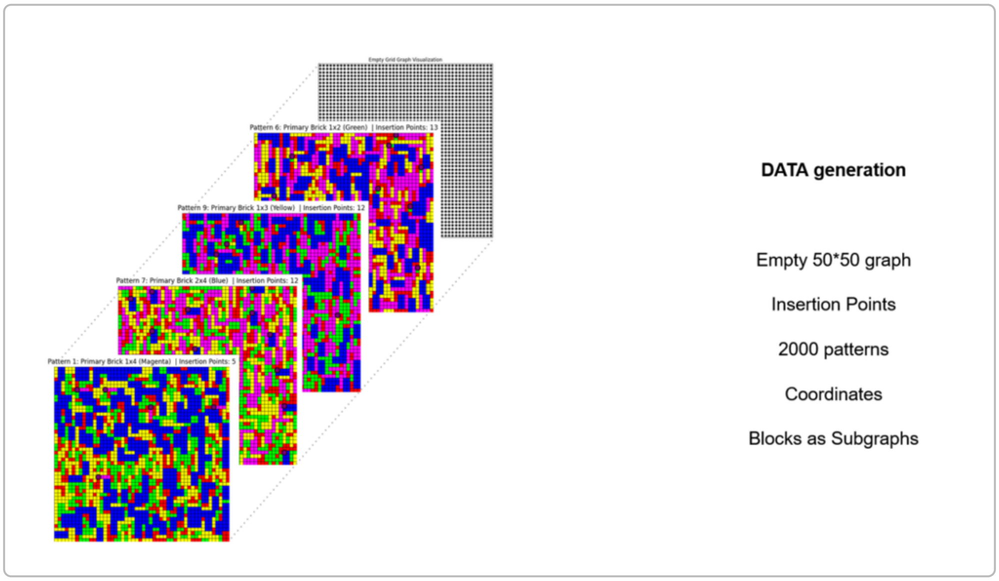
ChatGPT

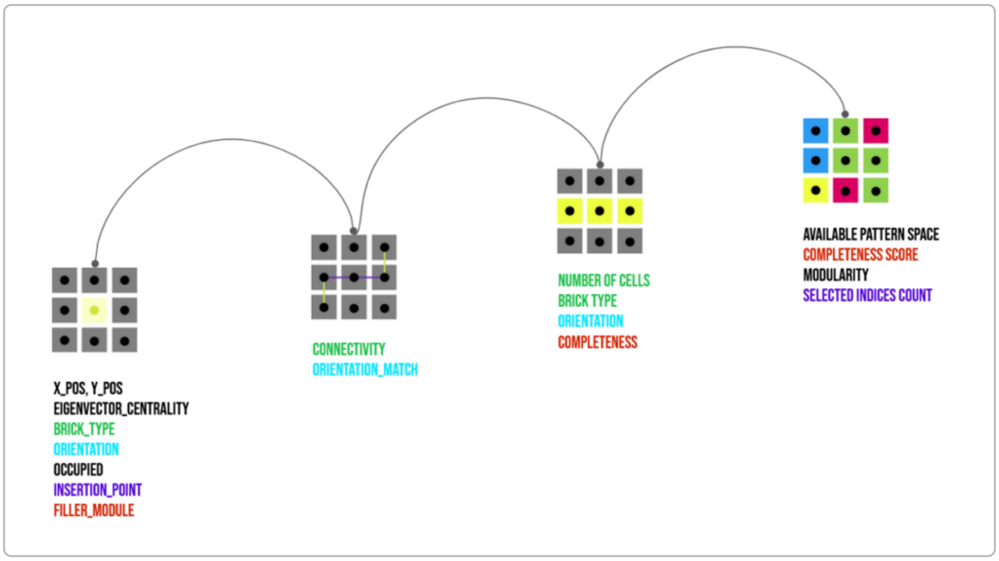
Graph ML for Post-Study Analysis and Cognitive Benchmarking



Rather than applying Graph ML only to live design inputs, we will leverage it on the *entire dataset* gathered after the study to benchmark user cognition. In practice, we construct a graph from the aggregated user data – for example, treating design actions, user responses, and performance measures as nodes (with features like task accuracy, time, or design attributes) and using edges to encode temporal or conceptual links. Graph Neural Networks (GNNs) can then process this graph to reveal deep relational patterns. GNNs use a **message-passing** mechanism that aggregates information from each node's neighbors, allowing the model to capture complex structural dependencies [1]. In education research, similar graph-based models have mapped students and concepts into a graph and achieved high prediction accuracy of learning outcomes [2] [1]. With our data, a trained GNN might classify nodes (e.g. user sessions) by proficiency level or cluster subgraphs of related tasks, effectively encoding a "skill profile" for each user.

Possible Graph-ML analyses include:
- **Graph construction:** Encode each user's interaction history as a graph. Nodes can represent design elements, decision points, or user-states (with features like confidence or correctness), and edges capture sequence or semantic relationships between them.
- **Graph neural modeling:** Train GNNs (e.g. GraphSAGE, GAT) on this dataset of graphs. These models learn node or graph embeddings by iteratively aggregating neighbor features, capturing both local and global context [1].
- **Outcome prediction:** Use the GNN to predict cognitive outcomes (for example, categorizing users by mastery or forecasting quiz success). This parallels educational GNNs that combine interaction graphs and student attributes to predict academic performance [2] [3].
- **Pattern and subgraph mining:** Analyze learned embeddings or attention weights to identify key substructures. For instance, certain subgraphs of the task graph might consistently correlate with rapid learning; these become valuable "case examples" for training.
- **Benchmark generation:** Apply graph clustering or community detection to group similar cognitive

profiles. Representative graph-structures (and underlying tasks) from each cluster can be used to construct benchmarks or training scenarios that target specific skill levels.



Graph-ML models often embed features at multiple scales. For example, in one modular-design GNN, node-level attributes (position, type, orientation) were combined with subgraph metrics (pattern completeness) and whole-graph scores (overall modularity)【55】. Analogously, we will annotate our graphs with cognitive features at various levels – such as individual task scores, clusters of related concepts, or overall task difficulty – so the GNN can learn from both fine-grained user choices and global performance trends.

Overall, this post-hoc Graph ML analysis will surface insights that feed back into our thesis goals. A GNN trained on the complete dataset can highlight which tasks, feedback types, or sequence of interactions led to the greatest cognitive gains. These findings inform **benchmarking** of user development: for example, the model might predict a user's spatial reasoning level or suggest new tasks to target observed weaknesses. In this way, Graph ML turns the collected data into a "knowledge graph" of learning, enabling deeper understanding and improvement of our design-learning system [1] [3].

Sources: Graph Neural Networks excel at modeling relational data and have been used in educational contexts to predict learning outcomes [1] [2]. Our approach builds on this by using GNNs to analyze the aggregated user interaction graph for cognitive benchmark insights.

---

[1] A review of graph neural networks: concepts, architectures, techniques, challenges, datasets, applications, and future directions | Journal of Big Data | Full Text
https://journalofbigdata.springeropen.com/articles/10.1186/s40537-023-00876-4

[2] [3] Improving academic performance predictions with dual graph neural networks | Complex & Intelligent Systems
https://link.springer.com/article/10.1007/s40747-024-01344-z