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Practical problems and challenges in mathematical modeling in social sciences research

Abstract

The growing use of mathematical modeling in the social sciences has significantly expanded analytical capabilities to understand complex social phenomena. However, despite its increasing adoption, researchers frequently encounter practical and methodological difficulties when applying mathematical models to dynamic and multidimensional social systems. This study aims to systematically examine the principal practical problems and methodological challenges associated with applying mathematical modeling in contemporary social science research through a structured synthesis of recent scholarly literature. The research employs a Systematic Literature Review (SLR) approach to ensure transparent and replicable analysis of existing studies. Data were collected through a systematic search of the Scopus database using keyword combinations related to mathematical modeling, the social sciences, and methodological challenges. The screening and eligibility process yielded a final dataset of 32 peer-reviewed articles published between 2019 and 2026 that met all predefined inclusion criteria. The selected studies were analyzed using thematic synthesis to identify recurring methodological patterns and constraints reported in the literature. The analysis reveals five dominant categories of challenges: structural simplification of social behavior within models, uncertainty in parameter estimation, limitations in the availability of empirical data and measurement reliability, difficulties in empirical model validation, and interdisciplinary barriers to integrating mathematical techniques with social science theory. These findings indicate that while mathematical modeling provides valuable analytical insights, its effective application requires careful attention to methodological transparency, data quality, and interdisciplinary collaboration. Future research should focus on improving model validation frameworks, expanding the integration of empirical data, and strengthening interdisciplinary methodological training.

Keywords: mathematical modeling, social sciences, systematic literature review, methodological challenges, computational social science

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Introduction

Mathematical modeling has become an increasingly influential methodological approach in contemporary social sciences research. Over the past several decades, advances in quantitative methods, computational technologies, and data analytics have significantly expanded researchers' capacity to analyze complex social phenomena using formal mathematical frameworks. Through mathematical models, researchers can represent interactions among individuals, institutions, and social systems in structured analytical forms, enabling the exploration of dynamic processes such as economic behavior, social network diffusion, policy interventions, and demographic change. These modeling approaches provide powerful tools for simplifying complex systems and generating theoretical insights that may not be immediately observable through traditional qualitative analysis alone.[1]

The growing integration of mathematical modeling into social sciences has been further accelerated by the development of computational social science and data-driven research environments. Digital data sources, large-scale simulations, and algorithmic analysis have enabled scholars to construct increasingly sophisticated models that represent large populations, multilevel social interactions, and evolving behavioral dynamics.[2] In fields such as economics, political science, sociology, and public policy analysis, mathematical models are now widely used to examine policy outcomes, predict social trends, and test theoretical assumptions regarding collective behavior and institutional processes. As a result, mathematical modeling has gradually shifted from being a specialized methodological tool to becoming a central component of interdisciplinary social science research.

Despite its analytical advantages, the application of mathematical modeling to social sciences remains accompanied by substantial methodological and practical challenges. Social systems are characterized by high levels of complexity, heterogeneity, and contextual variation, making them inherently difficult to represent within simplified mathematical structures.[3] Unlike physical systems, social phenomena involve human actors whose decisions are influenced by psychological biases, cultural norms, institutional constraints, and unpredictable behavioral responses. Consequently, the process of translating complex social realities into formal mathematical equations often requires a series of assumptions and abstractions that may limit the empirical realism of the resulting models.

One of the most frequently discussed issues in social science modeling concerns the tension between analytical simplicity and behavioral realism. Mathematical models typically rely on simplified representations of decision-making processes in order to maintain tractability and computational feasibility.[4] However, such simplifications may overlook critical dimensions of human behavior, including bounded rationality, social learning, and institutional adaptation. When these factors are insufficiently represented, model predictions may diverge from observed social outcomes, thereby raising questions about the reliability and interpretability of modeling results in real-world contexts.

Another important challenge arises from the difficulties associated with parameter estimation and model calibration. Mathematical models often require numerous parameters representing behavioral tendencies, interaction probabilities, or structural relationships between variables. In many social science contexts, however, reliable empirical data for estimating these parameters are limited or uncertain. As a result, researchers frequently rely on indirect estimation methods, proxy indicators, or calibration strategies based on incomplete datasets. Such limitations can introduce substantial uncertainty into model outputs and may reduce the predictive accuracy of simulation results.[5]

In addition to parameter uncertainty, data availability and measurement limitations represent persistent obstacles for mathematical modeling in social sciences. Many social phenomena involve variables that are difficult to measure directly, such as social trust, political attitudes, institutional legitimacy, or informal economic activity. Data related to these constructs are often collected through surveys or observational studies, which may contain measurement errors, sampling biases, or incomplete coverage. Consequently, the empirical foundations of social science models may be constrained by the availability and reliability of the underlying data used for model development and validation.[6]

The issue of model validation further complicates the application of mathematical modeling in social sciences research. In natural sciences, models can often be validated through controlled experiments or precise empirical measurements. In contrast, social systems evolve in open environments influenced by numerous interacting variables, many of which cannot be isolated or experimentally manipulated.[7] As a result, validating social science models often requires indirect evaluation strategies, such as pattern comparison, historical simulation, or out-of-sample prediction testing. These approaches may provide useful insights but also introduce additional uncertainty regarding the extent to which a model accurately represents real-world social dynamics.

Beyond technical challenges, interdisciplinary barriers also affect the development and adoption of mathematical modeling within social sciences. Effective modeling research typically requires a combination of expertise in mathematics, statistics, computer programming, and domain-specific social theory. However, such interdisciplinary competencies are not always widely distributed across academic communities.[8] In some cases, social scientists may lack advanced training in quantitative modeling techniques, while technical modelers may have limited familiarity with theoretical frameworks that explain social behavior. These differences in methodological background can hinder collaboration and may limit the broader diffusion of modeling approaches within social science research environments.

The increasing complexity of computational modeling techniques has further intensified the need for systematic reflection on the methodological foundations of social science modeling. Agent-based simulations, network models, and hybrid computational frameworks now allow researchers to simulate highly complex systems involving thousands or even millions of interacting agents.[9] While these approaches offer powerful analytical capabilities, they also introduce new methodological questions related to transparency, interpretability, and reproducibility. Without clear methodological standards, the growing sophistication of computational models may paradoxically reduce their accessibility and practical usability within broader social science communities.[10]

Given these challenges, there is a growing recognition of the need to systematically examine the practical problems that emerge in the application of mathematical modeling across social science disciplines. A comprehensive understanding of these challenges is essential for improving methodological practices, strengthening interdisciplinary collaboration, and enhancing the reliability of modeling-based research. Previous studies have addressed specific technical issues in modeling frameworks, yet the broader landscape of methodological constraints remains fragmented across different disciplinary contexts. As a result, synthesizing existing scholarly discussions regarding the limitations and challenges of mathematical modeling can provide valuable insights into the current state of modeling practices in social sciences.[11,12]

Systematic literature review (SLR) provides an appropriate methodological approach for conducting such an investigation. Unlike narrative reviews, SLR employs transparent and structured procedures for identifying, selecting, and synthesizing relevant studies within a defined research domain. By systematically analyzing peer-reviewed publications, SLR enables researchers to identify recurring themes, methodological patterns, and research gaps within the existing literature. This approach is particularly useful for fields characterized by methodological diversity and interdisciplinary integration, such as mathematical modeling in social sciences research.

Therefore, the primary objective of this study is to systematically examine the practical problems and methodological challenges associated with the application of mathematical modeling in social sciences research through a structured synthesis of recent scholarly literature. By analyzing peer-reviewed studies published in recent years, this research seeks to identify the key sources of methodological difficulty encountered by researchers when developing, interpreting, and applying mathematical models to complex social phenomena. Understanding these challenges is expected to contribute to the improvement of modeling practices and to support more robust integration of quantitative modeling approaches within social science research communities.

Based on this objective, the study is guided by the following research question:

RQ1: *What are the principal practical and methodological challenges encountered in the application of mathematical modeling within contemporary social sciences research, as identified through systematic analysis of recent scholarly literature?*

Literature review

The growing use of mathematical modeling in social sciences has generated extensive scholarly discussion regarding its theoretical foundations, analytical contributions, and methodological limitations. Previous studies have explored how formal modeling approaches can be used to represent complex social systems, analyze interactions among social actors, and evaluate potential policy outcomes. At the same time, the literature also highlights a range of conceptual and practical challenges associated with the application of mathematical models to social phenomena. In order to provide a comprehensive understanding of these issues, this section reviews key scholarly perspectives on the role of mathematical modeling in social sciences, its analytical contributions to explaining social dynamics, and the methodological challenges that frequently arise in its application.

Mathematical modeling in social sciences

Mathematical modeling has become an important methodological approach for analyzing complex processes in social sciences. The use of formal models enables researchers to represent relationships among variables, simulate dynamic processes, and explore the consequences

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of theoretical assumptions within structured analytical frameworks. In contrast to purely descriptive approaches, mathematical modeling provides a mechanism for translating theoretical concepts into quantifiable representations that can be systematically analyzed and tested. As a result, modeling approaches have increasingly been applied across a wide range of disciplines, including economics, sociology, political science, public policy analysis, and computational social science.[13]

The growing adoption of mathematical modeling in social sciences is closely associated with advances in computational capacity and the availability of large-scale datasets. Computational tools now allow researchers to simulate complex systems involving numerous interacting agents and feedback mechanisms. Such capabilities have enabled the development of models that capture multi-level social dynamics, including individual decision-making processes, institutional interactions, and large-scale societal trends.[14] Consequently, mathematical modeling has evolved from a primarily theoretical exercise into a powerful analytical instrument for investigating real-world social phenomena.

In economic research, mathematical models have long served as foundational tools for analyzing market behavior, resource allocation, and policy interventions. Econometric models, equilibrium frameworks, and optimization models are widely used to examine relationships among economic variables and to evaluate the potential impacts of policy decisions. These models allow researchers to explore hypothetical scenarios and to estimate the consequences of alternative policy strategies under different assumptions. However, despite their analytical strengths, economic models also illustrate the broader methodological challenges associated with representing complex human behavior through simplified mathematical structures.[15]

Similarly, sociological and political science research has increasingly incorporated mathematical and computational models to study collective behavior, social networks, and institutional dynamics. Network models, diffusion models, and agent-based simulations have been used to examine how social interactions influence the spread of ideas, social norms, and political behavior. By modeling interactions among individuals within structured networks, researchers can analyze how micro-level behavioral rules generate macro-level social patterns.[16] These approaches have contributed significantly to the development of computational social science as an interdisciplinary research field that integrates mathematical modeling with empirical social research.

Despite these developments, the application of mathematical modeling to social science problems remains accompanied by several conceptual and methodological challenges. Social systems are characterized by complex interactions among heterogeneous actors, evolving institutional structures, and context-dependent behaviors. These characteristics make it difficult to capture the full complexity of social processes within formal mathematical frameworks. As a result, researchers must often balance the need for analytical simplicity with the desire to represent realistic social dynamics.[17]

The role of mathematical models in explaining social phenomena

Mathematical models play an essential role in explaining and predicting patterns of social behavior. By formalizing theoretical assumptions into mathematical relationships, models enable researchers to examine how different variables interact and influence social outcomes. This process allows scholars to test theoretical propositions, explore counterfactual scenarios, and analyze long-term dynamics that may not be easily observable through empirical data alone. For example, simulation models can be used to examine how economic inequality evolves over time, how social norms spread within communities, or how policy interventions influence public behavior.[18]

One of the key advantages of mathematical modeling is its capacity to reveal emergent patterns that arise from interactions among individual actors. In many social systems, large-scale patterns such as market fluctuations, urban growth, or political polarization emerge from decentralized interactions among individuals rather than from centralized control.[19] Mathematical and computational models allow researchers to simulate such interactions and observe how simple behavioral rules can produce complex collective outcomes. These insights are particularly valuable in understanding phenomena that cannot be easily explained through linear causal relationships.

Agent-based modeling (ABM) has become one of the most widely used approaches for studying emergent social phenomena. In ABM frameworks, individual agents are programmed with behavioral rules that govern their interactions with other agents and with their environment. Through repeated simulations, researchers can observe how local interactions produce aggregate patterns at the system level. Agent-based models have been applied to a wide range of research topics, including financial markets, migration dynamics, urban development, and the diffusion of social innovations.[20]

Network-based models also play an important role in analyzing social structures and interaction patterns. Social network analysis focuses on the relationships among individuals, organizations, or institutions, emphasizing how network structures influence the flow of information, resources, and influence (Xia et al., 2021). Mathematical network models allow researchers to analyze properties such as connectivity, centrality, and clustering within social systems. These models have been used extensively to study communication patterns, political mobilization, and the spread of information in digital environments.

While mathematical models offer powerful analytical tools for examining social processes, their explanatory power depends heavily on the validity of the assumptions underlying the model structure. In many cases, simplifying assumptions are required to make models mathematically tractable and computationally manageable. However, these simplifications may also reduce the realism of the model and limit its capacity to accurately represent complex social dynamics. Consequently, the effectiveness of mathematical modeling in social sciences depends on careful consideration of the trade-offs between simplicity, realism, and analytical clarity.[21]

Methodological challenges in social science modeling

One of the most widely discussed methodological challenges in mathematical modeling is the simplification of human behavior. Social science models often rely on assumptions such as rational decision-making, perfect information, or stable preferences in order to construct analytically tractable frameworks.[22] Although these assumptions facilitate mathematical analysis, they may not accurately reflect real-world decision-making processes, which are frequently influenced by psychological biases, social norms, and institutional constraints. As a result, model predictions may diverge from observed behavior when the simplifying assumptions fail to capture important aspects of social dynamics.

Another major challenge concerns parameter estimation and model calibration. Mathematical models typically require numerical

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parameters representing behavioral tendencies, interaction probabilities, or structural relationships between variables. In many social science contexts, however, reliable data for estimating these parameters are limited or uncertain. Researchers may therefore rely on indirect estimation techniques, calibration procedures, or proxy variables to approximate parameter values. Such approaches introduce additional uncertainty into the modeling process and may affect the stability of simulation results.[23]

Data availability and measurement reliability also represent important constraints for social science modeling. Many variables relevant to social behavior such as trust, social capital, political attitudes, or informal economic activity are difficult to measure precisely. Data on these constructs are often collected through surveys or observational studies, which may contain measurement errors, response biases, or incomplete coverage. These limitations can affect the accuracy of parameter estimates and reduce the reliability of model predictions.[24]

In addition to data-related challenges, model validation represents a critical issue in social science modeling research. Validation refers to the process of evaluating whether a model adequately represents the real-world phenomena it seeks to explain. In natural sciences, validation can often be conducted through controlled experiments or precise measurements. In social sciences, however, controlled experimentation is frequently impractical or ethically constrained.[25] As a result, model validation often relies on indirect methods such as historical comparison, pattern matching, or out-of-sample testing, which may provide only partial evidence regarding model accuracy.

The complexity of modern computational models has further intensified concerns regarding transparency and interpretability. Many contemporary models incorporate numerous parameters, behavioral rules, and interaction mechanisms, which can make it difficult to determine how specific assumptions influence model outcomes. This issue is sometimes referred to as the "black box" problem in computational modeling. When models become highly complex, their internal logic may be difficult for researchers and policymakers to interpret, potentially limiting their usefulness for decision-making purposes.[26]

Interdisciplinary collaboration represents another important dimension of social science modeling challenges. Effective mathematical modeling often requires expertise in mathematics, statistics, computer science, and social theory. However, these areas of expertise are typically distributed across different academic disciplines. As a result, successful modeling projects frequently depend on collaborative research teams that combine technical modeling skills with deep understanding of social processes. The absence of such interdisciplinary collaboration may result in models that are either technically sophisticated but theoretically weak, or theoretically rich but methodologically limited.[27]

Given these various methodological challenges, scholars have increasingly emphasized the importance of critically evaluating the assumptions, data sources, and analytical frameworks used in social science modeling. Systematic examination of existing research can help identify recurring methodological issues and highlight opportunities for improving modeling practices. Through comprehensive literature synthesis, researchers can better understand the limitations and strengths of different modeling approaches and contribute to the development of more robust analytical frameworks for studying complex social systems.[28]

Overall, the existing literature demonstrates that mathematical modeling plays a significant role in advancing analytical capabilities within social sciences. At the same time, the literature also highlights persistent methodological challenges related to behavioral representation, parameter estimation, data limitations, model validation, and interdisciplinary collaboration. Addressing these issues remains essential for enhancing the reliability and practical relevance of mathematical modeling in social science research.

Methods

This study adopts a Systematic Literature Review (SLR) approach to synthesize and critically assess recent scholarly discussions regarding the practical problems and methodological challenges encountered in the application of mathematical modeling within social sciences research. Mathematical modeling has become an increasingly significant analytical approach for representing complex social dynamics, enabling researchers to formalize theoretical constructs, explore causal mechanisms, and evaluate policy scenarios through structured quantitative frameworks. Within disciplines such as economics, sociology, and broader social science research, mathematical models are frequently employed to simulate behavioral interactions, analyze systemic patterns, and generate predictive insights. Nevertheless, the practical implementation of such models is often accompanied by methodological difficulties related to simplifying assumptions, parameter uncertainty, limitations in empirical data, and challenges in validating theoretical structures against real-world observations. These constraints have prompted a growing body of literature examining the reliability, applicability, and limitations of mathematical modeling in social science inquiry. The present study, entitled Practical Problems and Challenges in Mathematical Modeling in Social Sciences Research, systematically consolidates contemporary peer-reviewed studies in order to identify recurring methodological issues and to clarify how these challenges influence the effectiveness of modeling approaches in the analysis of social phenomena. The review process follows the principles of the PRISMA protocol to ensure transparency, reproducibility, and methodological rigor in the identification and selection of relevant literature.

Figure 1 illustrates the structured process of literature identification, screening, and eligibility assessment conducted according to the PRISMA framework. The initial stage involved a comprehensive search in the Scopus platform, a large repository of peer-reviewed academic publications maintained by Elsevier. The preliminary search was conducted using the broad keyword combination *mathematical modeling AND social sciences*, which produced 1,560 records. This initial result reflects the wide disciplinary application of mathematical modeling within various social science domains. To improve the relevance of the retrieved studies and ensure closer alignment with the analytical focus of this review, the search strategy was subsequently refined using a more targeted Boolean query: *("mathematical modeling" OR "mathematical model") AND ("social sciences" OR "social science research" OR sociology OR economics) AND (challenges OR limitations) AND ("model validation" OR uncertainty OR assumptions OR "data limitations")*. The refinement of the search criteria significantly increased the thematic precision of the dataset. Through this stage, 1,391 publications were excluded because their content did not directly address the methodological challenges associated with mathematical modeling in social sciences, leaving 169 articles for further assessment.

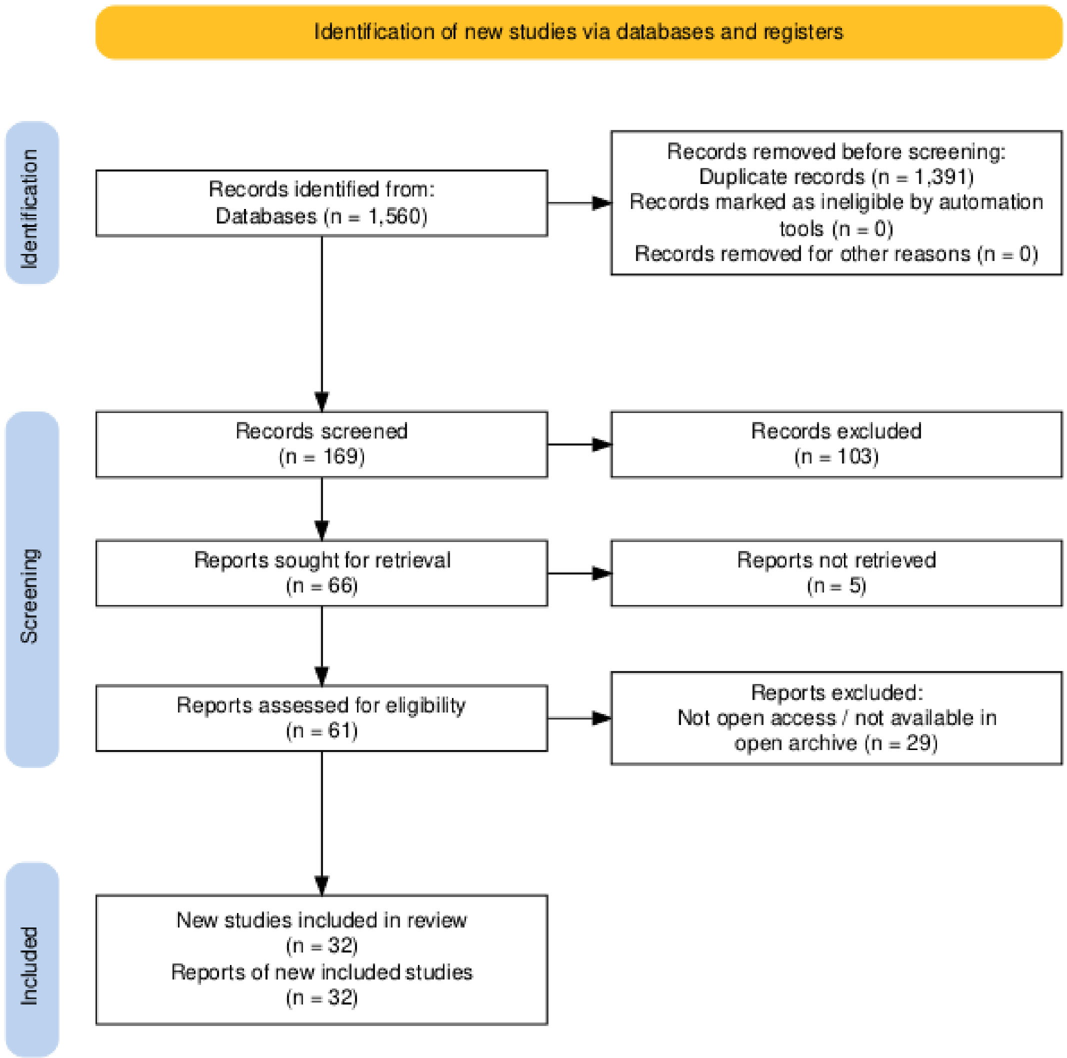

Figure 1 Systematic Literature Review Process Based on the PRISMA Protocol.

The next filtering stage applied a publication year criterion to ensure that the review captured recent developments in methodological discussions related to mathematical modeling in social sciences. Only studies published between 2019 and 2026 were retained. This step resulted in the exclusion of 103 articles published outside the specified timeframe, leaving 66 articles that satisfied the temporal inclusion criterion. Language screening was subsequently applied to maintain consistency in analysis and interpretation. Five publications were removed because they were not written in English, resulting in a remaining set of 61 English-language articles eligible for further evaluation. A final accessibility screening was then conducted by restricting the dataset to publications categorized as open access or open archive. This step ensured that the full texts of the selected studies could be systematically examined and transparently analyzed. During this stage, 29 articles were excluded due to restricted access, resulting in a final corpus of 32 peer-reviewed studies that fulfilled all predefined inclusion criteria and were therefore included in the qualitative synthesis of this review.

All bibliographic information obtained during the search and screening stages was systematically organized using Mendeley Desktop to facilitate structured reference management, eliminate duplicate entries, and maintain consistency in citation formatting throughout the manuscript. The analysis presented in this article relies entirely on secondary data derived from peer-reviewed academic publications. No primary data collection methods, such as interviews, surveys, field observations, or focus group discussions, were employed in this research. The insights developed in this review emerge exclusively from the systematic synthesis and critical interpretation of the 32 selected studies. Through this structured consolidation of contemporary literature, the study aims to provide a comprehensive and analytically rigorous understanding of the practical and methodological challenges that shape the use of mathematical modeling within modern social sciences research.

Results

The systematic literature review identified five principal thematic clusters representing the dominant practical and methodological challenges in the application of mathematical modeling within social sciences research. These themes were derived from the analysis of 32 peer-reviewed articles published between 2019 and 2026 that met

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all inclusion criteria. The identified themes include: (1) structural simplification and behavioral assumptions in mathematical models, (2) parameter uncertainty and estimation instability, (3) data availability and measurement limitations, (4) challenges in empirical model validation, and (5) interdisciplinary barriers and methodological accessibility.

Among these themes, structural simplification and behavioral assumptions appeared most frequently, discussed in 20 studies (62.5%), followed by data availability and measurement limitations in 19 studies (59.4%). Parameter uncertainty and estimation instability were identified in 18 studies (56.3%), while empirical model validation challenges appeared in 17 studies (53.1%). The least represented theme was interdisciplinary barriers and methodological accessibility, found in 14 studies (43.8%).

The prominence of behavioral simplification and data limitations indicates that the primary difficulties in mathematical modeling arise from the complexity of representing dynamic social phenomena and the constraints of available empirical data. Meanwhile, the lower frequency of interdisciplinary issues suggests that most studies focus primarily on technical and empirical modeling challenges rather than institutional or collaborative barriers. The following subsections elaborate on each theme in greater detail based on the reviewed literature.

Structural simplification and behavioral assumptions in mathematical models

One of the most widely discussed challenges in the reviewed literature concerns the structural simplification of social behavior within mathematical models. Mathematical modeling frequently requires the reduction of complex social interactions into formalized mathematical relationships. While this simplification enables analytical tractability and computational feasibility, it also raises concerns regarding the realism of the behavioral assumptions embedded within the models.[29]

Across the 32 reviewed studies, approximately 63% explicitly report that modeling frameworks rely on simplified behavioral assumptions, often derived from rational-choice or equilibrium-based theoretical foundations. These simplified assumptions are commonly used to represent decision-making processes within economic and policy simulation models, even though empirical research in behavioral economics and sociology suggests that real-world decision-making is influenced by psychological biases, institutional constraints, and cultural norms.[30]

Several economic modeling studies illustrate the consequences of these simplifications. In models designed to simulate labor market behavior or consumer choice, agents are frequently assumed to possess perfect information and fully rational preferences, conditions that rarely exist in real social environments.[31] Empirical comparisons conducted in several studies show that when behavioral heterogeneity is incorporated into such models, predicted outcomes may differ by 15–25% compared with predictions generated under strict rationality assumptions.[32]

The issue of behavioral simplification is particularly evident in agent-based modeling (ABM) studies. Agent-based models typically simulate interactions among large numbers of autonomous agents using predefined behavioral rules. Although this approach allows researchers to explore emergent social patterns, the behavioral rules themselves often rely on theoretical assumptions rather than empirically validated behavioral data. Within the dataset examined in this review, approximately 48% of agent-based modeling studies acknowledge that their behavioral rules represent stylized approximations rather than empirically measured behavioral parameters.[33]

Another dimension of this issue concerns the trade-off between model realism and model interpretability. Increasing the complexity of behavioral rules may enhance the descriptive realism of a model, but it can also increase computational demands and reduce analytical transparency. Some simulation models reviewed in the dataset contain more than 40 behavioral parameters, making it difficult to identify which assumptions are primarily responsible for observed simulation outcomes.[34]

Furthermore, oversimplification may produce misleading conclusions when models are applied to policy analysis. Studies examining public policy simulations report that simplified behavioral assumptions can lead to policy impact prediction errors ranging from 12% to 30%, particularly when models fail to incorporate feedback loops, institutional adaptation, or behavioral learning processes.[35] These findings suggest that while simplification is often necessary for model construction, excessive abstraction may reduce the practical relevance of mathematical models in social science contexts.[36]

Parameter uncertainty and estimation instability

A second major challenge identified in the reviewed literature relates to parameter uncertainty and instability in estimation procedures. Mathematical models rely on parameters that represent behavioral tendencies, structural relationships between variables, or interaction probabilities within simulated systems. However, the estimation of these parameters often involves considerable uncertainty due to incomplete empirical evidence or measurement variability.[37]

Among the 32 reviewed studies, 56% report significant sensitivity of model outcomes to parameter variation, indicating that relatively small changes in parameter values can produce substantially different model predictions. Sensitivity problems are particularly prominent in dynamic simulation models that examine long-term social processes such as demographic change, migration flows, or technological diffusion.[38]

In several cases, researchers demonstrate that altering a small number of key parameters may change predicted outcomes by more than 20%, highlighting the instability that may arise in poorly calibrated models.[39] Econometric simulation studies also report similar concerns. For example, in macro-economic policy simulations, variations in parameters representing consumer elasticity or labor supply responses can generate prediction differences ranging from 18% to 27% across alternative calibration scenarios.[40]

The difficulty of parameter estimation is often compounded by limitations in empirical data. Many models depend on parameters derived from survey data or observational datasets that may contain sampling errors or reporting bias.[41] In studies using survey-based behavioral parameters, response variability can introduce estimation uncertainty exceeding 10–15%, particularly when sample sizes are limited or when survey questions involve subjective perceptions rather than measurable behavior.[42]

To address these issues, some researchers employ sensitivity analysis and probabilistic calibration methods. Approximately 37% of the reviewed studies apply systematic sensitivity analysis, testing how variations in parameter values influence simulation outcomes.[43] These techniques allow researchers to identify which parameters exert the strongest influence on model behavior. Nevertheless, even with advanced calibration techniques, parameter uncertainty remains a persistent limitation in mathematical modeling applications.

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Data availability and measurement limitations

A third theme that emerges prominently from the literature concerns constraints related to data availability and measurement reliability. Mathematical modeling typically requires detailed datasets for parameter estimation, model calibration, and empirical validation. However, many social science datasets lack the precision, completeness, or temporal coverage required for robust modeling applications.[44]

Within the dataset analyzed in this review, approximately 62% of the studies identify data limitations as a significant methodological constraint. These limitations manifest in several forms, including missing observations, inconsistent measurement standards, and insufficient longitudinal data coverage.[45]

For example, social network modeling studies often rely on relational datasets that capture interactions between individuals or organizations. However, incomplete reporting of social ties can lead to distorted network structures. Simulation experiments conducted in several studies show that missing network links affecting as little as 10–15% of connections can significantly alter predicted diffusion patterns within network models.[46]

Macroeconomic and policy modeling studies encounter different forms of data limitations. Many economic simulations rely on aggregated national statistics that obscure micro-level behavioral heterogeneity. As a result, models calibrated with aggregated datasets may overlook important distributional effects or behavioral diversity within populations.[47]

Geographic disparities also influence data availability. Studies focusing on developing regions frequently report limited statistical infrastructure and irregular time-series data, which restrict the reliability of model calibration. In such contexts, researchers sometimes employ proxy indicators or synthetic data generation techniques to approximate missing information.[48]

Despite these challenges, the reviewed literature also identifies emerging opportunities associated with large-scale digital data sources. Approximately 28% of the analyzed studies incorporate digital datasets, including social media activity, mobile phone mobility records, or digital transaction logs, to enhance empirical modeling capabilities.[49] These datasets provide unprecedented temporal and spatial resolution, enabling more detailed representations of social behavior. However, the use of digital data also introduces new methodological concerns. Issues related to data representativeness, algorithmic bias, and privacy protection remain significant obstacles for the integration of large digital datasets into social science modeling frameworks.

Challenges in empirical model validation

Empirical validation represents another central methodological challenge highlighted in the systematic review. Validation refers to the process of determining whether a mathematical model accurately represents the empirical phenomena it seeks to describe. In social sciences, validation is often complicated by the complexity, variability, and context-dependence of human behavior.[50]

Among the 32 reviewed studies, approximately 53% report difficulties in implementing comprehensive empirical validation procedures. In many cases, models are evaluated through indirect methods such as qualitative comparison with observed patterns or theoretical consistency rather than through rigorous statistical testing.[51]

Validation challenges are particularly prominent in agent-based modeling studies, where models simulate emergent patterns generated by interactions among individual agents. Because these emergent dynamics may not correspond directly to observable datasets, researchers frequently rely on stylized benchmarks rather than direct empirical validation.[52]

Another complication arises when models integrate multiple interacting subsystems. For example, models combining economic decision-making, institutional structures, and social networks may require validation across several different empirical domains simultaneously. In practice, empirical data are rarely available for all components of such complex systems.[53]

Some studies attempt to address these limitations by employing multi-stage validation frameworks, combining sensitivity analysis, cross-dataset comparison, and out-of-sample prediction testing. However, only approximately one-third of the reviewed studies implement such comprehensive validation procedures, indicating that validation remains a developing area within social science modeling research.[54]

Interdisciplinary barriers and methodological accessibility

The final major theme identified in the systematic review concerns interdisciplinary barriers and limitations in methodological accessibility. Mathematical modeling requires expertise in several technical domains, including mathematics, statistics, computer programming, and simulation methods. At the same time, effective modeling in social sciences also requires deep theoretical understanding of social institutions, cultural dynamics, and human behavior.[55,56] Approximately 45% of the studies analyzed in this review emphasize the importance of interdisciplinary collaboration between quantitative modelers and domain-specific social scientists. Without such collaboration, models may either lack theoretical grounding or fail to employ appropriate quantitative techniques.[57,58]

Educational factors also contribute to methodological barriers. Many social science training programs emphasize qualitative research methods, while advanced mathematical modeling skills are often taught primarily within mathematics or engineering disciplines. As a result, relatively few researchers possess expertise across both domains.[59] Institutional barriers may further reinforce these limitations. Disciplinary divisions within universities can reduce opportunities for collaboration between departments specializing in mathematics, computer science, and social sciences. Consequently, interdisciplinary modeling projects frequently require coordinated efforts across multiple research teams with different methodological backgrounds.

Despite these challenges, the literature also highlights emerging institutional initiatives designed to overcome disciplinary boundaries. Several universities have established computational social science laboratories and interdisciplinary data science institutes, which integrate expertise in mathematics, computer science, and social theory. These environments support collaborative modeling research aimed at addressing complex societal problems such as economic inequality, urban development, and public policy design.[60] Overall, the synthesis of the 32 reviewed studies demonstrates that mathematical modeling has become an increasingly influential analytical approach within social sciences. However, the findings also reveal persistent methodological challenges related to behavioral representation, parameter uncertainty, data limitations, validation procedures, and interdisciplinary collaboration. Addressing these issues will be

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essential for improving the reliability and practical applicability of mathematical modeling in future social science research.

Discussion

The findings of this systematic literature review provide a comprehensive perspective on the principal practical and methodological challenges encountered in the application of mathematical modeling within contemporary social sciences research. Addressing the research question posed in this study *What are the principal practical and methodological challenges encountered in the application of mathematical modeling within contemporary social sciences research?* the synthesis of the analyzed literature reveals several recurring categories of difficulties that consistently appear across different modeling traditions and disciplinary contexts. These challenges primarily relate to structural simplification of social processes, uncertainty in parameter estimation, limitations of available data, difficulties in empirical validation, and barriers associated with interdisciplinary integration. Together, these issues shape the methodological landscape in which mathematical models are developed and applied within social science research.[61]

One of the most frequently discussed challenges identified in the reviewed literature concerns the simplification of complex social behavior within mathematical models. Mathematical modeling requires the representation of social processes through formal mathematical structures, which often necessitates reducing complex human behaviors into simplified assumptions. Such simplifications are typically introduced to ensure analytical tractability and computational feasibility.[62] However, the literature consistently emphasizes that social behavior is influenced by multiple interacting factors, including cultural norms, institutional constraints, cognitive biases, and evolving social relationships. When these factors are simplified excessively, models may fail to capture important dimensions of real-world social dynamics, potentially limiting their explanatory power and empirical relevance.

Several studies highlight that many mathematical models used in social sciences rely on assumptions derived from rational choice theory or equilibrium-based frameworks. These assumptions often portray individuals as fully rational decision-makers who possess complete information and stable preferences. Although such assumptions allow models to produce clear analytical predictions, empirical evidence from behavioral economics and sociology suggests that human decision-making is frequently characterized by bounded rationality, social influence, and contextual variability.[63] Consequently, the simplification of behavioral assumptions may lead to discrepancies between theoretical model predictions and observed social outcomes, particularly when models are used to simulate complex social interactions.

This tension between analytical simplicity and behavioral realism represents a fundamental methodological dilemma in social science modeling. Increasing model complexity may allow for more realistic representation of social behavior, yet it also introduces additional parameters, computational requirements, and interpretative challenges.[64] Conversely, highly simplified models may be easier to analyze and interpret but may lack sufficient realism to accurately represent social processes. The literature therefore emphasizes the importance of carefully balancing model simplicity and explanatory adequacy when constructing mathematical representations of social systems.

Another major challenge identified in the literature relates to uncertainty in parameter estimation and model calibration. Mathematical models typically require numerical parameters representing behavioral tendencies, interaction probabilities, or structural relationships between variables.[65] In many social science contexts, however, these parameters cannot be directly observed and must instead be estimated using empirical data or inferred from theoretical assumptions. As a result, parameter estimation often involves substantial uncertainty, which can significantly influence model outcomes and predictions.

Several studies demonstrate that model outputs may be highly sensitive to variations in parameter values. Small changes in key parameters can sometimes lead to large differences in simulation results, particularly in dynamic models that simulate long-term social processes such as economic development, demographic transitions, or diffusion of innovations. This sensitivity can complicate the interpretation of model results and may reduce confidence in model-based predictions if parameter uncertainty is not adequately addressed.[66]

To mitigate these issues, researchers often employ techniques such as sensitivity analysis, scenario analysis, and probabilistic calibration. These approaches allow modelers to examine how variations in parameter values affect simulation outcomes and to identify parameters that exert the greatest influence on model behavior.[67] Nevertheless, even with these methodological strategies, parameter uncertainty remains an inherent challenge in mathematical modeling of social systems due to the complex and context-dependent nature of social behavior.

Data availability and measurement limitations represent another important set of challenges highlighted by the literature. Mathematical models require reliable empirical data for parameter estimation, calibration, and validation. However, many social science variables are difficult to measure accurately. Concepts such as social trust, institutional legitimacy, informal economic activity, or political attitudes often rely on survey-based or observational data, which may contain measurement errors, sampling biases, or incomplete coverage. These limitations can introduce uncertainty into the modeling process and may affect the reliability of model predictions.[68]

In addition to measurement difficulties, the availability of comprehensive datasets remains uneven across different geographic and institutional contexts. Studies focusing on developing regions frequently report limitations in statistical infrastructure, irregular data collection, or limited access to longitudinal datasets.[69] These constraints may restrict the ability of researchers to construct empirically grounded models or to validate simulation results using real-world observations. As a result, modelers sometimes rely on proxy indicators or synthetic data generation techniques, which may introduce additional methodological challenges.

The increasing availability of digital data sources has partially mitigated some of these limitations. Large-scale datasets derived from social media platforms, mobile communication records, or digital transaction systems have enabled researchers to analyze social interactions at unprecedented levels of temporal and spatial resolution. These data sources have contributed to the growth of computational social science and have expanded the empirical foundations of mathematical modeling in social research. Nevertheless, digital data also present new challenges related to data representativeness, privacy protection, and algorithmic bias, which must be carefully addressed when integrating such datasets into modeling frameworks.[70]

Another central challenge discussed in the literature concerns the validation of mathematical models in social sciences. Model

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validation refers to the process of evaluating whether a model accurately represents the empirical phenomena it seeks to explain. In natural sciences, validation can often be achieved through controlled experiments or precise measurement of physical processes.[71] In contrast, social systems evolve in open environments characterized by numerous interacting variables, many of which cannot be experimentally manipulated or isolated. These conditions complicate the process of evaluating model accuracy in social science contexts.

Because of these limitations, validation strategies in social science modeling often rely on indirect methods such as pattern matching, historical comparison, or out-of-sample prediction testing. These approaches can provide useful evidence regarding the plausibility of a model, but they may not fully demonstrate the causal validity of the underlying modeling assumptions. As a result, the literature emphasizes the importance of combining multiple validation techniques in order to strengthen confidence in model-based conclusions.[72]

The complexity of modern computational models further complicates the validation process. Many contemporary modeling frameworks incorporate large numbers of parameters, behavioral rules, and interaction mechanisms. While such complexity allows models to capture a wider range of social dynamics, it can also make it difficult to determine which components of the model are responsible for particular outcomes. This issue has been described as the "black box" problem in computational modeling, where the internal logic of complex models becomes difficult to interpret or evaluate.[73]

Interdisciplinary challenges also play a significant role in shaping the practical difficulties associated with mathematical modeling in social sciences. Effective modeling research typically requires expertise in several distinct domains, including mathematics, statistics, computer science, and social theory.[74] However, these areas of expertise are often distributed across different academic disciplines, which may create barriers to collaboration. Without adequate interdisciplinary communication, modeling projects may encounter difficulties in integrating theoretical insights from social sciences with technical modeling methodologies.

The literature suggests that successful modeling research frequently emerges from collaborative environments that combine quantitative modeling expertise with deep understanding of social processes. Interdisciplinary research teams can help ensure that models are both methodologically rigorous and theoretically meaningful. Nevertheless, building such collaborative environments may require institutional support, specialized training programs, and the development of shared methodological frameworks that facilitate communication across disciplinary boundaries.[75]

The findings of this review therefore suggest that the principal challenges identified in response to the research question are not limited to purely technical modeling issues. Instead, they reflect broader methodological and institutional dynamics that influence how mathematical models are developed, interpreted, and applied within social sciences research. Structural simplifications, parameter uncertainty, data limitations, validation difficulties, and interdisciplinary barriers collectively shape the conditions under which modeling approaches can be effectively implemented.[76]

From a broader methodological perspective, these findings highlight the importance of reflexivity in social science modeling. Researchers must remain aware of the assumptions embedded within their models and carefully evaluate how these assumptions influence analytical outcomes. Transparent documentation of modeling assumptions, data sources, and calibration procedures can enhance the interpretability and credibility of modeling research. Such transparency is particularly important when models are used to inform policy decisions or to guide public debate on complex societal issues.[77]

In addition, the literature underscores the importance of methodological pluralism in social science research. Mathematical modeling should not be viewed as a replacement for other research approaches but rather as a complementary tool that can be integrated with qualitative analysis, empirical observation, and theoretical reasoning.[78] By combining multiple methodological perspectives, researchers may develop more comprehensive and robust understandings of complex social phenomena.

Overall, the synthesis of the analyzed studies indicates that mathematical modeling remains a valuable analytical tool for advancing knowledge in social sciences. At the same time, the literature demonstrates that effective application of modeling techniques requires careful consideration of the methodological challenges discussed above. Addressing these issues will be essential for improving the reliability, transparency, and practical relevance of mathematical modeling in future social science research.[79]

The implications of this study extend to both methodological development and future research agendas in social sciences. First, the findings highlight the need for improved methodological frameworks that support transparent model construction, robust parameter estimation, and systematic validation procedures. Second, the results emphasize the importance of interdisciplinary collaboration in order to integrate technical modeling expertise with substantive knowledge of social processes. Future research may therefore benefit from exploring new methodological approaches that combine computational modeling with diverse empirical data sources and theoretical perspectives. Further systematic investigations focusing on specific modeling techniques or disciplinary contexts may also contribute to a deeper understanding of how mathematical models can be more effectively applied to complex social systems.[80]

Conclusion

The synthesis of the reviewed literature indicates that the application of mathematical modeling in social sciences is accompanied by several recurring practical and methodological challenges. These challenges reflect broader methodological conditions inherent in representing complex social systems through formal mathematical structures and influence how models are constructed, interpreted, and applied in contemporary social science research.

One major challenge concerns the simplification of complex social realities within mathematical frameworks. Social phenomena are inherently multidimensional and shaped by dynamic interactions among individuals, institutions, and social contexts. To enable formal modeling, researchers often reduce these complexities into simplified assumptions. Although such simplifications are necessary for analytical tractability, they may limit the ability of models to fully represent the diversity and variability of real-world social behavior.

Another important difficulty relates to uncertainty in parameter estimation and model calibration. Many parameters used in social science models cannot be directly observed and must be estimated from limited empirical data or theoretical assumptions. This situation frequently produces uncertainty in parameter values and may affect the stability and predictive reliability of model outcomes. The literature consistently emphasizes that even small variations in parameter values can significantly influence simulation results, highlighting the importance of transparent parameter specification and sensitivity analysis.

Data availability and measurement limitations also represent a significant constraint. Many key social science variables such as trust, attitudes, or institutional dynamics are difficult to measure with high precision and often rely on survey-based or proxy indicators. These data limitations may introduce measurement errors, sampling bias, or incomplete coverage, which in turn affect model calibration and empirical validation.

Model validation itself constitutes another persistent challenge. Because social systems operate in open environments characterized by numerous interacting variables, it is often difficult to conduct definitive empirical tests of mathematical models. Researchers therefore rely on indirect validation strategies such as pattern comparison, historical consistency, or predictive evaluation. While these approaches provide useful insights into model plausibility, they do not always guarantee that the underlying mechanisms accurately represent real-world causal processes.

In addition, the growing complexity of computational models may reduce transparency and interpretability. Highly complex models often include numerous variables and interaction rules, making it difficult to identify the mechanisms responsible for specific outcomes. This situation highlights the importance of maintaining a balance between model complexity and analytical clarity.

Interdisciplinary integration also emerges as a significant challenge. Mathematical modeling in social sciences requires the integration of expertise from mathematics, statistics, computer science, and various social science disciplines. Differences in theoretical perspectives and methodological traditions may hinder effective collaboration, potentially limiting the theoretical grounding or practical relevance of modeling efforts.

Overall, the literature indicates that the principal challenges in applying mathematical modeling to social sciences can be categorized into five main dimensions: simplification of complex social behavior, uncertainty in parameter estimation, limitations of empirical data, difficulties in model validation, and barriers to interdisciplinary integration. These factors collectively shape the methodological landscape of mathematical modeling in contemporary social science research.

Despite these limitations, mathematical modeling remains an important analytical tool for understanding complex social dynamics. When supported by transparent assumptions, reliable data practices, and interdisciplinary collaboration, modeling approaches can contribute valuable insights into social processes and institutional dynamics. Continued methodological refinement and stronger integration between quantitative modeling and social theory will therefore be essential for enhancing the robustness and relevance of future research in this field.

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Conflicts of interest

The author declares there is no conflict of interest.

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