Uncovering Spatial Reasoning Strategies Using Eye-Tracking and Machine Learning: A Cognitive and Data-Driven Approach

1. Introduction

Spatial reasoning plays a pivotal role in STEM learning, problem-solving, and visual cognition. However, individuals often approach spatial tasks using different cognitive strategies, which in turn influence performance and learning outcomes. David Lohman (1989) proposed that these strategies range from piecemeal, bottom-up approaches to heuristic, top-down methods—each reflecting different cognitive demands and levels of expertise.

While such distinctions are well established in theory, identifying these strategies in real time has been challenging. Mary Hegarty and others have shown that eye-tracking can reveal strategic patterns of attention, such as fixation duration, AOI transitions, and scanpath entropy, offering a powerful window into underlying cognitive processes.

Despite growing interest in this area, few studies have systematically explored how combinations of eye-tracking metrics map onto these cognitive strategies using data-driven approaches. This research aims to bridge that gap by integrating machine learning with theoretical models to classify and interpret strategy use during spatial problem-solving tasks.

2. Objectives

This study aims to:

Identify key eye-tracking metrics associated with spatial reasoning tasks.

Develop a framework to classify cognitive strategies (e.g., planner, explorer, checker; or piecemeal vs. heuristic) based on these metrics.

Apply machine learning models to predict strategy type and performance from gaze behavior.

3. Research Questions

Which eye-tracking features most reliably indicate spatial reasoning strategies?

Can unsupervised or supervised machine learning models successfully classify participants into strategy groups?

How do the identified strategies relate to task performance and cognitive efficiency?

4. Methodology

Participants

~30–50 university students participating in lab-based spatial reasoning tasks (e.g., mental rotation, pattern completion).

Materials

Eye-tracker (e.g., Tobii Pro or EyeLink)

Spatial tasks adapted from cognitive psychology (e.g., paper folding, visual analogy problems)

Pre-task spatial ability assessments (e.g., MRT, SRT)

Procedure

Participants will complete a battery of spatial tasks while their eye movements are recorded.

Gaze data (fixations, saccades, transitions, AOIs) will be extracted and preprocessed.

Post-task accuracy and time data will be recorded.

Analysis

Feature engineering: Compute metrics like fixation duration, entropy, transition rates, dwell time, scanpath length.

Strategy labeling: Use rule-based heuristics (and optionally clustering) to assign tentative strategy labels.

Machine learning:

Unsupervised: K-means, HMMs, hierarchical clustering

Supervised: Random Forest, SVM, logistic regression

Interpretation: Identify features most predictive of strategy type and performance.

5. Expected Contributions

A validated set of gaze-derived indicators for common spatial reasoning strategies.

A machine learning pipeline for strategy classification in real-time educational settings.

Theoretical implications for cognitive modeling and practical implications for adaptive learning systems.

6. Theoretical Framework

This study is grounded in:

Lohman’s theory of cognitive strategies in spatial reasoning

Hegarty’s empirical findings on eye movement patterns and strategy use

Just & Carpenter’s eye–mind hypothesis linking visual attention and cognitive processing