

Цифровые образовательные среды и цифровые ресурсы в образовании / Digital Educational Environments and Digital Resources in Education

Научная статья

Original article

DOI: [10.12731/2658-4034-2026-17-1-952](https://doi.org/10.12731/2658-4034-2026-17-1-952)

EDN: [XLUDGS](https://edn.rjep.ru/XLUDGS)

UDC 37.072



Mediating complexity: computational models as tools for developing systemic thinking about urban education

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Abstract

Background. Urban educational systems are complex, characterized by nonlinear interactions between multiple stakeholders – students, teachers, administrators, families, and policymakers. These systems involve interconnected dynamics: school choice based on incomplete information shapes school composition and resources; competition between schools produces both improvements and stratification; teacher satisfaction directly affects educational quality and school stability. Traditional analytical approaches rely on linear models or reductionist analysis. They fail to capture how individual decisions aggregate into system-level patterns, how competitive dynamics reshape educational opportunities, or how system properties feed back into learning outcomes. Digital transformation in education extends beyond technology implementation. It involves creating cognitive tools that make complex systems visible, enable systematic experimentation, externalize assumptions, reveal emergent patterns, and support reproducible practice.

Purpose. To investigate how agent-based modeling combined with semantic media wikis functions as a mediating tool for developing educators' systemic understanding of urban educational complexity, and to demonstrate that properly designed computational tools operationalize theoretical principles from Vygotsky, Davydov, Papert, and Turkle into educational practice that transforms how educators think about complex systems.

Materials and methods. This study employs design-based research implementing three interconnected agent-based models in NetLogo examining urban educational complexity: school choice dynamics with information asymmetries, competitive dynamics between urban schools, and systemic factors affecting teacher retention and satisfaction. Models are integrated into a semantic media wiki platform (digida.mgpu.ru) serving

as collaborative documentation space. The research follows a seven-phase collaborative learning pipeline: model preparation and web conversion, platform integration using mw-embedNetlogo extension, initial guided exploration and discussion, systematic experimentation and data collection via BehaviorSpace, data organization on external repositories with integration through External Data extension, documentation of experimental processes and interpretation using visualization tools, and peer discussion and collaborative knowledge building in MediaWiki Talk spaces. Data include documented experimental work, discussion records, and evolution of understanding across wiki contributions. Analysis focuses on qualitative coding recognizing system properties (emergence, feedback loops, nonlinear causality, distributed causality) and tracking conceptual shifts from linear to systemic thinking, reductionist to holistic understanding, and policy naïveté to policy sophistication.

Results. Engagement with agent-based models of urban school systems leads to recognition of previously invisible system properties. Educators understand emergence - how segregation patterns, school rankings, and teacher turnover arise from individual decisions and institutional behaviors. They recognize feedback loops: how low teacher satisfaction leads to turnover which increases workload and further reduces satisfaction. They perceive nonlinear relationships: how small changes in information availability create dramatic shifts in school choice. They experience qualitative cognitive shifts: from linear causal thinking toward systemic thinking grasping circular causality; from reductionist analysis toward holistic understanding recognizing how multiple factors interact; toward policy sophistication recognizing cascading effects and unintended consequences. Model adaptation from research to educational versions demonstrates that reducing parameters, streamlining outputs, and optimizing procedures while maintaining validity creates epistemic tools supporting particular kinds of learning. Systematic data generation through BehaviorSpace reveals that single policy interventions produce limited effects while combined interventions addressing multiple dimensions produce substantial effects, demonstrating that urban education system outcomes emerge from how structural parameters interact. Students discover that outcomes involve threshold effects and nonlinearities invisible to intuition. Documentation within semantic wikis and peer discussion make learning processes visible and collective. The transformation from intuitive to systemic understanding constitutes the central result: students systematically engaging with computational models develop capacity for systemic analysis essential for educational leadership.

The scientific novelty of this study lies in its theoretical and empirical justification that computational models embedded in semantic wikis function as mediating tools for developing educators' systemic thinking about the complexity of urban education systems, rather than merely serving as illustrative digital resources. The study translates general theoretical positions of educational psychology into concrete educational prac-

tices of collaborative work with agent-based models in a wiki environment. In doing so, it refines the understanding of digitalization of education as the design of tools that support a shift from empirical description toward systemic and theoretically grounded analysis. The practical significance of this study lies in its proposal of a reproducible model of learning design in which educators develop a systemic understanding of urban education through collaborative work with computational models and documentation of results in a wiki environment. This approach can be directly integrated into pre-service and in-service teacher education programmes, enabling educators to independently explore the consequences of policy and management decisions within a safe digital environment.

Keywords: digitalization of education; agent-based modeling; systemic thinking; theoretical thinking; mediating tools; urban educational systems; computational learning environments; epistemic transparency; reproducible practice

For citation. Patarakin, E. D., Vachkova, S. V., & Petryaeva, E. Y. (2026). Mediating complexity: computational models as tools for developing systemic thinking about urban education. *Russian Journal of Education and Psychology*, 17(1-2), 471–505. <https://doi.org/10.12731/2658-4034-2026-17-1-952>

Опосредствование сложности: вычислительные модели как средства развития системного мышления о городском образовании

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Аннотация

Обоснование. Системы городского образования характеризуются сложными нелинейными взаимодействиями между множеством участников – учащимися, учителями, администраторами, семьями и политиками. Выбор семьями школ на основе неполной информации формирует состав учащихся и ресурсы; конкуренция между школами порождает как улучшения, так и стратификацию; удовлетворённость учителей влияет на качество образования и стабильность школ. Традиционные подходы опираются на линейные модели и редукционистский анализ. Они неспособны охватить, как индивидуальные решения агрегируются в системные паттерны, как конкурентная динамика переформатирует образовательные возможности, или как системные свойства влияют на результаты обучения. Цифровизация образования выходит за пределы внедрения технологий. Это создание новых когнитивных инструментов, которые делают видимыми сложные системы, позво-

ляют систематическое экспериментирование, экстернализируют предположения, раскрывают эмерджентные паттерны и обеспечивают воспроизводимость практики.

Цель – исследовать, как агент-ориентированное моделирование в сочетании с семантическими вики функционирует как опосредствующее средство развития системного понимания сложности городского образования педагогами, и продемонстрировать, что правильно спроектированные вычислительные инструменты операционализируют теоретические принципы Выготского, Давыдова, Пейперта и Тёркл в образовательную практику, трансформирующую мышление педагогов о сложных системах.

Материалы и методы. Исследование использует дизайн-ориентированный подход, реализуя три взаимосвязанные агент-ориентированные модели NetLogo, исследующие разные измерения сложности городского образования: динамику выбора школ с информационными асимметриями, конкурентную динамику между городскими школами, системные факторы, влияющие на сохранение учителей и их удовлетворённость. Модели интегрированы в платформу семантической вики (digida.mgpi.ru), служащую пространством для совместной документации. Исследование следует семиэтапной последовательности: подготовка моделей и преобразование в веб-версии, интеграция платформы с использованием расширения `mw-embedNetlogo`, первоначальное направленное исследование и обсуждение, систематическое экспериментирование и сбор данных через BehaviorSpace, организация данных на внешних репозиториях с интеграцией через расширение External Data, документирование экспериментальных процессов и интерпретация с использованием инструментов визуализации, обсуждение результатов и совместное построение знания в пространствах MediaWiki Talk. Качественные данные включают документированную экспериментальную работу, записи обсуждений и эволюцию понимания через вклады в вики. Анализ данных сосредоточен на качественном кодировании признания системных свойств (эмерджентность, обратные связи, нелинейная причинность, распределённая причинность) и отслеживании концептуальных сдвигов от линейного к системному мышлению, редукционистского к целостному пониманию.

Результаты. Взаимодействие с агент-ориентированными моделями систем городских школ приводит к изучению ранее невидимых системных свойств. Студенты приходят к пониманию эмерджентности - как паттерны сегрегации, школьные рейтинги и текучесть кадров возникают из индивидуальных решений. Они изучают обратные связи: как низкая удовлетворённость учителей приводит к текучести кадров, что повышает нагрузку и ещё больше снижает удовлетворённость. Студенты наблюдают как небольшие изменения в доступности информации создают заметные сдвиги в выборе школ. Они переходят от линейного мышления к системному мышлению. Адаптация моделей от исследовательских версий к образовательным

версиям демонстрирует, что сокращение параметров, упрощение выходных данных и оптимизация процедур при сохранении валидности создают эпистемические орудия, поддерживающие активные формы обучения. Студенты обнаруживают, что результаты включают пороговые эффекты и нелинейности, невидимые для интуиции. Документация в семантических вики и обсуждение среди сверстников делают процессы обучения видимыми и коллективными. Студенты, работающие с вычислительными моделями, развивают способность к системному анализу.

Научная новизна исследования заключается в теоретическом и эмпирическом обосновании того, что вычислительные модели в семантических вики выступают как опосредствующие средства развития системного мышления педагогов о сложных системах городского образования. Исследование переводит общие теоретические положения педагогической психологии в конкретные образовательные практики совместной работы с моделями в вики-среде. Тем самым уточняется понимание цифровизации образования как конструирования инструментов, которые обеспечивают переход от эмпирического к системному и теоретическому анализу. Практическая значимость исследования состоит в том, что оно предлагает воспроизводимую модель организации обучения, в которой педагоги осваивают системное понимание городского образования через совместную работу с вычислительными моделями и документирование результатов в вики-среде. Такой подход может быть встроен в программы подготовки и повышения квалификации учителей, позволяя им самостоятельно исследовать последствия управленческих решений в безопасной цифровой среде.

Ключевые слова: цифровизация образования; агент-ориентированное моделирование; системное мышление; теоретическое мышление; опосредствующие инструменты; системы городского образования; вычислительные образовательные среды; эпистемическая прозрачность; воспроизводимая практика

Для цитирования. Патаракин, Е. Д., Вачкова, С. М., & Петряева, Е. Ю. (2026). Опосредствование сложности: вычислительные модели как средства развития системного мышления о городском образовании. *Russian Journal of Education and Psychology*, 17(1-2), 471–505. <https://doi.org/10.12731/2658-4034-2026-17-1-952>

Introduction

Digitalization of education is often narrowly understood as the introduction of digital technologies into schools. Yet this understanding misses the deeper transformation. We define digitalization of education as the introduction of knowledge-mediating tools – instruments that externalize thinking, enable experimentation, and transform ways of knowing. These tools build on theoretical foundations developed over decades in psychology and ped-

agogy. Knowledge-mediating tools are instruments – material, digital, or symbolic. Models and diagrams externalize internal thinking. Software and computational environments make visible what was previously hidden. Notations and languages enable systematic expression. These tools serve several functions simultaneously. They externalize internal thinking and make visible what remains inaccessible to intuition. They enable systematic experimentation. Parameter variation happens without real costs. They provide feedback revealing unexpected consequences and patterns. They transform ways of knowing, change how we cognize, not merely the speed of cognition. They mediate activity and stand between learner and object of learning.

Digitalization in education involves three interconnected components. The instrumental component involves concrete digital tools enabling new ways of working. The methodological component involves procedures and practices applied with these tools. The epistemological component involves new ways of thinking about educational problems. This shift moves from observation to experimentation, from individual opinion to data, from intuition to testable hypotheses. This framework builds on the Russian psychological tradition. Lev Vygotsky argued that thinking is fundamentally mediated by cultural tools [1]. Development of new forms of thinking requires internalization of external tools and their associated psychological processes. Vygotsky's famous example involved counting. Young children count using fingers. The fingers mediate enumeration. This externalizes the counting process. Gradually, the child internalizes the act. The tool becomes internal. Yet the structure of thinking remains shaped by the tool's logic. Vygotsky's insight extends far beyond counting. When a domain becomes too complex for individual intuition, new tools mediate thinking. Mathematical equations mediate thinking about physical systems. Diagrams mediate thinking about organizational structures. Agent-based computational models can mediate thinking about complex social and educational systems. Contemporary generative AI systems extend this principle further, serving as active mediating partners that scaffold human reasoning and enable new forms of collaborative problem-solving in computational environments [2]. The principle remains constant: thinking that exceeds the limits of unaided cognition requires mediating tools. Vygotsky emphasized that tool effec-

tiveness depends on how it integrates into activity. A tool used passively as a source of information mediates differently than one used actively as an instrument for exploration. In educational contexts, this distinction proves crucial. A student observing a pre-built model and reading outputs gains information. Yet they may not develop internalized understanding. A student building models, exploring parameters, and reasoning about behavior develops deeper cognitive transformation.

Vasily Davydov developed Vygotsky's insights for scientific and educational contexts. He distinguished empirical thinking from theoretical thinking [3]. Empirical thinking observes individual cases, identifies properties, and develops classifications. An educator observing schools might categorize them as high-performing or low-performing. This captures variations but not underlying mechanisms. Theoretical thinking operates differently. It understands how system properties arise from structure. It grasps how structural changes produce changes in properties. Theoretical thinking penetrates to generative relationships. Davydov argued that theoretical thinking develops through specific activity with appropriate tools. These tools must reveal generative mechanisms. He called such tools adequate means. Adequate means externalize the structure of a system. They make visible the mechanisms generating observed phenomena. Agent-based models function as adequate means in Davydov's sense. They externalize system structure showing agents, attributes, decision rules, and interactions. By manipulating parameters and observing how behavior changes, educators engage in activity developing theoretical understanding. They move from empirical observation to grasping how structure generates patterns. The critical insight from Davydov is that theoretical thinking requires active engagement. Passive observation of models, however sophisticated, will not reliably produce theoretical thinking. Building models, modifying them, exploring parameter spaces, and reasoning about why patterns emerge – this active engagement generates the cognitive shift from empirical to theoretical thinking.

Seymour Papert extended Vygotsky's framework through constructionism [4; 5]. Where Piaget's constructivism emphasizes how minds construct understanding, constructionism emphasizes constructing external objects. Learning unfolds through building something tangible and meaningful. Pa-

pert argued that certain learning contexts prove particularly powerful: contexts where learners construct external objects they can inspect, modify, and reason about. Papert introduced the concept of objects to think with. Papert distinguished between two types of educational tools. Type 1 tools are amplifiers. They accelerate existing cognitive processes. They allow faster calculation or quicker access to information. Type 2 tools are epistemic tools. They generate new knowledge, create new ways of thinking and make visible what was previously inaccessible. Agent-based models function as epistemic tools. They embody principles about how systems work. They show how individual behaviors aggregate into system patterns and demonstrate feedback and threshold effects. When educators build models, they translate conceptual understanding into computational logic. This constructive engagement activates learning in ways that passive observation cannot.

Sherry Turkle extends these ideas through the concept of evocative objects [6]. She argues that objects we interact with are not merely instrumental. They are not simply tools for accomplishing tasks. Rather, objects evoke reflection and meaning-making. Objects we think with are often objects we think about. They become partners in thinking. They provoke us to reconsider our assumptions and deepen our understanding. Turkle demonstrates that people develop relationships with the objects they work with. A computer is not merely a machine, it becomes a thinking partner [7]. A model is not merely a representation, it becomes an object evoking reflection about the phenomena it represents. This evocative dimension proves crucial for learning. When educators work repeatedly with models, discussing results, modifying assumptions, and documenting understanding, the models become more than tools. They become objects that evoke sustained reflection and deeper thinking.

Marvin Minsky argued that education is not information transmission. It is development of capacity to build models. Children naturally construct models of the world through play and experimentation. Computers externalize these models. They make models visible, manipulable, and testable. Working with models is not learning about something. It is developing thinking capacity itself. Minsky's insight connects directly to our purposes. Agent-based models externalize the implicit models educators carry about

how schools work [8]. They make visible the assumptions built into those models. They allow testing those assumptions. They reveal consequences educators might not have anticipated. This modeling work develops not just knowledge about education but capacity for thinking systemically.

Stephen Wolfram advances these ideas further. He argues that computation is not merely a method for solving equations. Computation is a way to understand complex systems. Earlier, scientists built mathematical models and solved them analytically. Now, we can simulate systems and observe what happens [9]. Earlier, understanding complex systems required specialized training. Now, anyone can experiment and see emergent patterns. This democratization of computational understanding proves essential for education. It removes barriers that previously separated experts from non-experts. Educators need not be programmers or mathematicians. They can engage directly with computational models. They can build understanding through direct engagement. Paulo Blikstein extends these ideas into contemporary digital contexts. He argues that computational tools mediate thinking about complex domains when properly integrated into learning activities. The mediating power depends not on technical sophistication. It depends on environmental quality, collaborative processes, and connection to meaningful problems. Blikstein emphasizes democratization of invention [10]. Digital tools should not remain the province of experts. When properly designed, they enable anyone to engage in sophisticated thinking. This democratization is essential for education. It means pedagogical researchers can engage with computational models. Teachers can work with agent-based models. Students can build their own simulations. The barrier between professional researchers and educational practitioners decreases.

Urban educational systems face persistent and complex challenges. They must simultaneously prepare students for academic success, develop social competencies, address equity gaps, support teacher development, and respond to community needs. These multiple purposes often conflict with one another. Resources remain limited. Political priorities shift continuously. The complexity of urban education is fundamentally structural. These systems involve many types of agents: students, teachers, families, administrators, and policymakers. Each agent makes relatively independent

decisions based on imperfect information. Agents interact continuously in environments rich with feedback loops. Outcomes depend not on any single decision or variable, but on the complex patterns of interaction among many actors operating simultaneously. In such systems, human intuition often fails to predict or explain what actually happens. Educators frequently encounter surprising consequences of well-intentioned interventions. Policies designed to improve equity paradoxically produce stratification. Reforms intended to increase efficiency reduce innovation. Incentive structures meant to raise teacher quality accelerate teacher departure. Traditional analytical approaches struggle with this complexity. Statistical association identifies correlations but cannot capture feedback loops. Case studies illuminate particular contexts but generalize poorly. Controlled trials establish causal relationships but cannot reveal system-wide cascading effects. Policy arguments present logical arguments about how systems should work but often fail when confronted with actual behavior. None of these approaches can adequately represent the nonlinear, feedback-rich dynamics that characterize actual urban educational systems.

Computational approaches have emerged as powerful tools for thinking about such complexity. Agent-based modeling specifically represents how individual decisions and behaviors aggregate into system-level patterns. Yet such models remain surprisingly rare in educational practice. Most educators have limited familiarity with computational modeling. More fundamentally, the crucial question of how models can support genuine learning and thinking – rather than simply providing information or answers – remains largely unexamined in educational contexts.

This research investigates how agent-based modeling integrated with collaborative digital platforms and structured learning activity can function as a psychological tool in Vygotsky's sense. Computational models, properly designed and implemented, can support educators' development of systemic thinking. The central claim is straightforward. Educators develop sophisticated understanding of complex systems through model engagement. This occurs when models function as objects to think with, not sources of answers. This occurs when models integrate into collaborative environments supporting collective knowledge-building. This occurs when working with

models constitutes deliberate learning activity. Computational models then function as mediating instruments. They externalize system structure. They enable exploration of how structure produces behavior. They support collaborative interpretation. They facilitate development of theoretical understanding. They operationalize in contemporary digital contexts principles Vygotsky articulated decades ago and engage educators in the constructive activity Papert recognized as powerful.

Materials and methods

This study employs a design-based research approach. Design-based research iteratively develops and tests educational interventions in authentic contexts. The research implements three interconnected agent-based models examining different dimensions of urban educational complexity. These models integrate with a Semantic MediaWiki platform serving as a collaborative documentation space. The research follows a structured seven-phase collaborative learning pipeline. Data collection focuses on qualitative analysis of documented work, discussion records, and evolution of understanding across wiki contributions.

The research uses Semantic MediaWiki as the primary platform for implementation and data collection. MediaWiki has been adapted for educational purposes over many years [11]. It functions as both a collaborative documentation tool and a knowledge management system. The platform enables collective documentation of learning processes, experimental work, and discussions among participants. Semantic MediaWiki extension adds structured knowledge representation capabilities. The extension allows organizing information according to formal ontologies. This supports participants in building interconnected knowledge bases. Both educators and students contribute to developing shared conceptual structures [12].

The study implements three agent-based models using NetLogo. NetLogo is a programmable modeling environment designed for exploring complex phenomena. It enables definition of agents with attributes and behaviors [13]. It provides tools for systematic experimentation through BehaviorSpace extension. Models run in web-based environments, removing technical barriers to participation. Educators and students access models

directly through web browsers without requiring software installation or programming knowledge [14]. The three models examine different dimensions of urban educational system complexity. The first model represents school enrollment dynamics under competitive conditions with information asymmetries [15]. The second model explores competitive dynamics between urban schools [16]. The third model investigates systemic factors affecting teacher retention and satisfaction [17]. These models operationalize theoretical understanding of urban education into computational logic. They make visible the assumptions embedded in common understandings of how school systems function.

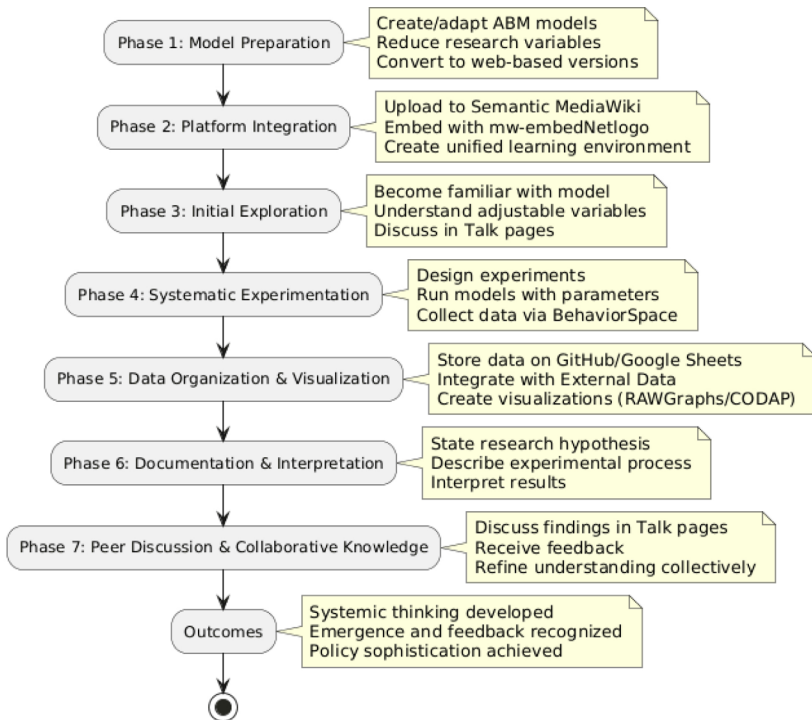


Fig. 1. Organizational pipeline

This research implements a structured yet flexible organizational pipeline that guides educators and students through systematic engagement

with computational models of urban educational systems. The pipeline integrates multiple phases of activity – model preparation, collaborative exploration, data collection, analysis, and discussion – creating what we refer to as a “mediated learning environment.” This environment leverages both computational tools (agent-based models in NetLogo) and collaborative knowledge platforms (Semantic MediaWiki) to support the development of systemic thinking (Figure 1).

The pipeline is designed around a fundamental insight from Vygotskian theory: cognitive development occurs not through isolated individual effort, but through participation in culturally organized activities mediated by tools. In this case, the “tools” are both computational (agent-based models) and social (wiki platforms for collaborative documentation and discussion). By organizing educational activity around this pipeline, we create conditions where participants can develop systemic thinking through deliberate engagement with models, data, peers, and persistent documentation.

Phase 1: Model Preparation and Adaptation. The first phase involves creating or adapting multi-agent models for educational purposes. Original agent-based models developed to study complex phenomena are often characterized by a large number of adjustable parameters and research variables, which can overwhelm learners encountering these tools for the first time. Rather than presenting the full complexity of the original models, we systematically reduce the number of research variables and adjustable parameters to create versions appropriate for educational contexts. This adaptation process preserves the core dynamics that illustrate systemic properties – such as emergence, feedback loops, and nonlinear relationships – while removing unnecessary complexity that might obscure these educational targets. Following model adaptation, the models are converted into web-based versions. This technical transformation is essential because it allows models to be run directly within web browsers without requiring participants to install specialized software or understand programming environments. Web versions democratize access to computational thinking tools, removing technical barriers to participation while maintaining the pedagogical power of model building and experimentation. A model that would normally require installation of NetLogo software and some under-

standing of coding becomes accessible to educators who simply need to open a browser and click to run the model.

Phase 2: Platform Integration Through Semantic MediaWiki. Once web-based versions of the models are prepared, they are uploaded to the Semantic MediaWiki platform (digida.mgpu.ru). This platform serves multiple functions simultaneously: it functions as a repository for model documentation, a collaborative workspace for shared thinking, and a central hub for integrating multiple tools and data sources. Rather than existing as stand-alone applications, the agent-based models are embedded directly into wiki pages using a specialized extension (*mw-embedNetlogo*), which has been specifically developed to support educational use of computational models within wiki environments. This integration approach provides several pedagogical advantages. First, it creates institutional robustness for the learning process. By embedding models within the wiki platform, all key materials – model descriptions, model interfaces, documentation, and participant contributions – remain accessible and interconnected within a single educational platform. Participants do not need to navigate between multiple tools or websites; instead, they encounter a unified learning environment where computational models, collaborative documentation, and data visualization coexist. This contrasts with typical educational approaches where students use separate software (e.g., NetLogo), then separate data analysis tools (e.g., spreadsheets), then separate discussion platforms (e.g., email or discussion forums). Second, this integration supports what we term “mediated continuity” – the sense that the tools and materials of the learning environment continuously support and reference one another, creating a coherent epistemic space where all elements of the learning activity connect meaningfully.

Phase 3: Initial Model Exploration and Collective Discussion. Participants begin their engagement with the models through guided exploration. Initial sessions involve becoming familiar with model interfaces, understanding what variables are adjustable, learning what outputs the model produces, and grasping the core dynamics represented. This introductory phase moves quickly into collaborative discussion. Participants use the Talk (discussion) pages embedded within the MediaWiki platform to discuss their initial observations of model behavior, pose questions about why particular dynamics

emerge, and begin generating hypotheses about how changes to parameters might affect system outcomes. This phase is critical for establishing shared understanding. Through discussion in the Talk spaces, participants externalize their initial conceptualizations of the models, encounter different interpretations from peers, and begin the process of moving from surface-level observation toward more systematic investigation. A participant might initially observe “when we increase this parameter, the outcome gets bigger,” but through discussion with peers and guided questioning, they begin asking “why does it get bigger? What mechanism in the model produces this relationship? Is this relationship linear or nonlinear?” The asynchronous nature of wiki-based discussion allows participants who may be distributed across different locations or time zones to contribute their thinking without real-time coordination requirements. Unlike synchronous discussion that occurs and is then lost, asynchronous wiki-based discussion leaves a permanent record that can be reviewed, built upon, and used as a resource for future learning.

Phase 4: Systematic Experimentation and Data Collection. Following initial exploration and collective discussion, participants design and conduct systematic experiments with the models. Each experiment involves selecting particular parameter values, running the model under those conditions, observing the outcomes, and recording data about how system properties change. Participants can collect data in two ways: by manually recording observations and screenshots from individual model runs, or by using the BehaviorSpace extension built into NetLogo, which automates the process of running models across multiple parameter combinations and systematically collecting quantitative data about model behavior. This phase represents the transition from passive observation to active investigation. Participants are no longer simply looking at what the models do; they are now asking specific questions (“What happens to school segregation if family information about school quality improves? Does it decrease segregation, increase it, or have no effect?”) and designing experiments to answer those questions. The experimental process itself becomes a tool for thinking about urban educational systems – through the act of translating their conceptual questions into parameter changes and observing the resulting dynamics, participants develop more sophisticated understanding of how systems actually work.

Phase 5: Data Organization and Collaborative Visualization. Once experiments are completed and data collected, participants organize their findings in shareable formats. To support distributed collaboration and transparency, data is stored in accessible external platforms such as GitHub repositories or Google Sheets, which allow multiple participants to contribute data, comment on findings, and build shared datasets. These external data sources are then integrated back into the wiki environment using the External Data extension, which automatically retrieves and displays data from external sources within wiki pages. This creates a continuous circulation of information: participants create data, store it externally, the external data is retrieved and displayed within the wiki, and is then discussed and built upon.

This phase serves multiple purposes. Practically, it allows the research team to aggregate findings across multiple participants and multiple experiments, creating a collective dataset that reveals patterns no individual researcher could identify alone. Pedagogically, it demonstrates to participants that computational data need not remain siloed within individual computers or notebooks; data can be shared, discussed, and built upon collaboratively. The process of uploading data, formatting it for others to use, and explaining what it represents becomes part of the learning process, developing practices of transparency and reproducibility that are central to scientific thinking. Following data collection and organization, participants move to data visualization. Raw quantitative data from model experiments can be difficult to interpret; a table of numbers showing how school segregation changes across different parameter values may not reveal patterns clearly. Visualization transforms tables of numbers into visual representations that reveal patterns. Participants use web-based visualization tools such as RAWGraphs [18] or CODAP [19], which offer powerful visualization capabilities without requiring programming knowledge. These tools allow participants to quickly generate multiple visualizations exploring different representations of the same data—a scatter plot, a line graph, a heat map—and to select visualizations that most clearly reveal the patterns they discovered. Once visualizations are created, they are embedded back into the wiki pages alongside the raw data and model descriptions, creating integrated knowledge artifacts that combine simulation, data, and visual interpretation.

Phase 6: Knowledge Documentation and Interpretation. Having collected data, visualized findings, and created visual representations, participants document their experimental process and interpret their results. Documentation typically follows a structured format: participants explicitly state the research hypothesis they tested, describe the specific model experiments conducted to test that hypothesis, report what the results showed, and discuss what the results mean for understanding urban educational systems. This documentation becomes a permanent record within the wiki, available for other participants to read, critique, and build up. The act of documentation is itself a form of learning activity. By writing about their experimental process and interpreting their findings, participants engage in what we term “external representation of thinking” – they must make explicit what would otherwise remain implicit, tacit, or partially understood. A participant might have had intuitions about how a system works based on observing model behavior, but writing about these intuitions, explaining them clearly to others, and connecting them to evidence from model experiments forces more rigorous thinking. Research has consistently demonstrated that this process of externalizing understanding through writing, explaining, or documenting significantly deepens conceptual learning. Furthermore, the wiki format makes this documentation visible and subject to feedback from peers, creating what we might call “public thinking” – the vulnerability of making one’s reasoning visible to others often strengthens the quality of that reasoning.

Phase 7: Peer Discussion and Collaborative Knowledge Building. The final phase of the pipeline involves collaborative discussion of results. Within the MediaWiki Talk spaces associated with each wiki page, participants discuss findings from their own experiments and those conducted by peers. This discussion serves multiple functions: it provides opportunity for participants to receive feedback on their interpretations, to learn how different experimental designs illuminate different aspects of system dynamics, to identify patterns across multiple experiments, and to collectively refine understanding of urban educational systems. A participant might document an experiment showing that increases in teacher workload lead to decreases in teacher satisfaction. A peer might then point out that this relationship appears to be nonlinear - satisfaction doesn’t decrease proportionally with

workload increases, but appears to show threshold effects. Another peer might ask whether this relationship holds across all types of schools or varies by school context. Through this discussion, understanding becomes more nuanced and sophisticated. Participants move from simple observation (“increasing workload decreases satisfaction”) to more complex understanding (“increasing workload has nonlinear effects on satisfaction that may vary by context”). The discussion also reveals patterns that might not be visible to an individual researcher but emerge through collective analysis. This phase exemplifies what we describe as “mediated collaborative learning.” Discussion is not ephemeral – it does not occur in real-time conversations that are subsequently lost. Instead, discussion is documented in persistent wiki pages, where the thinking processes of the community are visible, reviewable, and buildable. New participants can read previous discussions to understand how others have interpreted model results, what questions have been explored, and what patterns have been identified. Over time, the accumulated discussions constitute a form of collective knowledge-building where the understanding of the group advances through deliberate, documented, asynchronous collaboration. This creates what might be termed “learning at scale” – where the insights of individual researchers become resources for collective understanding, and where the understanding that develops is more sophisticated than what could emerge from individual efforts alone

Results

The research implements three interconnected agent-based models integrated into the digida.mgpu.ru platform. Each model examines different dimensions of urban educational system complexity. Each model makes visible hidden mechanisms and feedback processes. Together, they form a computational representation of how structural factors, individual decisions, and institutional dynamics interact to shape urban education. The three models integrated into digida.mgpu.ru represent substantial adaptations from their original research versions. The original models were designed to answer specific research questions with maximum parameter flexibility. Research versions included numerous adjustable variables allowing exploration of nearly every model dimension. Research versions included detailed output displays

showing model dynamics at fine-grained resolution. These features serve research purposes well. They allow researchers to examine system behavior across parameter space comprehensively. Educational use requires different design choices. Students and educators need focused learning experiences, not overwhelming complexity. Excessive parameters confuse rather than clarify. Too many output graphs obscure rather than illuminate. Web-based environments require different computational approaches than desktop applications. These considerations drove substantial redesign. The educational versions systematically reduced the number of accessible research variables. Variables peripheral to core learning objectives were removed or fixed at standard values. The models retain sufficient flexibility for meaningful exploration but eliminate parameters whose adjustment produces marginal effects on key outcomes. Output displays were streamlined. Graphs showing minor variations were removed. Remaining visualizations clearly show relationships central to understanding system dynamics. Computational procedures were modified to ensure web-based stability and responsiveness. The original models sometimes required extended computation time. Web versions needed to complete runs rapidly so students could conduct many experiments in limited time. Procedures were optimized. Data structures were simplified where possible. These changes maintained model validity while improving practical usability. This adaptation process itself constitutes important pedagogical work. Educators and researchers collaborated to identify what truly matters for understanding urban education systems. The resulting models are not merely simplified research versions. They represent deliberate design choices reflecting pedagogical priorities. They are epistemic tools designed to support particular kinds of learning rather than comprehensive research tools designed to answer all possible questions.

Model 1: School Choice Under Information Asymmetries.

The first model represents school enrollment dynamics in competitive educational markets with information asymmetries. The model is available at https://digida.mgpu.ru/index.php/School_Choice_ABM. It represents a city where students and schools are distributed geographically. Students differ in family income. Schools differ in academic achievement levels. Some schools operate as private institutions charging tuition. Others function as

public schools. A critical feature involves how information about school quality is distributed. Wealthy families possess complete information about school performance. Lower-income families have limited information. They may not know school quality levels. They may lack resources to access distant schools. Students make enrollment choices based on their circumstances and information. Wealthy students can pay tuition and travel distance. They choose schools considering both quality and location. Lower-income students cannot afford private schools. They cannot easily travel to distant schools. They often choose nearby schools regardless of quality. This creates a fundamental asymmetry. Identical schools serve different populations based on income and information access. The model includes policy interventions simulating real educational policies. For example, traffic light systems inform low-income families about school performance through simple color signals. Red indicates low performance. Green indicates high performance. Yellow indicates intermediate performance. This policy attempts to address information asymmetry. Yet even with improved information, low-income families face constraints. They may lack transportation. They may prioritize proximity to work. Perfect information does not equalize opportunity when other constraints bind.

Students can manipulate multiple independent variables in this model. They can adjust the proportion of private schools. They can modify the income distribution of families. They can change how much families value school quality versus proximity. They can toggle information policies on and off. They can specify what information low-income families receive. By running experiments with different parameter values, students discover how structure shapes outcomes. They observe how the same policy produces different effects under different structural conditions. They recognize that school choice policies cannot overcome structural constraints of geography and poverty. This model supports educators and students in understanding school segregation not as a natural phenomenon but as an emergent outcome of how choice systems are structured. It reveals how information asymmetries create inequality even when explicit discrimination is absent. It demonstrates why educational policies addressing only information may fail when structural constraints remain unchanged.

Model 2: Competitive Dynamics Between Urban Schools.

The second model examines competitive dynamics between schools in urban environments. The model is available at https://digida.mgpu.ru/index.php/School_Education_Competition. This model represents how schools respond to competition. When school choice policies allow students to select schools, schools must attract and retain students. This creates competitive pressures. The model represents schools with different characteristics. Schools have quality levels that can improve or decline. Schools have reputations that develop over time. Schools have budgets affected by enrollment numbers. When students choose high-quality schools, those schools gain resources. They can improve further. Lower-quality schools lose students. They lose resources. They struggle to improve. This creates a reinforcing cycle. Winners accumulate advantages. Losers fall further behind. Competition creates both productive and destructive effects. Schools may improve quality to attract students. This represents a positive effect of competition. Yet competition also creates stratification. Advantaged schools attract more resources. Disadvantaged schools cannot compete. Over time, inequality increases. Schools serving wealthy communities become stronger. Schools serving poor communities become weaker. The system sorts students by prior advantage. It amplifies initial inequalities rather than reducing them.

Students can adjust parameters in this model. They can modify how strongly school reputation affects student choice. They can change how quickly schools improve or decline in response to enrollment changes. They can adjust the initial quality distribution of schools. They can specify how much resources matter for improvement. They can simulate different policy interventions: funding formulas benefiting disadvantaged schools, caps on school quality differences, or investments in capacity building. By running experiments, students discover that identical policies produce different effects depending on initial conditions and parameter settings. Small changes in how strongly reputation matters can produce large differences in system outcomes. Resource advantages create cumulative advantages. The model reveals competitive dynamics as a mechanism producing stratification. It shows that competition alone does not guarantee efficiency or equity. System structure determines whether competition improves or worsens educational opportunity.

Model 3: Teacher Satisfaction, Retention, and Urban System Stability

The third model, available at [https://digida.mgpu.ru/index.php/Teacher_Satisfaction_\(model\)](https://digida.mgpu.ru/index.php/Teacher_Satisfaction_(model)), represents systemic factors affecting teacher retention and satisfaction in urban schools. This model operationalizes a critical insight: teacher quality, stability, and student outcomes interconnect through feedback loops. Teacher satisfaction directly affects retention. Teacher retention affects school stability. School stability affects educational quality. Educational quality affects student outcomes. These represent not independent variables but interconnected dynamics. The Teacher Satisfaction model represents a population of teachers distributed across urban schools. Teachers have attributes reflecting their circumstances: years of experience, salary level, working conditions, professional development opportunities, and current job satisfaction. Schools differ in their capacity to provide supportive working conditions. Some schools operate with adequate resources, manageable class sizes, and stable leadership. Others struggle with resource constraints, large classes, and frequent administrative changes. The model operationalizes well-documented research findings about teacher satisfaction. Teachers value fair compensation, but salary alone does not determine satisfaction. Professional respect, opportunities for meaningful work, collegial relationships, and adequate resources matter equally. Administrative support and clear career pathways affect retention. Teachers can tolerate many challenges if they feel respected and supported. Conversely, teachers with adequate salaries may leave if they experience disrespect or isolation. The critical innovation in this model involves representing feedback loops explicitly. When schools lose experienced teachers through departure, schools face consequences. New teachers require mentoring, reducing time available for teaching. Loss of institutional knowledge increases mistakes and inconsistencies. Remaining teachers experience increased workload compensating for absences. Increased workload reduces satisfaction among remaining teachers. Their satisfaction declines. More teachers depart. The system enters a negative spiral where initial teacher losses trigger cascading departures. Conversely, stable schools with low turnover accumulate advantages. Experienced teachers mentor newer teachers. Institutional knowledge accumulates. Con-

sistent practices improve. Workload distributes across stable teams. Teacher satisfaction remains high. Low turnover occurs. These schools achieve stability. The system reaches a stable equilibrium where low turnover reproduces conditions supporting low turnover.

All three models follow a unified data generation scheme. This scheme allows systematic exploration of how model outcomes vary across parameter space. The Teacher Satisfaction model exemplifies this approach clearly. Understanding this scheme provides insight into how computational thinking and systematic experimentation operate in educational contexts.

The Teacher Satisfaction model includes eight independent variables that students can systematically explore (Figure 2).

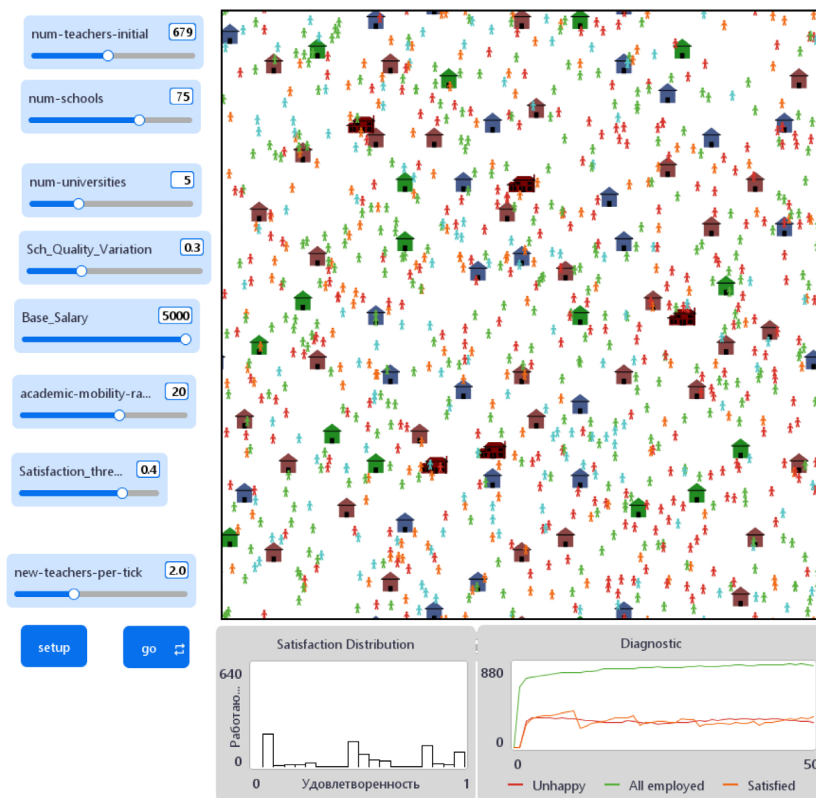


Fig. 2. Interface of the Teacher Satisfaction model

Consider first the parameters defining the urban context. The model represents 75 schools distributed across a simulated city. These schools serve teachers who graduate from 5 universities distributed geographically. These numbers create realistic urban scale without overwhelming computational demands. The model assumes initially 500 teachers distributed across these schools. These parameters define the basic context within which all other dynamics unfold. The model includes four parameters defining teacher characteristics and behaviors. Academic mobility radius (ranging from 5 to 25 kilometers in different experiments) represents how far teachers will travel to work. Teachers differ in how far they will commute. A teacher willing to travel only 5 kilometers has few options in a large city. Teachers willing to travel 25 kilometers have many school choices. This parameter affects job search behavior. It affects which teachers apply to which schools. It shapes the pool of available teachers for each school. The satisfaction threshold (ranging from 0.1 to 0.5) represents what minimum satisfaction level teachers require before departure. Some teachers tolerate difficult working conditions. They stay despite low satisfaction. Others are quick to leave if conditions disappoint. This parameter ranges from 0.1 (only extremely unhappy teachers depart) to 0.5 (teachers depart if satisfaction falls below moderate levels). This range captures realistic variation in teacher persistence. Teacher salary represents a fundamental working condition. The model explores salary levels from 1000 to 5000 units in monthly increments. These salary levels interact with satisfaction in complex ways. Higher salaries support satisfaction. Yet salary alone cannot overcome other dissatisfactions. The model explores this interaction across a range representing different investment levels in teacher compensation. New teachers entering the system (ranging from 1 to 3.5 teachers per year) represent the flow of graduates into teaching. High flows of new teachers might help schools replace departing teachers. Yet they also create management burdens. Mentoring new teachers requires experienced teacher time. Managing rapid turnover is difficult. The model explores this dynamic across realistic entry rates. School quality variation (fixed at 0.3) represents how much schools differ in their quality and working conditions. A system with high variation has some excellent schools and some poor schools. A system with low variation has schools more similar to each other. The model fixes

this parameter because pedagogical focus concentrates on other dynamics. The model generates data across nine dependent variables measuring system outcomes. Mean satisfaction across all teachers shows overall system health. If mean satisfaction declines, the system faces emerging problems. Disaggregated satisfaction measures reveal inequality. Mean satisfaction in good schools versus poor schools shows whether satisfaction divides track school quality. Satisfaction inequality measures show whether the system is becoming more or less equitable in how teachers are treated. Employment rate shows what percentage of available teachers remain employed and working. Unemployment rate shows what percentage have departed. Teacher turnover rate shows how many employed teachers depart each year. These measures reveal system stability. High turnover indicates instability. High unemployment indicates systemic failure to retain teachers. Mean school vacancy rate shows how many teaching positions remain unfilled. Schools struggling to attract teachers accumulate vacancies. Cumulating vacancies indicate systemic dysfunction.

By running experiments across parameter combinations, students and researchers accumulate understanding of how different system characteristics affect outcomes. What happens when we increase salaries? Satisfaction improves moderately. Yet without addressing workload (represented through class size and support), salary increases alone produce limited retention improvements. What happens when we increase mobility radius? Teachers gain more options. They leave unsatisfactory schools more readily. Poor-quality schools suffer higher turnover unless they improve conditions. What happens when satisfaction thresholds change? When teachers tolerate more difficulty, turnover decreases but at the cost of teacher well-being. Systems optimizing only for low turnover might achieve stability at the cost of forcing teachers to endure unacceptable conditions.

This systematic exploration reveals that urban education system outcomes are not predetermined. They emerge from how structural parameters interact. Change parameters, and outcomes change. Yet outcomes do not change proportionally. Small salary increases matter little without workload improvements. Yet combined improvements across multiple dimensions produce disproportionate effects. The system has threshold effects and nonlinearities that simple intuition misses.

Running these experiments in BehaviorSpace allows educators to accumulate data across hundreds of model runs efficiently. A student might run 100 variations exploring how salary affects outcomes across different mobility and turnover rates. Another student might run 100 variations exploring how satisfaction thresholds interact with quality variation. Collectively, students accumulate understanding about the design space of urban education systems. They recognize which parameters matter most. They discover which changes produce lasting effects. They develop intuition about system behavior that goes far beyond abstract knowledge.

This data-driven exploration differs fundamentally from typical policy discussion. Policy makers often assume particular relationships and advocate specific solutions. “Increase teacher salary” seems obviously correct. The model allows testing: correct under what conditions? With what timing? Salary increases help, but only when combined with what else? These questions move beyond ideological disagreement toward empirical exploration. The model does not eliminate disagreement. But it focuses disagreement on testable assumptions rather than untestable ideology. The Teacher Satisfaction model includes multiple independent variables allowing systematic exploration. Students can adjust teacher salaries, examining whether salary increases alone improve retention. They can modify class sizes, testing whether workload affects satisfaction. They can change administrative support levels, exploring whether leadership quality matters. They can adjust professional development resources. They can specify demographic characteristics of teacher populations. They can introduce policy interventions: salary increases, mentoring programs, professional development investments, or administrative reforms. Particularly important, the Teacher Satisfaction model reveals threshold effects and nonlinear relationships. Small improvements in working conditions when combined might produce large increases in retention. Conversely, small declines might trigger cascading departures. This nonlinearity contradicts intuitions assuming proportional relationships. A school experiencing 10% teacher departure might stabilize or might enter a spiral of accelerating departures depending on how remaining teachers respond. Policy interventions must account for these nonlinearities. The model also operationalizes equity concerns directly. Teachers from disadvantaged

communities may experience additional stressors. They may serve students with greater needs. They may face cultural mismatch or discrimination. The model can represent how these factors interact with other working conditions. Students can explore whether equal policies produce equal outcomes when teachers face different baseline stressors. The model reveals how addressing only surface-level factors while ignoring structural inequities fails.

Students using these three models engage in systematic experimentation. They form hypotheses about how urban educational systems function. They design specific experiments testing these hypotheses. They collect data from model outputs. They observe how system properties change as they manipulate parameters. They discover that their intuitions about how systems work often prove incorrect. Systems behave in counterintuitive ways. Obvious policies produce unexpected consequences. For example, a student might hypothesize that improving school quality information would reduce segregation. They would run the School Choice model with and without information policies. They would discover that information alone, without addressing structural constraints, produces minimal effects on segregation. Alternatively, a student might expect that salary increases would solve teacher retention problems. Running the Teacher Satisfaction model, they would discover that salary matters but functions within a complex web of factors. Salary increases help only when combined with working condition improvements. These discoveries differ fundamentally from abstract knowledge about systems. Reading that “complex systems have threshold effects” remains abstract. Discovering threshold effects through repeated experimentation with models embeds understanding differently. The body learns. The intuition shifts. Students begin expecting nonlinear relationships. They begin recognizing feedback loops in new situations. They develop systemic thinking not as an intellectual exercise but as lived experience.

As students conduct experiments, they document findings within the wiki platform. They record what hypotheses they tested. They describe parameter values they used. They report outcomes they observed. They discuss what results mean for understanding urban education. This documentation creates permanent records accessible to other students and educators. Students discuss their findings in MediaWiki Talk pages. They learn how peers

conducted similar experiments with different parameters. They discover that experimental results depend on assumed parameter values. What appears as a universal law might reflect specific assumptions. This realization develops sophistication about scientific thinking. Students recognize that model results depend on model assumptions. They understand why replication matters. They appreciate uncertainty. Peer discussion also reveals collective understanding emerging across individual experiments. One student might run 10 experiments exploring information policy effects. Another might run 10 experiments exploring income distribution effects. Collectively, they accumulate understanding about how system structure shapes outcomes. No individual experiment provides complete understanding. Collective discussion synthesizes understanding from many experiments. Engagement with these three computational models supports transformation in how educators think about urban educational systems. Initial intuitions emphasize individual factors. Good teachers produce good outcomes. Quality schools attract good students. Information helps people make better choices. These intuitions contain truth but miss systemic dimensions. Systematic engagement with models reveals how structure shapes behavior. Individual agency matters, but operates within structural constraints. Good teachers in under-resourced schools face challenges good teachers in well-resourced schools do not face. Quality schools in wealthy neighborhoods attract different students than identical schools in poor neighborhoods. Information helps only when people have resources to act on information.

This shift from intuitive to systemic thinking, from individual to structural explanation, from seeing outcomes as inevitable to recognizing them as contingent on system design – this transformation constitutes the central result of the research. Students who engage systematically with computational models demonstrate this shift. They begin asking different questions. They propose different solutions. They develop capacity for systemic analysis essential for educational leadership.

Discussion

The results demonstrate a fundamental insight: digitalization of education is not technology implementation. It is not about introducing gadgets, plat-

forms, or applications. Rather, digitalization involves creating new cognitive tools that transform what educators and students can see, do, and think. The three computational models integrated with Semantic MediaWiki exemplify this principle. NetLogo, BehaviorSpace, and GitHub are often described as digital tools. Yet this description misses their deeper function. They operate as epistemic instruments in the sense Davydov and Papert articulate: they externalize system structure, enable hypothesis construction, facilitate systematic experimentation, make thinking visible, and support reflection. Through these epistemic instruments, educators and students accomplish several cognitive transformations simultaneously. They see complex systems instead of accepting complexity as incomprehensible. Rather than relying on intuition about urban education, they build formal computational models externally. They experiment without real costs, observing consequences of parameter changes in simulation. They make their assumptions visible, recognizing that model results reflect assumed relationships. They discover emergent patterns through systematic exploration, moving beyond linear causal thinking. They work with reproducibility, understanding that experimental results should replicate when conditions replicate. This represents fundamentally different cognitive activity than traditional educational approaches. When students read policy analyses, they encounter arguments about why particular policies should work. When students engage with computational models, they test whether policies actually produce claimed effects across varying conditions. Reading that “information improves school choice” remains abstract. Running the School Choice model with and without information policies, observing minimal segregation reduction, produces embodied understanding of why information policy alone fails.

Vygotsky showed that thinking is mediated by cultural tools. Davydov showed that theoretical thinking develops through activity with adequate means – tools revealing system structure. Papert showed that learning through construction of external objects proves particularly powerful. Turkle showed that objects we think with become partners in thinking, evoking reflection and meaning-making. Computational models satisfy all these theoretical requirements simultaneously. They serve as mediating instruments in Vygotsky’s sense. They function as adequate means in Davydov’s sense. They

are objects to think with in Papert's sense. They evoke reflection in Turkle's sense. The research demonstrates that when properly designed and integrated into deliberate learning activity, computational models support theoretical thinking development about complex systems.

The research operationalizes "digitalization develops systemic thinking" from an appealing but vague claim into concrete, visible, measurable practice. When a student forms a hypothesis about how teacher salary affects retention, this activates causal thinking. When that student runs a Teacher Satisfaction model experiment, the simulation reveals emergent effects invisible to intuition. When the student discovers results contradict their expectations, learning occurs. When the student observes nonlinear relationships and threshold effects through repeated experiments, systemic understanding develops. When the student revises hypotheses based on data, scientific thinking unfolds. Each step is concrete, observable, and measurable. This operationalization distinguishes the research from much educational technology literature that claims tools develop thinking without demonstrating how. The research shows precisely how. Students form hypotheses. They conduct experiments. They observe data. They discuss results. They revise understanding. Documentation in the wiki platform makes this entire process visible to other students and researchers. The transformation from intuitive to systemic thinking becomes traceable in student work.

A distinctive strength of the approach involves reproducibility as pedagogical principle. When students upload data to GitHub, when they document experiments in wikis, when they use BehaviorSpace to generate systematic data, they create reproducible science. A peer student can examine their experiments. They can replicate them with identical parameters. They can verify results. They can modify parameters and explore variations. This reproducibility serves pedagogical purposes beyond scientific validity. It demonstrates what scientific thinking actually involves. It shows that science is not individual genius making breakthroughs. Science is systematic exploration, careful documentation, and verification through replication. Students learn this not through lectures about scientific method but through practicing it. Reproducibility also democratizes research. Students need not be statistical experts. They need not understand complex mathematical models. They can

understand models written in NetLogo because the language was designed for clarity. They can replicate experiments because BehaviorSpace automates systematic variation. They can verify results through examining documented work. The barrier between expert researchers and educational practitioners decreases. Systemic thinking becomes accessible. The research suggests practical implications for teacher education. Teachers navigating complex urban education systems need tools supporting systemic analysis. Traditional preparation emphasizes classroom management, content knowledge, and individual pedagogy. These remain important. Yet they do not prepare teachers to think systematically about how school systems work. Computational models offer practical tools for this preparation. Teachers engaging with models discover system properties. They recognize feedback loops in real schools. They appreciate why simplistic policy solutions often fail. They develop patience with complexity. They become less likely to blame individual teachers or students for system-level outcomes. They develop perspective for systemic rather than individual problem-solving. For policy makers, the research suggests that understanding system dynamics matters for effective policy design. Policies treating education systems as simple input-output systems often fail. Policies ignoring feedback loops, threshold effects, and unintended consequences produce disappointing results. The models provide tools for exploring policy effects across varying conditions. They support evidence-based policy design focused on testable assumptions rather than ideological positions.

The research demonstrates that digitalization of education, properly understood, transforms what educators and students can think. Not through replacing human thinking with machines. Rather, through creating cognitive tools that externalize complexity, enable systematic exploration, make assumptions visible, reveal emergent patterns, and support reproducible practice. The three agent-based models integrated into digida.mgpu.ru exemplify this transformation. They operationalize theoretical insights from Vygotsky, Davydov, Papert, and Turkle into educational practice. They demonstrate that systemic thinking develops through activity with epistemic instruments designed to make system structure visible. For educational practice, the implications are significant. Teachers and educational researchers can engage with sophisticated computational models without specialized training. Models embedded

in accessible web platforms support learning at scale. Documentation in semantic wikis makes learning processes visible and collective. Data uploaded to GitHub creates reproducible science at the educational level. For theory, the research contributes to understanding how cognitive tools mediate development. It demonstrates that Russian and Western educational traditions converge on common insights: that new forms of thinking develop through activity with tools designed to externalize what would otherwise remain inaccessible to unaided cognition. When rooted in solid educational theory and designed around cognitive development principles, digital tools can genuinely transform how educators and students think about the systems they inhabit. This transformation – from intuitive to systemic thinking, from individual to structural explanation, from complexity as obstacle to complexity as opportunity for investigation – constitutes digital transformation’s true promise.

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Поступила 13.01.2026

После рецензирования 15.02.2026

Принята 17.02.2026

Received 13.01.2026

Revised 15.02.2026

Accepted 17.02.2026