CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter reviews existing literature related to artificial intelligence in education, interactive e-learning systems, usability evaluation, and AI-driven learning support tools. It synthesizes findings from previous research, identifies persistent gaps in STEM learning technologies, and outlines how EduVision addresses these gaps. The chapter concludes with a conceptual framework guiding the design of the proposed system.

2.1 Related Literature Review

2.1.1 AI Applications in STEM Education

Xu and Ouyang (2022) conducted a decade-long systematic review of AI technologies applied in STEM learning. Their study revealed that AI has been widely used in intelligent tutoring, automated assessment, personalized learning pathways, and real-time learner analytics. These systems significantly improved comprehension and motivation. However, the tools reviewed were mostly isolated applications—requiring learners to use separate systems for explanations, summaries, and assessments.

2.1.2 Intelligent Tutoring and Learning Principles

Baillifard et al. (2023) evaluated the effectiveness of personal AI tutors based on microlearning, spaced repetition, and step-by-step explanations. Their findings showed measurable improvements in students' performance when using AI tutors consistently. Despite this, the authors noted that these systems rarely support handwritten notes, mixed-media documents, or complete revision workflows. They primarily operate on clean digital content.

2.1.3 AI in Foundational STEM Learning

Memari and Ruggles (2025) explored AI-supported learning systems for early STEM education. They reported high gains in conceptual understanding through adaptive scaffolding, multimodal feedback, and visual explanations. However, they emphasized that most systems do not handle real-world challenges such as poor-quality images, messy handwritten notes, or varied document formats—issues that especially affect Kenyan learners who rely heavily on notebooks and printed materials.

2.1.4 Generative AI as a Learning Scaffold

Wang et al. (2024) examined generative AI tools used by university students in STEM courses. While learners relied heavily on AI for worked examples and explanations, the study found that many systems acted only as "answer generators." Without structured reasoning, this created shallow understanding. The authors recommend AI tools that support guided reasoning and pedagogical alignment instead of merely producing answers.

2.1.5 AI and Sustainable Learning Competencies

Alkhawaja et al. (2025) investigated how AI systems influence skills such as digital literacy, critical thinking, and problem-solving. They concluded that AI improves self-paced learning and autonomy. However, many tools are built for global audiences and rarely align with localized curricula or contextual challenges. This creates a gap for country-specific systems tailored to regions like Kenya.

2.1.6 Usability Evaluation in E-Learning Systems

A study by He et al. (2024) proposed a comprehensive usability framework for educational platforms, combining efficiency, mental model alignment, learner satisfaction, and error prevention. The evaluation showed that usability significantly impacts learning outcomes. However, many e-learning systems still depend heavily on satisfaction surveys without measuring actual learning performance or cognitive load.

2.1.7 Interactive and Multimodal Learning Tools

Létourneau et al. (2023) evaluated interactive learning systems using 3D models, animations, and simulation-based explanations. Their results showed increased engagement and improved learning retention. Nonetheless, such systems rarely integrate OCR, document parsing, Q&A, and summarization into a single platform. Fragmentation forces students to switch between apps for different learning tasks.

2.2 What Existing Literature Has Already Implemented

The reviewed studies show several AI-driven implementations:

2.2.1 Intelligent Tutoring Systems (ITS)

AI tutors can generate explanations, adapt to learner pace, and provide feedback. However, most ITS platforms work only with structured, digital content and lack support for raw handwritten inputs.

2.2.2 AI-Generated Summaries and Content Simplification

Existing systems support summarization, concept simplification, and reduction of cognitive load. Yet none combine these features with document uploads, handwritten note processing, or integrated revision workflows.

2.2.3 Automated Reasoning and Problem Solving Engines

Step-by-step problem solvers exist, especially in mathematics and physics. Still, they rarely interpret user-generated materials like class notes or textbook snapshots.

2.2.4 Learning Analytics and Adaptive Support

AI systems track learning progress and provide adaptive recommendations. However, these systems generally lack localization for Kenyan or African curricula.

2.2.5 OCR-Driven Educational Tools

Although OCR is used in digitization tasks, very few educational systems integrate OCR with personalized explanations, flashcard generation, or automatic revision structuring.

2.3 Gaps / Lacunas Identified in Literature

From the studies reviewed, several gaps persist:

1. Fragmentation of tools – No integrated system combining OCR, summaries, Q&A, analytics, and revision tools.
2. Poor support for unstructured input – AI tutors struggle with handwritten notes, low-quality scans, and mixed-media documents.

3. Weak step-by-step STEM reasoning – Most systems generate answers without structured reasoning, leading to shallow learning.
4. Lack of localization – Many tools are built for Western contexts and do not align with Kenyan curricula or resource environments.
5. Limited revision automation – No system automatically extracts key points, generates flashcards, and organizes revision material from uploaded documents.
6. Inadequate learning performance measurement – Many studies rely on satisfaction surveys, ignoring cognitive load and actual learning gains.
7. Usability concerns – Existing evaluation models show weak discriminant validity and rarely capture meaningful learning outcomes.usability gap for students dependent on handwritten notes.

2.4 Conceptual Framework

The conceptual framework guiding EduVision is based on the integration of Al-enabled document processing, content understanding and personalized tutoring. The framework consists of:

Input Layer

1. Students upload notes, textbook pages, scans or PDF documents.
2. Student also enters queries on difficult STEM concepts

Processing Layer

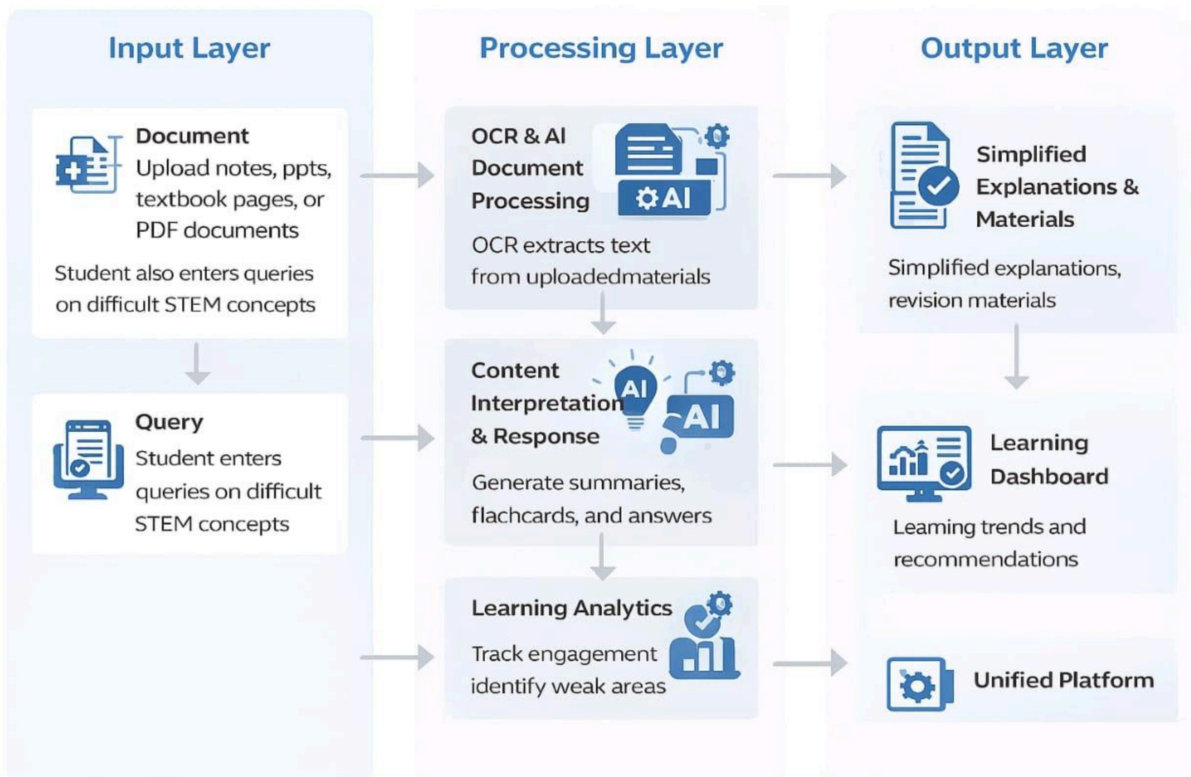
1. OCR extracts text from uploaded materials.
2. Al models interpret extracted content, generate summaries, produce flashcards, and answer questions
3. Learning analytics track engagement and identify weak areas.

Output Layer

1. Students receive simplified explanations, revision materials, and visual scaffolds.
2. A dashboard displays learning, trends and recommendations.

3. All tools exist in one unified platform, reducing fragmentation.

This conceptual model positions EduVision as an integrative AI learning assistant tailored to STEM needs and local academic contexts.



2.5 Chapter Conclusion

The reviewed literature demonstrates considerable progress in AI-driven tutoring systems, content simplification tools, interactive simulations, and OCR technologies. However, existing solutions remain fragmented, lack localization, and fail to interpret handwritten or low-quality study materials common among Kenyan learners. Additionally, many systems focus on user satisfaction rather than learning performance or cognitive load. These gaps justify the development of EduVision—an integrated, context-aware AI learning assistant designed to support Kenyan STEM students through document understanding, personalized tutoring, structured revision workflows, and adaptive learning analytics.

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