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Future-Focused:

Educating in an Era of Continuous Change

Data to design: Simulating instructional strategies with agent-based modelling

John Vulic
UNSW Sydney

Michael J. Jacobson
The University of Sydney

James A. Levin
University of California, San Diego

What if we could simulate a learning environment like a living, evolving ecosystem? Our research views education as a complex adaptive system and applies methods from computational science to study it. We build agent-based models that simulate how learning happens in classrooms, drawing on both quantitative and qualitative data. These models allow us to run simulations that are updated with real classroom data over time. This helps us explore questions such as: "Which teaching methods best support student learning and knowledge transfer?" Our modelling suggests that Productive Failure may be especially effective in promoting deeper learning and transfer. We conclude by discussing how these insights highlight the potential of computational modelling in education research.

Keywords: Computational educational research, Agent-based modelling, Productive Failure, Direct Instruction, Instructional design, Learning transfer, complex systems, educational modelling

Conceptual Rationale and Aims

The main goal of our research is to demonstrate how classroom learning can be modelled using existing data and to run computational experiments that test whether our models reflect real-world outcomes. When results diverge from observed patterns, we identify gaps and areas for further investigation. Our computer-modelling approach responds to recent calls to advance computational research in education (Williamson, Potter, & Eynon, 2019) and seeks to represent facets of complex educational systems across multiple levels (Jacobson, 2020). We conclude by discussing how this modelling approach can inform the design of classroom studies and support broader educational research.

Literature Review

In studying learning and education, researchers have employed a range of methodological approaches, each offering distinct strengths and limitations in addressing complex systems. Jacobson, Levin, and Kapur (2019) argue that computational science methods, widely used in other fields, can enhance educational research by modelling complex learning environments and interactions across system levels. Quantitative methods are valuable for testing patterns but may overlook context and subjectivity (Johnson & Onwuegbuzie, 2004), while qualitative methods provide depth but face limits in generalisability and replication (Denzin & Lincoln, 2018, pp. 1–15). Computational modelling has been proposed as a way to bridge these approaches, combining the rigour of quantitative research with the contextual richness of qualitative inquiry (Jacobson, Levin, & Kapur, 2019).

Building on the growing application of computational approaches in education, researchers have explored methods that capture dynamic and non-linear processes across system levels. We propose the use of a multi-mediator modelling (MMM) approach (Levin & Datnow, 2012), which integrates features of agent-based modelling, a bottom-up method using algorithms (Wilensky & Rand, 2015), and system dynamics, a top-down method using equations (Smith, 2007). Computational methods, including agent-based modelling, system dynamics, and MMM can simulate interactions among multiple agents or factors over time, capturing complex and non-linear behaviours that are difficult to analyse with other methods (Jacobson, Kapur, & Reimann, 2016). These methods complement traditional research by providing dynamic visualisations, enabling the testing of hypothetical interventions, and informing real-time educational decision-making.

Our study applies computational educational research to compare teaching approaches using real-world data, aiming to generate evidence-based insights that capture the complexity of classroom learning more effectively than traditional methods. We focus on two contrasting instructional designs. The first is Productive Failure (PF) (Kapur, 2008), in which students attempt to solve complex problems without immediate guidance, often encountering initial failure. This process engages prior knowledge and prompts learners to generate diverse ideas and representations, which can then be refined through explicit teaching to support deeper conceptual understanding. The second is Direct Instruction (DI), derived from the structured teaching model developed by Engelmann and Carnine (1982), which employs clear, sequenced lessons designed to promote mastery and transferable skills. In our study, we examine the sequencing of DI followed by student-centred problem-solving. This comparison allows us to explore how different instructional sequences influence learning outcomes within complex classroom environments.

In a meta-analysis of 53 studies, Sinha and Kapur (2021) compared three teaching methods: Instruction followed by Problem Solving (I-PS), often referred to as direct instruction; Problem Solving followed by Instruction (PS-I), associated with problem-based learning; and Productive Failure (PF). PS-I broadly requires that problem solving precede instruction, whereas PF specifically involves presenting learners with complex, novel problems designed to elicit failure, thereby activating prior knowledge and generating diverse solution methods to prepare them for subsequent instruction. They found that PS-I led to better outcomes than I-PS, with a Hedges' g effect size of 0.36—around 1.8 times more effective than regular teaching (Hedges, 1981). PF demonstrated even stronger results, with a Hedges' g of 0.58, or 2.9 times greater impact. Jacobson et al. (2017) reported an even higher effect size for PF at 0.95, 4.8 times more effective than I-PS. These findings highlight the strong potential of approaches like PF to improve learning outcomes. This paper explores whether such results can be replicated and better understood through computational educational research.

Method

The learning models for this project were created with the agent-based modelling system NetLogo (Wilensky, 1999) and are illustrated in Figures 1 to 8. These models represent the educational problem space as a complex system (Jacobson et al., 2019), with nodes (circles) denoting agents or elements and links (lines) representing their interactions. Two separate models were built: one simulating the Productive Failure (PF) approach and the other simulating Direct Instruction (DI), each run independently.

At the first level, each model captures the instructional phase, showing either PF or DI structures. In PF, this includes exploration and consolidation phases within a typical 60-minute lesson; in DI, it consists of instruction followed by problem-solving. The second level models student affect, particularly affective boost, defined by Kapur (2024) as the motivational lift experienced while working toward a learning goal, shaped by recognition of progress, goal proximity, and task satisfaction. The third level represents cognitive development, including prior knowledge and schema formation, such as inert or elaborated schemas. External nodes represent the key learning outcomes of knowledge and transfer.

Visualisations use green lines to indicate positive interactions (0 to +1) and red lines for negative interactions (–1 to 0), with numeric node values showing cumulative effects across simulations. Independent variables are adjusted using box sliders for each node, with initial values displayed in Figures 1 to 8. Key variables include:

- PF fidelity (the extent to which a lesson aligns with PF principles; Kapur, 2008)
- Affective Boost Low (low engagement states; Kapur, 2024)
- Compatible and incompatible prior knowledge (Bransford, 2000)
- Inert schema (Renkl, Mandl, & Gruber, 1996)
- No Assembly (fragmented knowledge with limited transfer; Chi, Feltovich, & Glaser, 1981).

We conducted four computational experiments starting from a Pretest state, varying only the pedagogical approach fidelity across the PF and DI models. Effect size data from Sinha and Kapur (2021) informed the activation values assigned to PF and DI fidelity nodes: a value of 0 represented no instruction, 0.20 corresponded to the I–PS effect size, 0.36 to PS–I, and 0.58 to PF.

Results

Table 1 shows the independent variable settings and the corresponding outcomes for the dependent variables Knowledge and Transfer in the computational model experiments.

Table 1
Independent Variable Settings and Dependent Variable Results for Three Computer Experiments. Instructional fidelity effect sizes from Sinha & Kapur (2021).

Experiment	**Independent Variables**		**Dependent Variables**		
				PF	**DI**
Pretest	**Instructional Fidelity Effect Size**	**0.00**	**Knowledge**	**0.00**	**0.00**
	AB Low	0.67			
	Compatible Prior Knowledge	0.07			
	Incompatible Prior Knowledge	0.67	**Transfer**	**0.00**	**0.00**
	Inert Schema	0.60			
	No Assembly	0.34			
1	**Instructional Fidelity Effect Size**	**0.20**	**Knowledge**	**0.08**	**0.00**
	AB Low	0.67			
	Compatible Prior Knowledge	0.07			
	Incompatible Prior Knowledge	0.67	**Transfer**	**0.00**	**0.00**
	Inert Schema	0.60			
	No Assembly	0.34			
2	**Instructional Fidelity Effect Size**	**0.36**	**Knowledge**	**0.49**	**0.05**
	AB Low	0.67			
	Compatible Prior Knowledge	0.07			
	Incompatible Prior Knowledge	0.67	**Transfer**	**0.16**	**0.00**
	Inert Schema	0.60			
	No Assembly	0.34			
3	**Instructional Fidelity Effect Size**	**0.58**	**Knowledge**	**0.73**	**0.25**
	AB Low	0.67			
	Compatible Prior Knowledge	0.07			
	Incompatible Prior Knowledge	0.67	**Transfer**	**0.59**	**0.00**
	Inert Schema	0.60			
	No Assembly	0.34			

Figures 1 to 8 show screenshots of the Learning Model's link and node states at the pretest stage and across each experiment for both the PF and DI models. The instructional fidelity effect sizes used in each model are based on findings from Sinha and Kapur (2021).

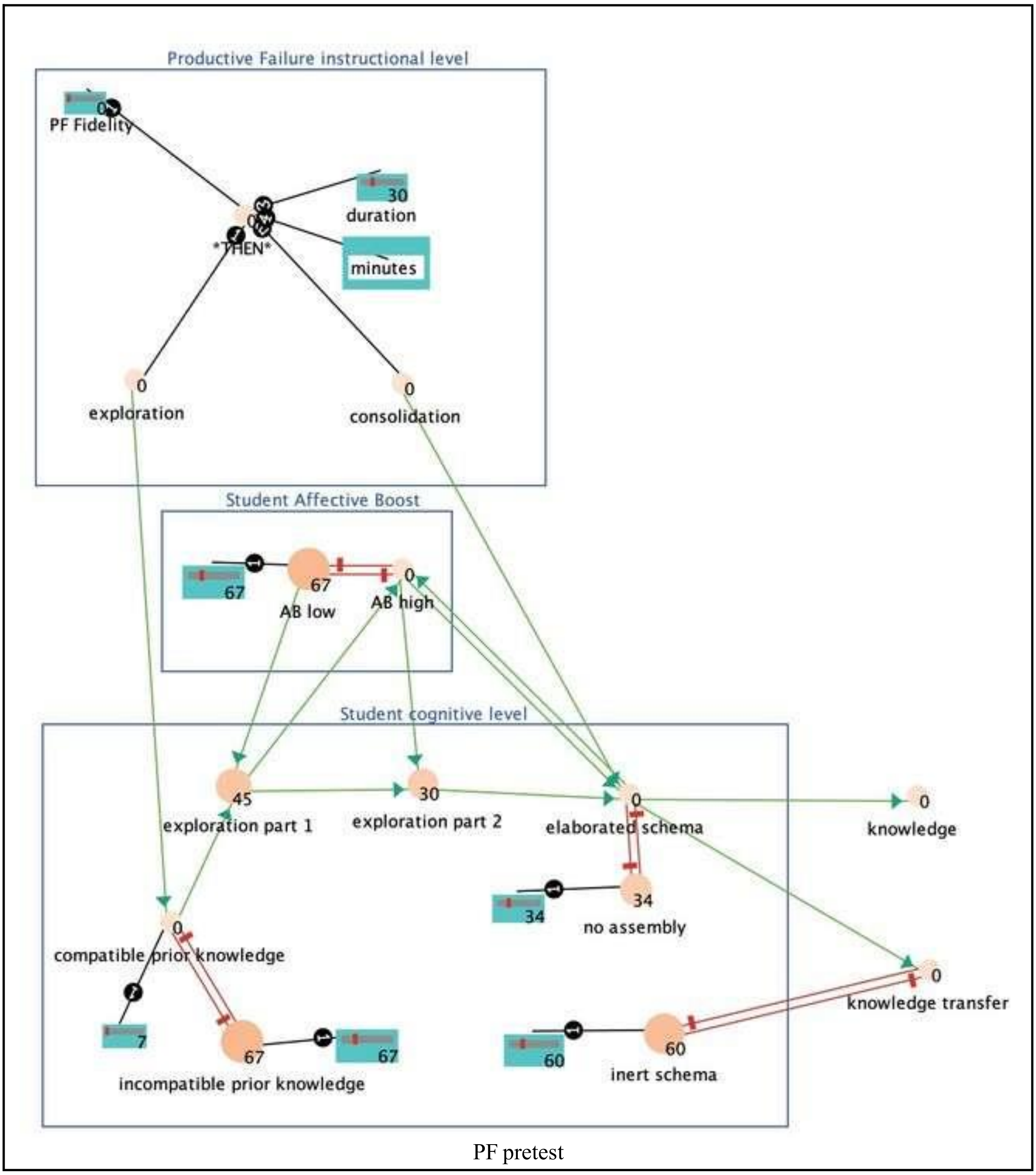

Figure 1. Screenshot of the PF Model link/node states for the pretest, with instructional fidelity effect size set to 0.00.

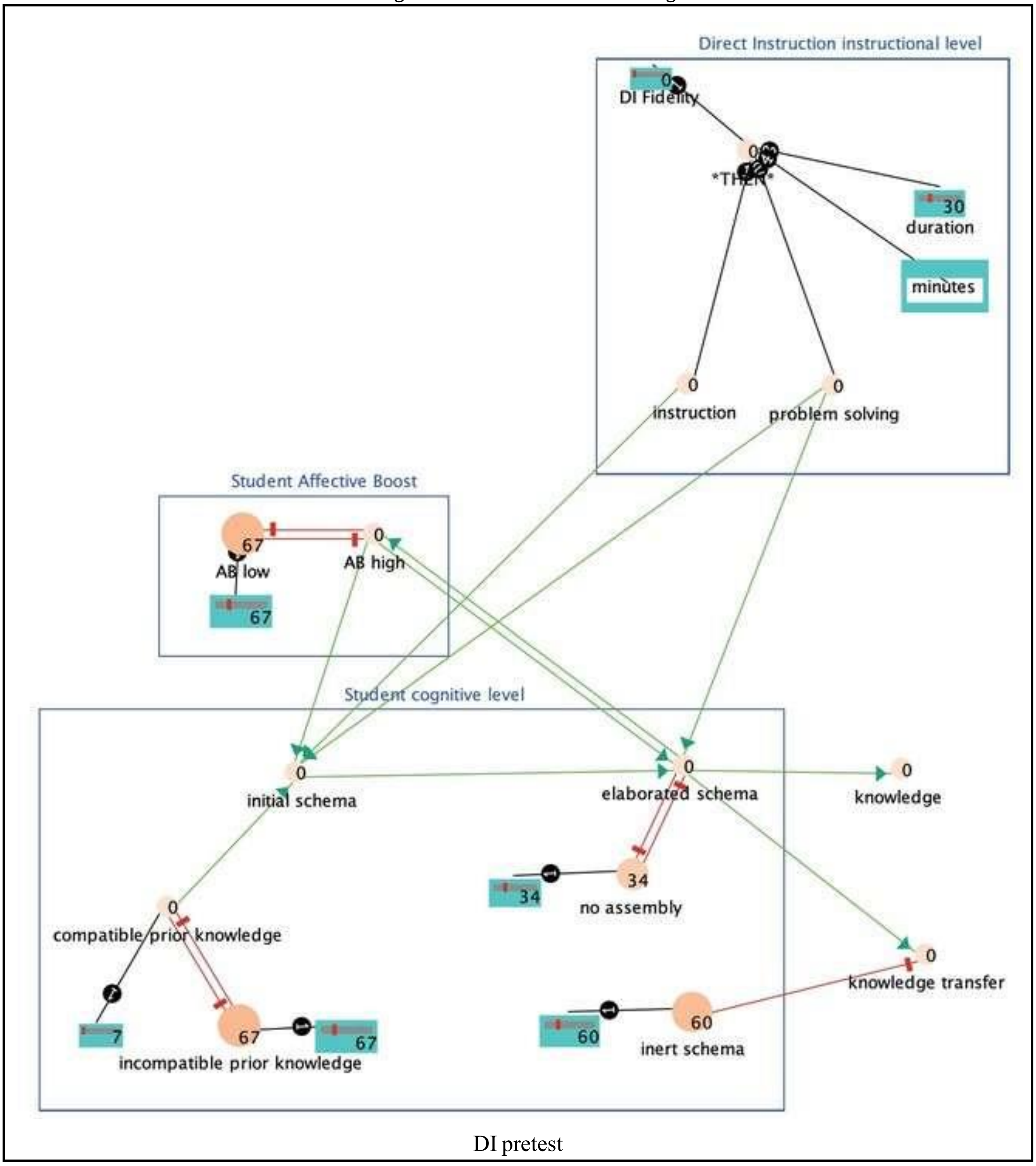

Figure 2. Screenshot of the DI Model link/node states for the pretest, with instructional fidelity effect size set to 0.00.

In the first experiment, the instructional fidelity effect size was slightly increased to 0.20 in both models (see Figures 3 and 4), representing a low level of structured instructional support. Under these conditions, the Productive Failure model (Figure 3) showed a small gain in knowledge acquisition (effect size = 0.08), whereas the Direct Instruction model (Figure 4) showed no measurable improvement. Neither model produced any increase in transfer performance, suggesting that low instructional fidelity was insufficient to support deeper learning or the application of knowledge beyond memorisation.

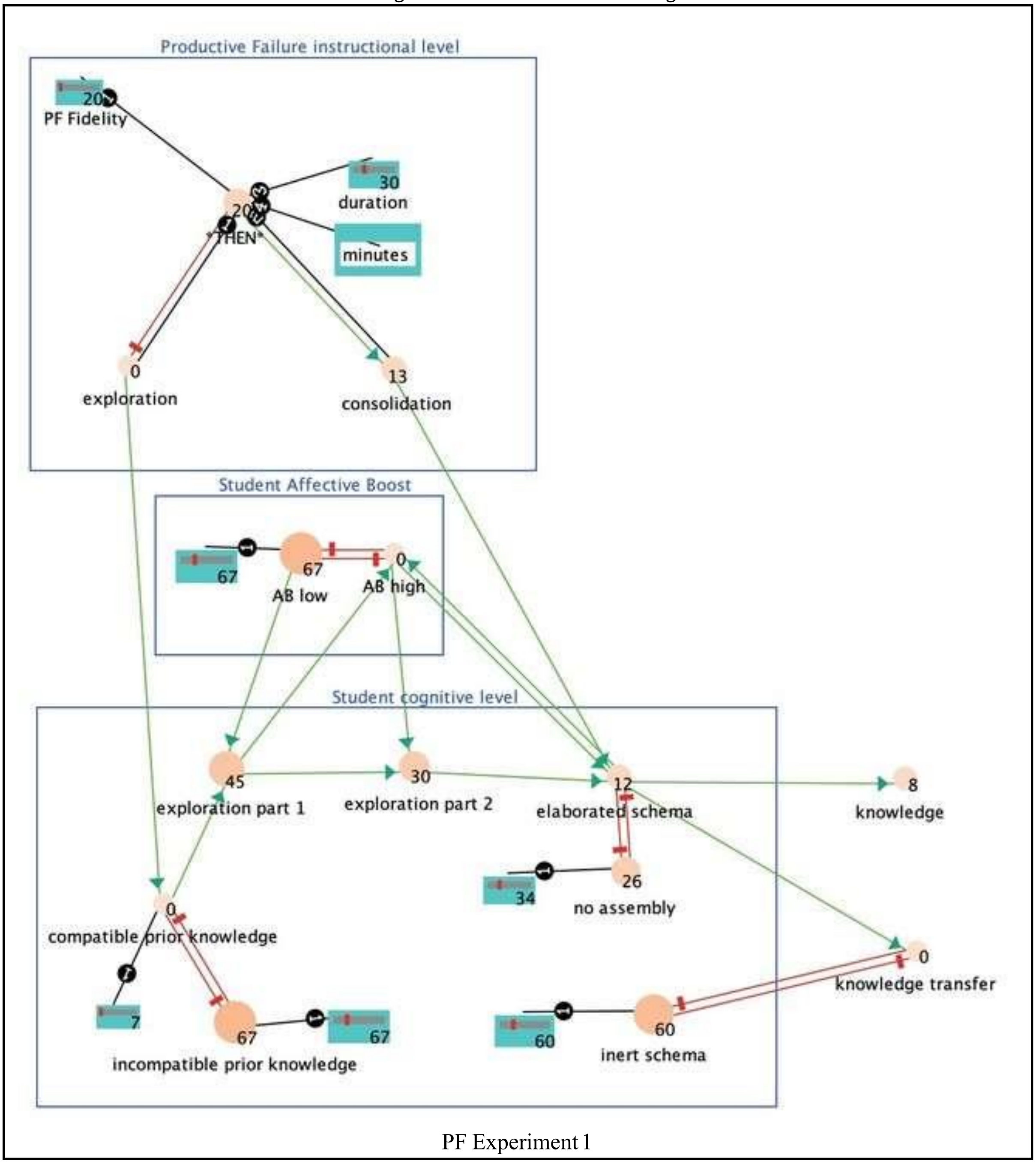

Figure 3. Screenshot of the PF Model link/node states for Experiment 1, with instructional fidelity effect size set to 0.20.

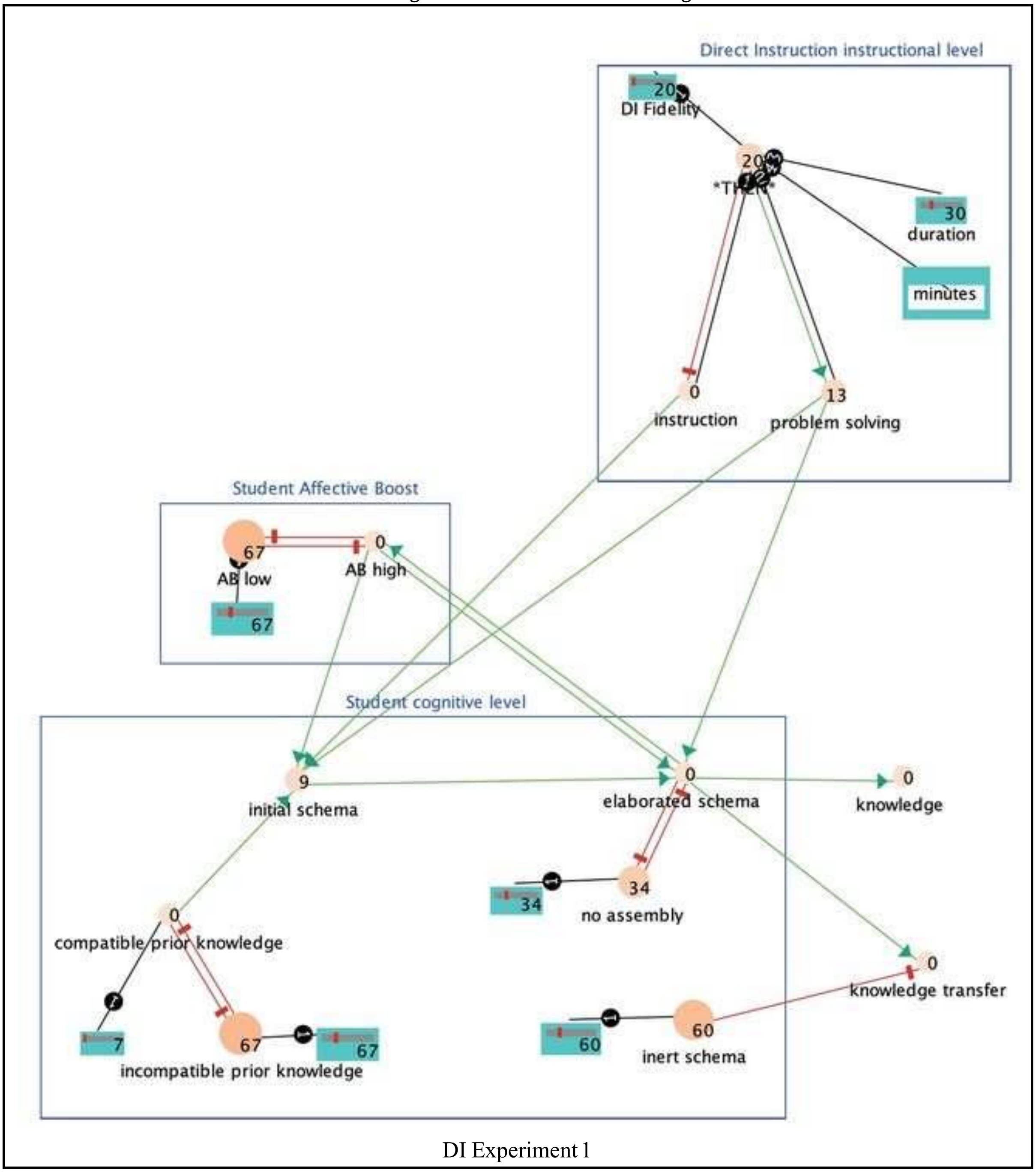

Figure 4. Screenshot of the DI Model link/node states for Experiment 1, with instructional fidelity effect size set to 0.20.

With instructional fidelity increased to an effect size of 0.36, Experiment 2 revealed more pronounced differences between the two instructional approaches. The Productive Failure model produced a moderate gain in knowledge (effect size = 0.49) and a small improvement in transfer (effect size = 0.16). By contrast, the Direct Instruction model yielded only a minimal gain in knowledge (effect size = 0.05) and no improvement in transfer.

In Experiment 2 of the PF model (Figure 5), noticeable shifts emerged in the node configurations: increases were observed in Affective Boost High and Elaborated Schema nodes, accompanied by decreases in Affective Boost Low and Inert Schema nodes. By contrast, the Experiment 2 DI model (Figure 6) showed no increase in affective boost and only a minimal decrease in the No Assembly node, with all other elements remaining unchanged. These results suggest that Productive Failure begins to demonstrate clearer advantages over Direct Instruction as the fidelity of instructional elements improves.

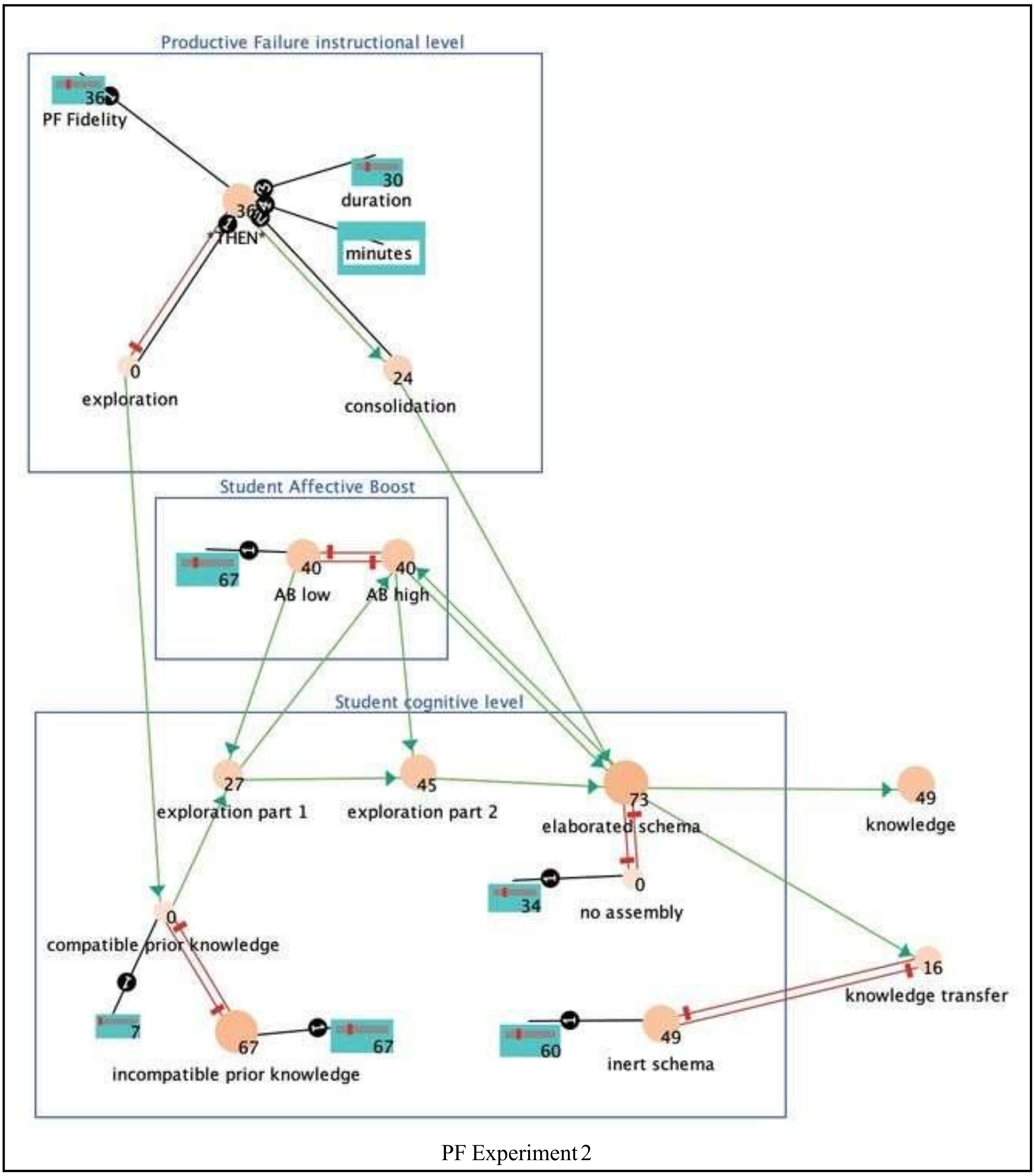

Figure 5. Screenshot of the PF Model link/node states for Experiment 2, with instructional fidelity effect size set to 0.36.

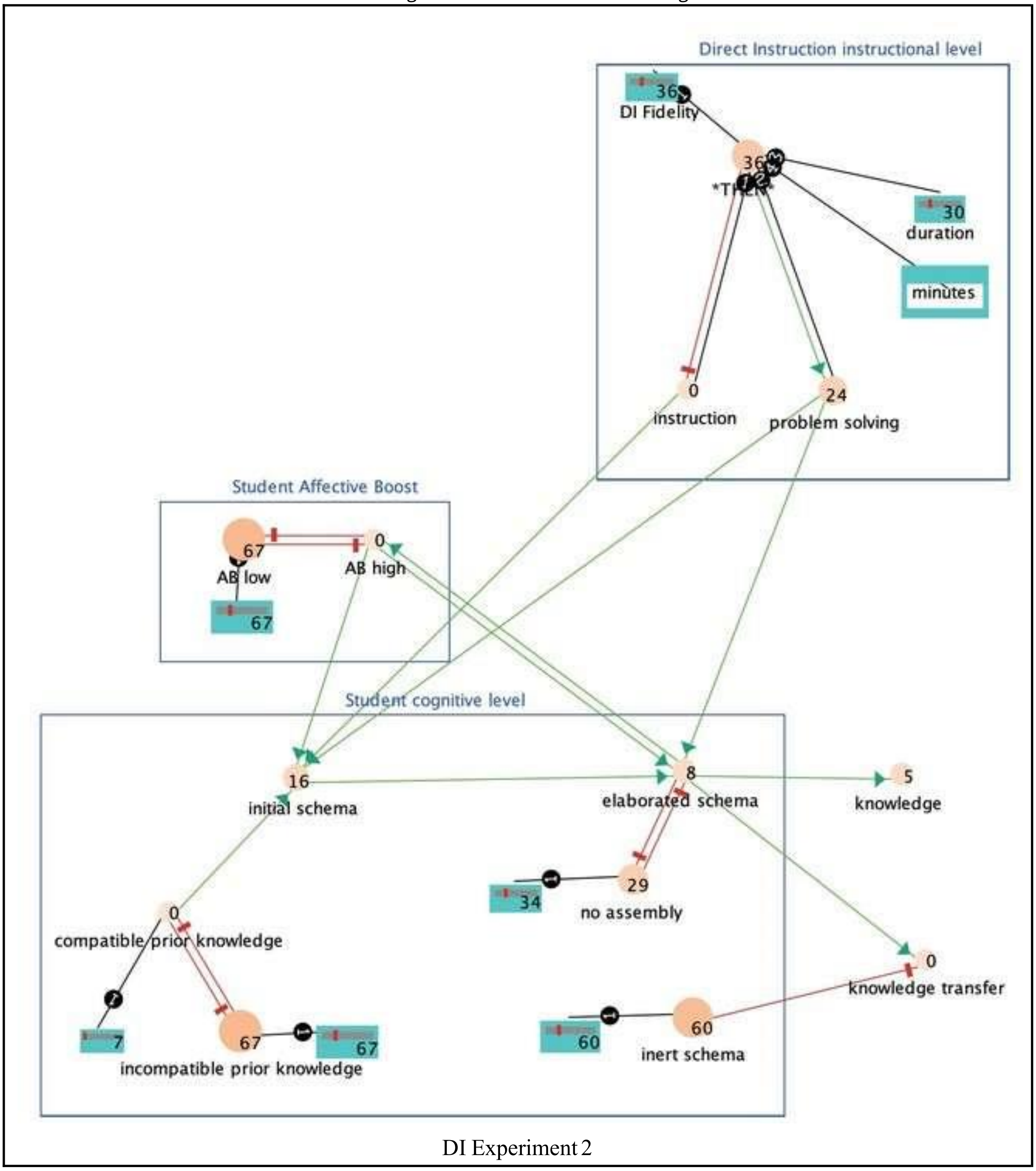

Figure 6. Screenshot of the DI Model link/node states for Experiment 2, with instructional fidelity effect size set to 0.36.

Experiment 3 involved the highest level of instructional fidelity, with an effect size of 0.58 (see Figure 7). Under these conditions, the Productive Failure model demonstrated substantial gains in both knowledge (effect size = 0.73) and transfer (effect size = 0.59), underscoring its effectiveness when implemented with high fidelity. The Direct Instruction model showed a modest improvement in knowledge (effect size = 0.25) but continued to produce no gains in transfer performance (see Figure 8). These results suggest that the advantages of Productive Failure become increasingly evident as instructional fidelity rises, particularly in supporting the transfer of learning to new contexts, an area where Direct Instruction consistently demonstrated limited impact.

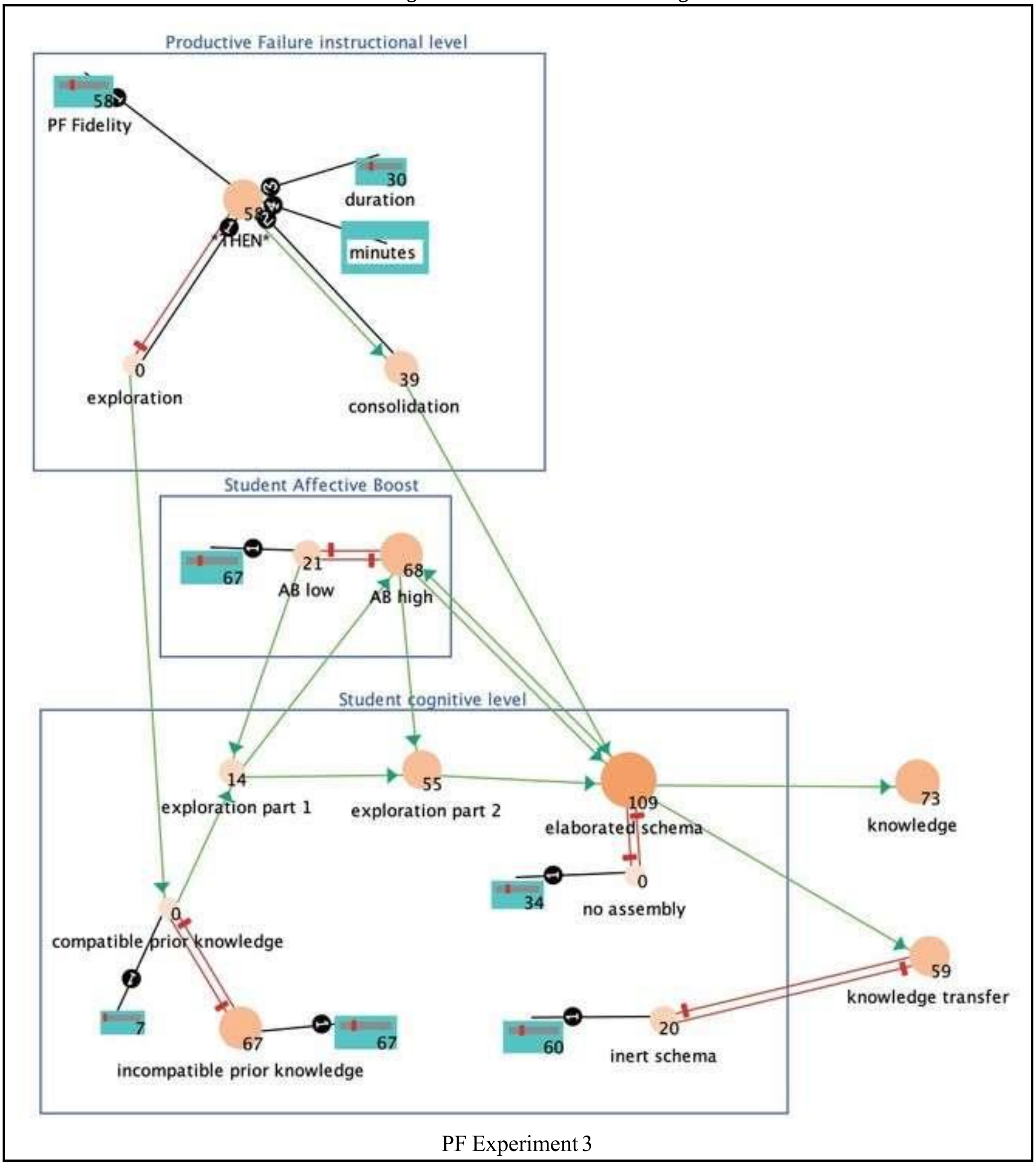

Figure 7. Screenshot of the PF Model link/node states for Experiment 3, with instructional fidelity effect size set to 0.58.

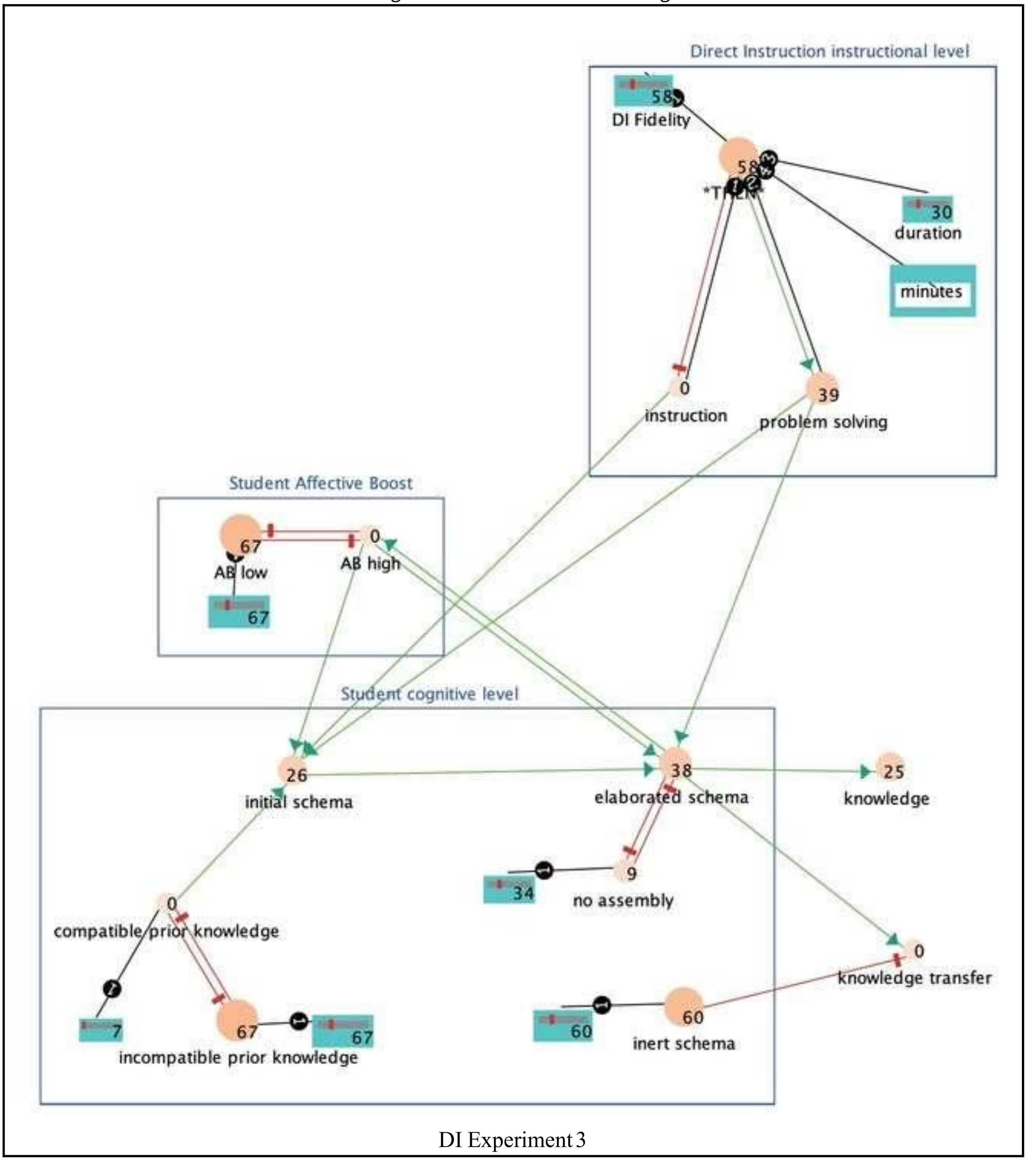

Figure 8. Screenshot of the DI Model link/node states for Experiment 3, with instructional fidelity effect size set to 0.58.

Discussion

The results of these computational experiments provide early support for aspects of the model that align with real-world findings, particularly the trend of PS-I approaches outperforming I-PS, as demonstrated in Sinha and Kapur (2021). In Experiment 2, the knowledge gain for Productive Failure (0.49) was approximately 9.8 times greater than that for Direct Instruction (0.05), exceeding the 1.8 times advantage reported in the meta-analysis for high-fidelity PF. In Experiment 3, PF outperformed DI by a factor of 2.9 in knowledge acquisition (0.73 vs. 0.25) and showed a clear advantage in transfer (0.59 vs. 0.00). These outcomes are consistent with empirical patterns, although the transfer gains in the model appear even stronger, possibly reflecting the idealised conditions under which PF was simulated. Such differences highlight opportunities to refine the model; for example, if transfer gains are overestimated, this may indicate a need to adjust how the model represents cognitive processes such as schema elaboration or motivational factors such as affective boost. Comparing model outputs with real-world data supports iterative refinement, enabling the model to evolve over time. This process can enhance the model's accuracy and utility as a predictive and explanatory tool for instructional design research.

Conclusion

This paper presents research that employs computational modelling as a tool in educational inquiry. By conceptualising classroom learning as a complex system, this approach makes it possible to examine how factors such as affective boost, prior knowledge, and schema development interact to shape learning and transfer outcomes. We first validated the model against real-world data and then conducted computational experiments to test variable combinations not yet explored in empirical studies. This process demonstrates how computational modelling can inform the design of future research by shaping research questions, anticipating outcomes, and guiding experimental design across diverse educational contexts. We advocate for the broader integration of computational methods alongside traditional quantitative and qualitative approaches. Combining these methods can yield deeper insights into learning as a dynamic process and support more evidence-informed decision-making in education. Feel free to visit the Multi-Mediator Models of Learning project repository via the link below. There you will find the PF and DI models used in this paper, along with additional models: https://mmm.ucsd.edu/mmm.html.

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