necessary improvements, the Final AI Application (FAI) is developed, which is user-friendly and ready for deployment.

Finally, in the Deployment and Monitoring (D&M) stage, the application is deployed in the educational environment, with continuous monitoring to ensure it operates effectively and evolves based on user feedback.

This approach ensures that the AI application is not only technically robust but also tailored to meet the real-world needs of its users, enhancing educational experiences and improving administrative efficiency.

IV. CONCLUSION

In this paper, we explored a novel approach that integrates design thinking principles with machine learning to create user-centric solutions. By emphasizing empathy, problem definition, ideation, prototyping, and user feedback, this methodology ensures that machine learning applications are not only technically robust but also aligned with the real needs and preferences of end-users. The case study on an AI-driven personalized learning platform demonstrates the effectiveness of this approach, resulting in solutions that are more intuitive, impactful, and widely adopted. Overall, combining design thinking with machine learning enhances the development process, leading to more innovative and user-friendly outcomes.

V. FUTURE SCOPE

Wider Application Across Industries: The integration of design thinking with machine learning can be applied beyond education, benefiting industries such as healthcare, finance, and retail. Future work could explore specific use cases in these sectors to validate the methodology's versatility.

Advanced AI Integration: As AI and machine learning technologies evolve, incorporating more advanced algorithms, such as deep learning and reinforcement learning, within this design thinking framework can lead to even more sophisticated and effective solutions.

Ethical and Inclusive Design: Future research should focus on ensuring that design thinking-driven machine learning models are ethically sound and inclusive. This includes addressing biases in AI models and ensuring that solutions are accessible to all user groups, including those with disabilities.

Automated Design Thinking Tools: The development of automated tools that incorporate design thinking principles into the machine learning workflow could streamline the process, making it easier for teams to adopt this approach and achieve consistent results.

Long-term User Engagement: Future studies could explore how the design thinking-driven approach impacts long-term user engagement and satisfaction with machine learning solutions, providing insights into the sustained value of this methodology.

Scalability and Adaptability: Research could focus on how the design thinking-driven approach can be scaled and adapted for large-scale machine learning projects, ensuring that it remains effective in more complex, real-world scenarios.

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