A Graph-Theory Approach for Testing Children's Block Construction

Nina Peleg
Centre for Brain and Cognitive Development
Centre for Educational Neuroscience
School of Psychological Sciences
UCL Institute of Education
Birkbeck, University of London
London, UK
npeleg01@student.bbk.ac.uk

Jamal Rizvi
Centre for Brain and Cognitive Development
School of Psychological Sciences
Birkbeck, University of London
London, UK
jrizvi03@student.bbk.ac.uk

Andrew Tolmie
UCL Institute of Education
Centre for Educational Neuroscience
Department of Psychology
University College of London
London, UK
andrew.tolmie@ucl.ac.uk

Ori Ossmy
Centre for Brain and Cognitive Development
Centre for Educational Neuroscience
School of Psychological Sciences
Birkbeck, University of London
London, UK
ori.ossmy@bbk.ac.uk

***Abstract*—Block construction is a central activity in childhood, engaging key motor and cognitive capabilities. Skills such as problem-solving, planning, and the intuitive understanding of physical principles are required during block building, all of which are foundational to later academic achievement in domains such as science, technology, engineering, and mathematics. Past research has predominantly taken an outcome-oriented approach overlooking the underlying mechanisms and their connections to other skills. Here, we introduce a graph-theory framework to capture and analyze the sequential steps in children's block construction activities. We tested our framework using a dataset of adults (*n* = 18) and children (*n* = 12; ages 7–10) building Duplo models. We took a process-oriented approach by using a novel video-annotation scheme that allowed us to generate graphical structures of the building process and extract measures that provided valuable insights into the differences between children and adults in the construction process. Our findings show that while adults take fewer steps, they take more time per step, and that children struggle to recover from errors more than adults. The framework is openly shared with the scientific community, aiming to provide the groundwork for other researchers who are interested in shifting from an outcome-oriented to a process-oriented approach when studying block construction.**

Keywords—graph theory; child development; block construction; motor development; perception-action

I. INTRODUCTION

Block construction is a fundamental part of children's experience during their early years, involving the creative and systematic arrangement of physical units (e.g., wooden or plastic blocks) to generate or replicate structures in the environment [1]. From tower building in toddlers to more sophisticated designs in older preschoolers, the construction activities cultivate central visuo-spatial and cognitive functions [2], [3]. The block-building process engages skills such as problem-solving, planning, and the intuitive understanding of physical principles, all of which are foundational to later academic success in domains such as science, technology, engineering, and mathematics [1]. Hence, block construction exerts an enduring influence on everyday tasks, from navigating one's surroundings to innovating solutions in vocational or educational contexts.

Traditionally, developmental researchers have taken a normative, outcome-oriented approach to block construction, by identifying the ages at which children succeed in building specific structures accurately or replicating original, creative designs [4]. Indeed, previous studies established that block construction begins in toddlerhood [5] and improves with age and experience [4], [6]. However, this outcome-oriented approach addresses only the question of when children can solve a particular problem. This approach does not provide insights into the mechanisms of *how* children build constructions—that is, how building unfolds from moment to moment to lead to success or failure.

Thus, while this outcome-oriented approach is beneficial to assess the existence of spatial skills or lack thereof [7], children can reach the same outcome via different paths. That detailed sequence of actions or planning strategies that underpins final constructs has been neglected in most previous research [8]. Recently, a few studies highlighted the importance of a process-oriented approach [3], [9]. Yet even these studies neglected critical aspects of the construction process, such as the errors children make and the strategies they use to overcome them. Such information could shed light on individual differences in developmental mechanisms underlying spatial skills and planning. Addressing these limitations requires deeper, process-based analyses of block construction tasks.

Nevertheless, adopting a process-oriented approach presents inherent analytic challenges. Children's construction steps can evolve in non-linear or multilayered ways, necessitating precise documentation and effective annotation schemes to capture granular transitions. Moreover, complexities arise in reconciling children's emerging motor skills and evolving cognitive capacities with an analytic approach flexible enough to link actions to subgoals. Here, we combine tools from graph theory with a novel video annotation framework to rapidly convert children's block constructions into structured graphical representations that provide measures of how construction steps integrate into paths of action. We demonstrate our approach by testing children and adults in a novel construction task in which they are required to build models that differ in complexity. We share our analytic materials with the aim of creating a tool for researchers interested in block construction and its role in child development.

II. RELATED WORKS

The main line of research into block construction emphasizes when children achieve particular completed structures. For example, Casey et al. [2] tested preschoolers' abilities to replicate a set of preconfigured block models, showing that early proficiency in these tasks predicts gains in spatial reasoning—a foundational skill for later success in mathematics. Similarly, Verdine et al. [4] demonstrated that higher complexity in children's free-form block buildings correlates with better performance on standardized tests of spatial visualization. These findings align with Tian and Luo's [10] examination of kindergarteners, where the primary measure was the final accuracy of replicated models; the moment-to-moment construction process itself remained largely unaddressed. Overall, outcome-oriented research has validated the strong relationship between successful block building and children's emerging competencies in geometry and numeracy [11], [12].

A process-oriented approach complements these findings by detailing the production of block constructions and examines processes of planning as well. Landau et al. [6] conducted an earlier studies of children's building sequences, revealing that young children's step-by-step block placements reflect organized—albeit sometimes rudimentary—strategies. Cortesa et al. [13] introduced a specialized behavioral coding scheme to capture children's layer-by-layer actions. Their analyses showed that children's construction paths (excluding errors) are often systematic and exhibit common subgoals, even when the end products differ in accuracy. This evidence indicates that concentrating on transitions between building steps can expose the evolving nature of children's spatial thinking and intuitive grasp of physical properties [14].

A smaller body of work explores comparisons between children's and adults' block compositions, offering a window into developmental shifts and expertise differences. Shelton et al. [3], for example, studied college students' construction sequences, revealing common "layer-building" patterns that reduce cognitive load. Although adults typically progressed at a faster pace and demonstrated more complex subgoal planning, the overarching approach—such as starting from a stable base—mirrored patterns reported in child studies [13]. In a related work, McKee et al. [8] argued that technologies like semi-automated scoring and video annotation can systematically capture building paths in both adults and younger populations, pointing to where developmental differences arise. These cross-age investigations suggest that core building strategies endure across the lifespan, while the complexity of planning and the capacity to coordinate multiple subgoals expand with maturity and experience.

III. EXPERIMENTAL USE CASE

To evaluate our novel annotation framework, we tested 7- to 10-year-olds and adults in a novel block construction task in which they were asked to assemble eight construction models from Duplo blocks from four schemas, each from a different point of view (Fig. 1a). Participants could not build the models successfully from one schema alone and therefore were required to integrate spatial information from the different schemas and use complex building strategies. To characterize their correct and incorrect actions, we developed a novel annotation and graphing framework. We share this framework with other researchers to allow them to address further research questions about variation in performance, building strategies, errors, and error recoveries, during complex block construction asks.

A. Dataset

Our dataset consists of 12 school-age children (age range: 7.49 – 10.34 years, M = 8.52 years, SD = 0.98 years, 7 boys, 5 girls), and 18 adults (age range: 20.58 – 42.71, M = 26.71, SD = 6.56), 7 male, 11 female). Across children, race and ethnicity were reported as White or White British (58.33%), Mixed or multiple ethnic groups (33.33%), and Asian or Asian British (8.33%). Across adults, race and ethnicity were reported as White or White British (66.66%), Mixed or

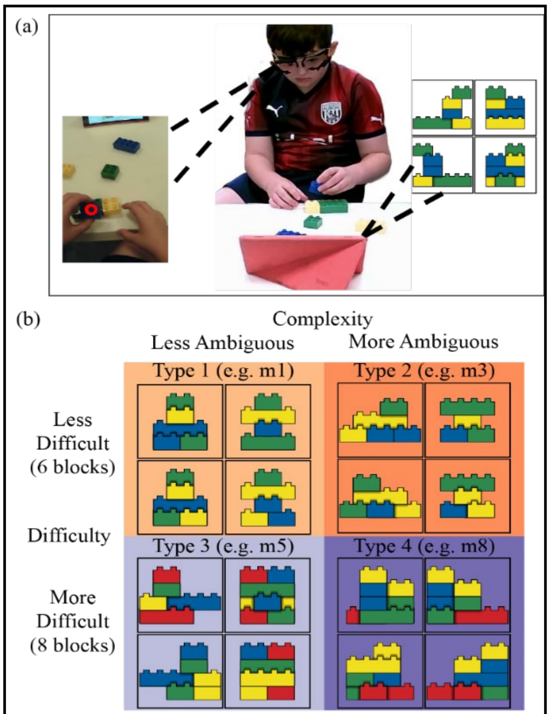

Fig. 1. Experimental use case a 2D-3D block construction study. **(a)** Child building model 2. **(b)** Exemplar schemas for the different model types (showing m1, m3, m5, m8).

multiple ethnic groups (16.66%), Asian or Asian British (11.11%), and Black or Black British or African (5.55%).

B. Task

Participants constructed up to eight Duplo models one after another. At the start of each model, they were provided with the required Duplo blocks and four schematic images depicting the structure from different viewpoints, incorporating depth cues (Fig. 1b). Information from a single schema is not sufficient to disambiguate placement of specific blocks, and therefore participants had to use all four schemas to build the model.

Models varied in both difficulty and complexity. Difficulty was determined by the number of blocks in each model, with models m1–m4 containing six blocks and models m5–m8 containing eight (Fig. 1b). Complexity was manipulated by controlling how much disambiguating spatial information was included in each model's schema (Fig. 1b). Specifically, depicting the longer blocks lengthwise was key to helping participants distinguish long from short blocks within color-matched pairs. Models m1, m2, m5, and m6 included more disambiguating information, whereas models m3, m4, m7, and m8 included less. Beside those differences, all models were balanced in number of blocks per image, as well as overall height and width.

C. Procedure

Testing took place at the Centre for Brain and Cognitive Development at Birkbeck, University of London. After we obtained consent from adult participants or children's parents, participants were seated in a child-sized chair at a table and were fitted with eye-tracking glasses (Pupil-labs Core; https://pupil-labs.com/products/core). We also placed a camera in front of them to capture their actions (Fig. 1a). The four viewpoint images were presented to them on a tablet (7-inch Amazon Fire) that was placed on the table.

Following eye-tracking calibration, participants were presented with an example model consisting of three blocks and corresponding schematics. They were instructed to use color, block size, and shadow-based depth cues to guide their construction. After completing two practice trials involving four-block models, participants began the eight construction trials. Participants were told to build the models at their own pace. Children could request assistance from the researcher at any time; upon request, the researcher sat with the child and posed open-ended questions to facilitate the process but did not provide direct instructions of the next steps. Adults were given up to 30 minutes to complete as many models as possible, with the option of stopping at any time. Children were afforded up to 45 minutes and could also discontinue at their discretion.

IV. PROCESS-ORIENTED ANALYTIC PROCEDURE

Full details of our analytic procedure may be found here: https://github.com/Physical-Cognition-Lab/A-graph-theory-approach-for-testing-children-s-block-construction.
Including full code, video annotation manual, examples and extraction script, as well as constructed graphs.

We initiated our analyses by developing a new video annotation framework that systematically extracts each participant action from the head-mounted eye-tracker's scene video. Data was video-coded on Datavyu software (www.datavyu.org). The time taken to annotate varied across participants due to differences in construction time and construction patterns.

Each action—defined as any interlock, even between blocks—was coded in a way that captures the size, color, and orientation of all blocks involved. Coders also annotated whether each newly placed block was added or removed (i.e., constructed, or deconstructed) relative to the model, and recorded its spatial relations (above, below, and exact offset) to every block it interlocked with. Because a new block can technically interlock with up to six existing blocks, the annotation framework accommodated up to six relations of this kind.

Several challenges arose during annotation. First, although all coding used the participant's perspective, individuals often rotated their model, making it difficult to track continuity across actions. Second, for children, blocks occasionally fell or snapped off the model. To address these issues, coders annotated the participant's reorientation of the model and any blocks that fell. Third, participants sometimes added multiple blocks or two interlocked blocks simultaneously, so *multi-block* actions were annotated as separate actions one frame apart and then combined during pre-processing as a single action. Finally, participants occasionally abandoned one model to begin another, which was addressed by annotating the start of new constructions while still defining an action as a single block interlocking with an existing model.

After video annotation, the data were exported from Datavyu into CSV files, with each row representing a single coded action and each cell describing one aspect of that action. First, we generated strings from the contents of each action cell (e.g., "yl_a_h_bs_._0_0") that captured the spatial relations among blocks within the action. These strings do not reflect the action itself but rather the ways in which blocks relate spatially.

To account for participants rotating their models, we created '*isotope strings'* to represent equivalent relations from different viewpoints. Orientation coding helped track perspective changes over time. *Multi-block* actions and actions involving multiple 'relation blocks' were split into separate rows and then recombined as single actions. The final data structure retained one row per action per participant. Enriched with a unified relational string, all corresponding *isotope strings*, and information about the viewpoint at which the action occurred relative to prior actions in the same trial.

A. Creating 'Construction States'

After annotation, we shifted our focus from actions to the spatial constructions states those actions created. For each action, we generated a concatenated string that reflects the resulting configuration. Specifically, if an action was classified as a "construct," the associated spatial-relation string was appended to the concatenated; if it was "deconstruct" or "fall", the string was removed from the concatenated string.

Importantly, "deconstruct" actions sometimes occur from a different viewpoint than their corresponding construction actions. Consequently, viewpoint annotations and isotope strings were used to track how spatial relations changed with each view, ensuring that the correct relation strings were properly removed. As a result of these steps, each action was associated with a concatenated string, capturing the precise set of actions defining the state that follows that action.

States were then evaluated for correctness. For each state, spatial relations were checked against the canonical set (valid spatial relations for each assembled model). A state was deemed correct only if all relevant relations matched from a single consistent viewpoint.

B. Conversion to Graph-Structured Data

We assigned a unique numerical ID to each spatial relation string, which could occur only after accounting for the viewpoint information because *isotope strings* share the same ID. Thus, each state was represented by a set of these numerical IDs and whether it was correct or not (e.g., 1, 3, 7 TRUE), capturing all spatial relations within that state.

In the resulting graphical representation, each state corresponds to a node, while edges between nodes represent actions. To construct these edges, we labelled the current state as ‘node_from’ and the subsequent state as ‘node_to.’ The direction of each edge was then determined by comparing the number of blocks in the spatial relations of node_from to those in node_to, denoted by *direction*. Finally, we calculated the *frequency* of each action by counting how often identical pairs of node_from and node_to occurred. This framework enables the creation of a complete graphical structure, including *nodes, edges, directions, and frequency, and* it allows us to track each participant’s traversal of this structure through sequential action numbers.

V. EVALUATION

We performed our evaluations using R 4.3.3 on a Windows 11 operating system. On a machine equipped with 32 GB of RAM, a 13700H CPU, and a 15.8 GB GPU, processing the adult dataset took 125.31 seconds, while the child dataset required 152.30 seconds.

We generated one graph per model (see Fig. 2a for an exemplar graph of one of the models; all other graphs can be found in repository). First, average graphs were made for adults and children separately, reflecting all the nodes and edges present across the group. Then individual graphs were made, reflecting each participant’s path. Each node in the graph reflects an independent state, structured hierarchically based on the number of blocks in that state. Node color denotes state correctness: green for correct, yellow for incorrect. Edge color denotes the direction of the edge: blue for construction (addition of blocks) and red for deconstruct (removal of blocks), with edge width denoting the edge probability on a group level. As observed in Fig. 2a, children visit many more incorrect nodes (more yellow nodes) and take longer paths (more edges and thicker edges).

Using a graphical approach allows us to immediately evaluate several important measures from construction paths. For each measure evaluated, we employed Bayesian mixed-effects models to analyze differences between adults and

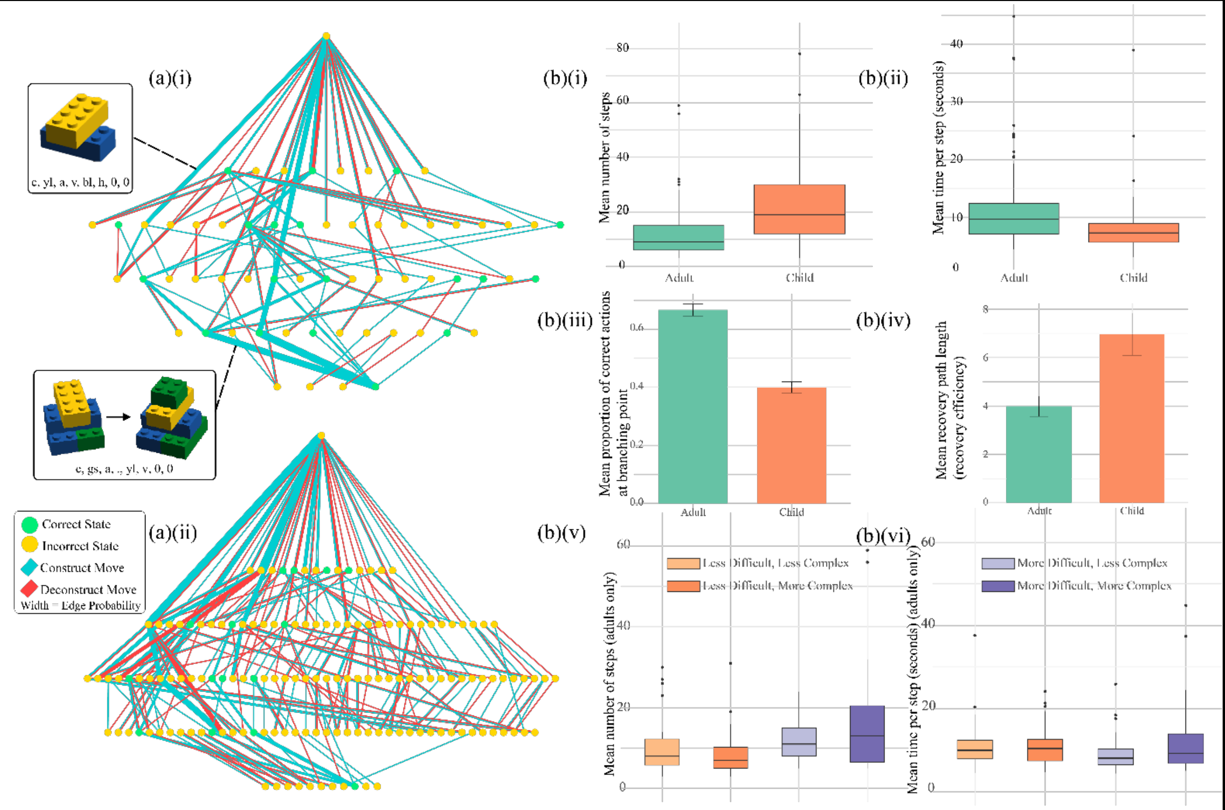

Fig. 2. Analyses **(a)** Graphical representations of group-level construction paths for Model 1, for adults (i) and children (ii), examples of action annotation. **(b)** Measures extracted from graphical representations. (i) Mean number of steps taken across all models (ii) Mean time per step (seconds) across all models. (iii) Mean proportion of correct actions at branching points. (iv) Mean recovery path length (v) Mean number of steps, by model type for adults only. (vi) Mean time per step (seconds), by model type for adults only.

children. Models were implemented using brms package [15] with default priors from the package. For each model, 4 chains were run with 4,000 iterations each, including 2,000 for warm-up, resulting in 8,000 samples per model. Models accounted for repeated measures within participants and model types.

Adults (M = 7.61, SD = 1.14) completed more models than children (M = 6.17, SD = 1.03), and adults (M = 7.00, SD = 1.71) completed more models successfully than children (M = 2.92, SD = 1.83). We evaluated strategy as the number of steps in the path and time per step (Fig. $2b_{i}$ and $2b_{ii}$). Bayesian mixed-effects models were used to examine the effect of a group (adult or child) on a number of steps in the path and time per step. For a number of steps in the path, we found an effect, β = 0.74, 95% CI [0.44, 1.03], that children (M = 23.86, SD = 15.54) are more likely to take more steps in the path than adults (M = 12.26, SD = 10.84). Similarly, for time per step, we found an effect, β = -0.30, 95% CI [-0.54, -0.07], where children (M = 8.13, SD = 4.80) are more likely to take less time per step than adults (M = 11.05, SD = 6.34).

We then calculated group-level measures to understand and compare efficient paths (Fig. $2b_{iii}$ and $2b_{iv}$). We explored differences in branching factor, measured as the proportion of actions (construct only), correct at each branching point, between nodes from adult graphs and nodes from child graphs. A Bayesian mixed-effects model with log-normal family confirmed an effect of group (adult or child) on branching factor, β = -0.70, 95% CI [-0.90, -0.50], where nodes from child graphs (M = 0.40, SD = 0.02) are more likely to have a lower proportion of correct actions at each branching point than nodes from adult graphs (M = 0.67, SD = 0.02). We then calculated a measure of recovery efficiency, measured by the number of steps taken to get back to a correct state from making an incorrect action. A Bayesian mixed-effects model with log-normal family confirmed an effect of group (adult or child) on recovery efficiency, β = 0.39, 95% CI [0.12, 0.67], where children (M = 6.97, SD = 0.87) are more likely to take more steps to recover from incorrect actions than adults (M = 3.99, SD = 0.42).

Within our study design, we also manipulated difficulty and complexity (see section IV) to understand how the level of information affects the construction process. To that end, we compared the strategy measures across different types of models (Fig. 1b, types 1, 2, 3, 4). We compared the number of steps in path and time per step, in adults only since not enough children completed more difficult and complex models (Fig. $2b_{v}$ and $2b_{vi}$). A Bayesian mixed-effects model with log-normal family (model type was entered as a fixed-effect) was run. It confirmed a positive effect of model type for type 3 (β = 0.29, 95% CI [0.04, 0.54]), and type 4 (β = 0.53, 95% CI [0.28, 0.78]) compared to type 1 (intercept), but not for type 2 (β = -0.08, 95% CI [-0.33, 0.16]). Post-hoc analysis was conducted by estimating the marginal contrasts between the models using the estimate_contrast function (CIT). It confirmed differences between type 3 and type 1 (β = 3.42, 95% CI [0.48, 6.53]), and type 4 and type 1 (β = 7.04, 95% CI [3.57, 11.08]). It further showed differences between type 3 and type 2 (β = 4.20, 95% CI [1.39, 7.26]), and type 4 and type 2 (β = 7.88, 95% CI [4.46, 11.76]), with type 3 and type 4 being more likely to take more steps. No differences were found between type 3 and type 4 (β = 3.63, 95% CI [-0.26, 7.86]). We did not find a similar result for time per step, where there was no effect of model type on time per step (compared to type 1: type 2, β = -0.01, 95% CI [-0.17, 0.15]; type 3, β = -0.13, 95% CI [-0.29, 0.04]; type 4, β = 0.07, 95% CI [-0.10, 0.24]).

VI. SUMMARY AND FUTURE WORK

This paper showcases a novel annotation and graphing framework for evaluating the process by which children assemble block constructions. By openly sharing the framework with other researchers and demonstrating its potential to show differences between adults and children in a novel spatial task, we argue for a more process-oriented approach to measuring performance in construction tasks which are widely used in cognitive and educational research.

In particular, our framework allows for the analysis of both accurate and inaccurate building concurrently. This reflects a significant methodological break from past literature, where often, if process-oriented, only one of errors, or full step paths, will be characterized [3], [16]. The ability to extract meaningful measures about where errors lie within paths allows for a more detailed characterization of construction. For example, we compared differences in branching factor between adults and children using their graph nodes, finding that nodes from adult graphs had a higher proportion of correct actions following them. This finding suggests that children are more likely to deviate from efficient or "correct" paths.

Our analysis of recovery efficiency found that children take more actions than adults to return to a "correct" path once they make an incorrect action, suggesting that children are slower and less efficient in correcting their errors. While previous studies have explored children's errors in block construction, this exploration has focused on errors in isolation (e.g., [16]), rather than understanding how they appear within paths of action. Further research should explore how different variables affect the efficiency of error correction, whether children's error recovery improves as they continue building or dependent on information available to them. Taken together, our framework allows for an in-depth analysis of the ordinality of errors and their recovery. That is, whether making errors at different stages of building lead to different recovery lengths.

Our work also focused on how both children and adults deal with differing amounts of ambiguous information and difficulty in construction tasks. We found that adults take more steps in building more difficult models compared to easier ones (as measured by number of blocks), but not in building models with more ambiguous information compared to less ambiguous information. Previous research suggests that adults are particularly efficient and timely at integrating different spatial representations [17], [18]. Given this, it may be that difficulty is a more significant factor in influencing strategy efficiency. Alternatively, our manipulation of information ambiguity might be too subtle, especially when restraints from the number of blocks prevented more distinct levels of ambiguous information. More research is needed to directly test how these differing levels of information influence strategies used in building.

Our use case highlights the importance, novelty, and utility of our framework. In current literature, analysis of paths and their variation in relation to complexity, have been confined to simplistic models where few errors occur (e.g., [3]). This graphical approach allows for analysis of more complex block construction tasks and thus paves the way for more studies like this which use complex block construction as a way to understand how action planning strategies are used in complex problems. Moreover, measures and analyses from this framework can be combined with other streams of data, such as gaze tracking, motion tracking, or neural recordings. Such integration will provide insights into real-time action planning cascades [19], [20], [21].

Finally, our framework has implications for educational and cognitive interventions which involve block constructions [1]. The traditional outcome-oriented approach neglects the mechanisms through which such interventions impact educational outcomes or cognitive abilities, especially at the individual level. Our framework allows a more individual analysis, thereby informing intervention studies that may be tailored to specific deficits in the underlying process.

ACKNOWLEDGEMENTS

We thank Vanessa Madiera, Marta Isola, Soyeon Kim, Jordan Ofwono, Stavros Tanas for supporting data collection, human annotation, and analyses.

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