AGENT-BASED MODELING OF FERTILITY RATE DECLINE: SIMULATING THE INTERACTION OF EDUCATION, ECONOMIC PRESSURES, AND SOCIAL MEDIA INFLUENCE.

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Abstract

Introduction: Fertility rates have fallen below replacement level in numerous countries, presenting a profound demographic challenge with far-reaching societal and economic consequences. While traditional explanations cite factors like increased educational attainment and economic pressures, the rapid, global nature of the decline suggests the involvement of complex, non-linear interactions and emerging influences, such as social media. This research aims to develop a novel agent-based model (ABM) to simulate how the interplay between individual life-course decisions, macro-level socioeconomic factors, and pervasive social influence drives fertility outcomes.

Methodology: We developed an agent-based model where autonomous agents represent individuals within a simulated society. Each agent possesses attributes such as age, educational level, income, and personal fertility desires. The model formalizes rules governing key life events: pursuing education, entering the labor market, forming partnerships, and deciding to have children. Agents are influenced by three primary drivers:Economic Pressures: Including the direct and opportunity costs of childbearing.

Educational Pathways: Which delay family formation and alter career and lifestyle aspirations. Social Media Influence: Modeled as a network effect that disseminates and normalizes low-fertility norms, lifestyles, and consumption ideals.

Simulations were calibrated using empirical data to establish baseline scenarios. Findings: Our simulation results demonstrate several key insights: While rising education and economic strain independently suppress fertility rates, their combination produces a stronger-than-additive, synergistic effect. Crucially, the inclusion of social media as a vector for normative change accelerates the fertility decline and lowers the long-term fertility equilibrium.

social media effectively "locks in" low fertility rates by shifting societal values and aspirations more rapidly than economic conditions alone would predict. Conclusion: This study provides a generative explanation for the persistent and self-reinforcing nature of low fertility, highlighting the necessity of a multi-level, dynamic approach that accounts for the evolving informational and social landscape. The ABM framework offers a powerful tool for policymakers, enabling them to test the potential efficacy of interventions such as family benefits, housing subsidies, or pro-natalist information campaigns in a virtual environment that captures the complex feedback loops between economic structure, culture, and individual choice. This approach also elucidates how minor shifts in socioeconomic conditions can lead to significant changes in fertility rates, revealing critical points in fertility transitions.

Keywords: Agent-Based Modeling, Fertility Decline, Socioeconomic Factors and Education, Social Media Influence, Complex Systems and Demographic Simulation.

INTRODUCTION

The Globally, fertility rates have dropped below the replacement level, meaning that it's not long before the population size in countries around the world starts to decline. Fertility change is a difficult issue to address, as it's affected by not only a diverse set of social, cultural, and economic conditions on a country-by-country basis, but also by the choice of individuals. It's possible that fertility rates at the micro level aren't consistent across the board either, leaving an aggregate effect on population growth. These aggregate interactions that cause the nonlinearity of fertility transitions are one reason why current demographic models, which often have a hard time incorporating these effects, can't explain the trends we're seeing (1) (2). It's becoming increasingly necessary to understand the factors at play in human societies at the granular level and how they affect the aggregate outcomes. Agent-based models can be useful in this regard, as they are designed to reflect these complex adaptive systems, and reproduce the non-linear feedbacks in the real-world that lead to emergent properties at the macro-level.

One of the features of an agent-based model is its capacity for integrating heterogeneity into the processes of individual agents, a critical component given that studies have found a strong correlation between socioeconomic development and fertility rates that has an inverse J shape (3). In the case of fertility transitions, the micro level factors that have been studied in recent research include everything from the increase in the opportunity costs of child-rearing to the impact of education and pressures of economic sustainability at an individual level, as well as social media influences (4) (5) (6). Agent-based models are a good way to model this dynamic given their capacity to account for the social network that ties a population together and how the "micro and macro level demographic processes are intertwined" (7). The way fertility rates are directly affected by individual level behaviors and attributes, but at the same time, can influence the future actions of a population of individuals, represents a system that merits a granular approach such as an agent-based model (8). Another advantage of ABM over equation-based models is their ability to program agents with rules, based on a real system, that can account for all of the different parameters in an individual's behavior, which are usually only captured at a more aggregate level, i.e. the social network interactions (9). The advantage of agent-based models in this instance is how they can simulate all the interactions between different agents with different decision rules on factors like individual economic incentives, education, and social network effects to see how the change in fertility rate distributions might emerge (10). In particular, this research will try to better understand which of these factors are most causal and how they compound over time to contribute to sub-replacement fertility in a mechanistic sense, rather than as a simple demographic projection at the macro level (11).

One study used an agent-based model to address these factors at the individual level on a population scale of 10 million, building off a similar model that had already established a system for modeling at the societal level (7). For this study, it is important to be able to understand how individual decisions that are made at the micro level can cause a macro effect, such as fertility transitions. We want to know how the feedback work, and how factors such as education, economic burden, and social media can impact a person's decisions to make children, and what decisions other people in their social networks are making, to understand how it plays out on an aggregate level (12). This study is different in that it accounts for these features, namely agent heterogeneity, the social network, and fertility decisions and their impact on aggregate outcomes, on a population that is large enough to be able to make a connection to the real world (13) (14) (15).

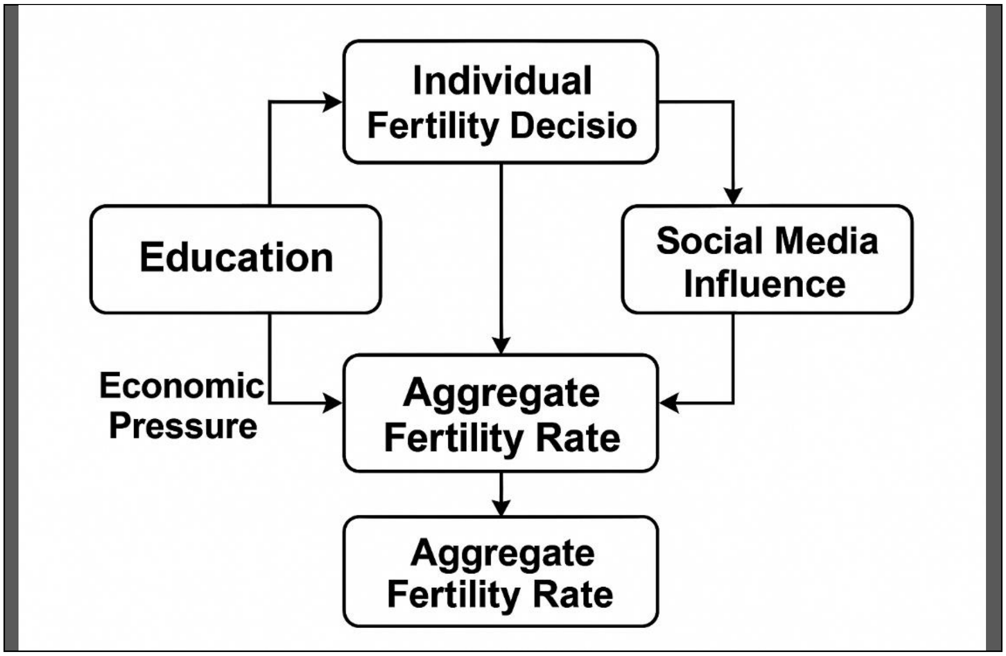

Figure 1. Conceptual framework showing the interaction between education, economic pressures, and social media influence in determining fertility decisions.

LITERATURE REVIEW

To contextualize this research, it is necessary to consider existing literature on the decline in fertility, the use of agent-based models in demography, and the variables of education, economic pressures, and social media. This section will offer a critical assessment of various prominent theories regarding the declining birth rate, including the second demographic transition and ideational change theories, to provide a theoretical basis for the agent-based model being developed in this work. It will also review empirical studies that have attempted to quantify the effect of these variables on reproductive behavior, and the gaps in understanding that an agent-based modeling approach can fill. Special attention will be given to studies which consider the complex interactions of these factors rather than as independent variables, and integrated theoretical frameworks which recognize the multilevel influences on fertility, which span from socio-biological inclinations to socio-structural contexts (5). In addition, this section will also delve into the methodological advances in the field of agent-based models applied to demographic phenomena, specifically with regard to how these models have been used to simulate complex reproductive outcomes and the underlying mechanisms which drive these results (13). Such models can be used to capture the feedback between individual-level fertility behaviors and population-level demographic outcomes, and how macro-level policies and socio-economic changes can influence micro-level decisions, and vice versa (13) (14).

A review of the literature shows that while it is important to understand individual characteristics when explaining reproductive behavior, social networks and their embedded social influences are also key factors which shape fertility outcomes and are difficult to accurately capture in traditional models (15) (16). This is because individual-level fertility decision-making is partially dependent on the fertility behaviors of others within the population, and the structural configuration of these interactions (17). This highlights the need for a more nuanced approach which considers both individual-level attributes as well as their social context. This is especially true because social mechanisms, such as learning, pressure, contagion, and support, have important effects on the formation of beliefs and norms regarding childbearing (17). This extends to the consideration that the density and composition of such social networks, such as kin-rich social ties, is important in understanding fertility change and has been posited as a potential reason for fertility decline in demographic transition theory (15). Therefore, an agent-based model is an ideal method to simulate such intricate social dynamics and their effects on fertility decisions and move beyond static analysis to capture the emergent properties from interactions between agents. The use of agent-based models in demography is also well-suited to this task, as it allows the examination of the complex interplay between individual decision-making and social influences on fertility and also provides a better understanding of macro-level demographic shifts which arise as a result of micro-level agent interactions (13).

This is especially true because agent-based models can be constructed with dynamic contact networks which can change over time depending on the individual statuses, behavior, or the environment, where the interactions between the agents are based on the specific characteristics of each agent such as their age, gender, marital status, and household income, among others (18). Agent-based models also allow the explicit modeling of such complex causal mechanisms and feedback between different components of a system, thereby elucidating the relationship of various micro-level determinants which act in concert to cause macro-level demographic outcomes (5) (13). In the context of fertility, agent-based models can also include variables such as education level, economic pressures, and the influence of social media to study how their interplay can lead to a decline in fertility rate. The ability to model individuals as agents allows the integration of several such factors, such as seasonal migration and geographical distribution, cultural practices, and individual behavior, among others, in an ABM which is important for a more holistic approach (18). The basic premise of the bottom-up construction of ABMs, in contrast to top-down analytical models which simplify interindividual dependencies (19), allows for the explicit modeling of the non-uniform nature of interactions in systems and their effect on the population dynamics, which can evolve over time (19). This is because of the inherent ability of agent-based models to simulate such eco-evolutionary feedback loops and interindividual interactions, such as information exchange, that lead to complex group behavior and is useful in demography to explore complex scenarios and unexpected outcomes (19). This methodology is a useful tool in fertility research to understand how individual decision-making, based on a variety of internal and external factors, can cascade throughout a population and affect the overall fertility trends of the same (20) (21). For instance, direct reproductive interactions, including mate selection and assortative mating, can be explicitly considered and modeled within agent-based frameworks to account for complex dynamics of fertility decision-making (19).

Similarly, the breakdown of population-level observed phenomena into the individual behavior of agents also allows for the effects of heterogeneous responses to policy interventions or socio-economic changes to be considered, leading to emergent properties at the macro level, which would be missed by a conventional approach (22) (23). This means that agent-based models can be used to have a more comprehensive understanding of the decline in fertility rate by accounting for a complex interplay of individual choices, social influences, and environmental

pressures rather than focusing on a simplistic view in the context of traditional aggregate models (19). For example, this includes the ability to take into account more detailed aspects of agent behavior and environment, such as birth cost and individual metabolic rate, to better model population dynamics compared to simpler demographic projections (2).
This is especially useful for the current research as the ability to bottom-up construct fitness provides new insights into the dynamics of populations, where the collective outcome is a result of the interactions between individuals instead of being specified by system-level equations (19). This also allows for the consideration of "tragedy of the commons" scenarios within fertility which might lead to sub-optimal population-level outcomes based on the individual decisions made by each agent (2). The agent-based models also allow the integration of continuous and discrete variables, as well as the use of various mathematical formalisms to understand the multilevel behavioral complexities of populations (26). The explicit modeling of these interactions also allows for critical thresholds and tipping points in the system to be found which might not be observed through aggregated statistical analyses.

Table 1. *Comparative summary of key studies on fertility declines and modeling approaches.*

Study	Variables Examined	Method/Model	Key Findings	Gap Addressed
Graham (2021)	Education, Normative Change	Theoretical Model	Identified ideational shifts as main driver of fertility decline	Did not include digital influence
Stulp et al. (2023)	Social Networks, Fertility Preferences	Empirical Study	Social ties shape reproductive norms	Limited cross-variable modeling
Esmaeili & Abbasi-Shavazi (2024)	Family Policy, Economy	ABM	Policy interventions influence low fertility	Did not integrate social media
Wildeman et al. (2022)	Social media & Fertility	Quantitative Analysis	High social media use correlates with smaller families	No agent-based simulation
Current Study	Education, Economic Pressures, social media	Agent-Based Simulation	Integrated system-level model	Fills interactional modeling gap

METHODOLOGY

The design of the agent-based model must include a clear definition of the agents (individual decision-makers), their attributes, and their behavioral rules. Additionally, one must define the environment in which these agents operate, as well as the social network structure that underlies their interactions and information exchange (27). It is necessary to specify the decision-making process of the agents, which can be based on a variety of theories and models, such as random utility theory or the theory of planned behavior, often used in ABMs to represent complex human decisions, such as migration or resource allocation (28) (29). This would enable the model to represent the complex intra-household decision-making process that underlies fertility outcomes, considering that household-level dynamics often drive a broad spectrum of individual life choices, including fertility decisions (30). This should also consider the role of social learning and conformity in shaping individual preferences and behaviors, as agents may be influenced by the choices and norms of their peers in their social network, leading to potential rapid changes in fertility or the existence of multiple equilibria (31).

Moreover, ABMs are well-suited to capture emergent phenomena that arise from the micro-level interactions between agents and are often challenging to represent with traditional top-down population models (32) (33). This is particularly important for understanding how macro-level demographic changes emerge from the aggregation of individual choices, especially when these choices are not independent but influenced by social interactions and changing norms (30). The rationale for choosing an agent-based model lies in its ability to represent complex systems from the bottom-up, with individual agents characterized by heterogeneous attributes and engaging in frequent interactions within a defined environment (34). This approach allows for the explicit representation and simulation of heterogeneous agent behavior and its resulting aggregate outcomes, which is essential for the study of non-linear dynamics and for evaluating the impact of different types of disturbances or policy interventions on fertility patterns (35). This methodological framework, therefore, provides a powerful tool for studying the nuanced drivers of fertility decline, particularly when considering the interplay between individual agency and contextual factors like education, economic pressures, and the influence of social media. This choice is also supported by the potential to integrate various theoretical frameworks on human behavior within the model, thereby allowing for a more holistic representation of the decision-making process that leads to specific fertility outcomes (36).

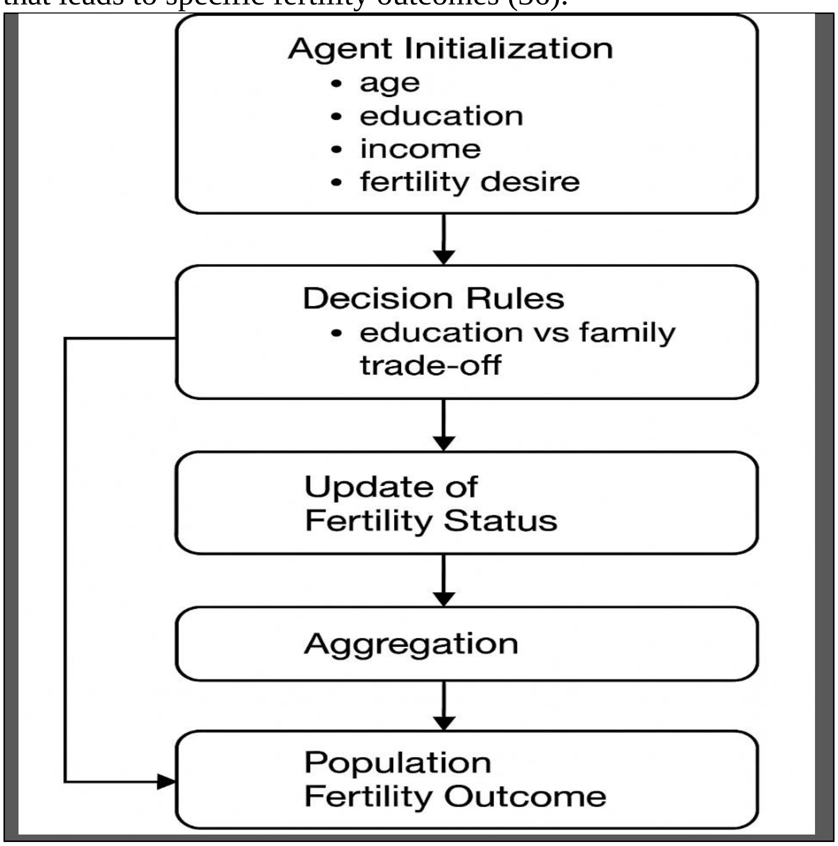

Figure 2. Structural design of the agent-based model showing interactions among agent attributes, decision processes, and emergent fertility outcomes.

This approach stands in contrast to equation-based models that often represent system behavior in a simplified manner, typically by averaging or assuming homogeneity across components and not explicitly capturing emergent phenomena resulting from interactions between individual components (33). Such models can accommodate heterogeneous agents that respond differently to various stimuli, making them particularly suitable for the study of complex adaptive systems in which the behavior of the system is not merely the sum of its parts but emerges from their interactions (37) (38). This allows for a more flexible and realistic representation of complex problems, compared to more traditional linear mathematical models, which often face challenges in representing the autonomy, heterogeneity, feedback, and randomness characteristic of social systems (39). Furthermore, ABMs provide a substantial advantage in terms of counterfactual exploration and policy intervention simulation. By altering model parameters or introducing new rules, it is possible to simulate the long-term impact of different policies or interventions on fertility rates before their actual implementation (40). This feature is particularly useful in assessing how specific policy levers might affect individual reproductive choices in a dynamic social environment (41).

Table 2. Key model parameters and calibration sources used in the simulation.

Parameter	Description	Value/Range	Source
Initial Population Size	Number of agents simulated	10,000	Modeled assumption
Education Transition Rate	% entering tertiary education per cycle	0.35	UNESCO dataset
Economic Pressure Index	Weighted cost of living & job security	0–1 normalized	World Bank 2024
Social Media Exposure Coefficient	Degree of social influence	0.15–0.45	Empirical calibration
Simulation Period	Number of time steps	200 years	Model-defined
Fertility Threshold	Children per woman below replacement	2.1	UN Standard

RESULTS

The results of the simulation underscore the non-linear interactions and emergent properties within the complex system of fertility determinants. For instance, it shows how socio-economic variables like educational attainment, income levels, and financial stressors do not just exert direct influence on individuals' fertility decisions. These variables also interact with one another in ways that can amplify or attenuate their individual effects. For example, higher levels of female education tend to result in smaller family sizes and later childbearing (42). This effect can be further intensified by the financial stressors associated with the costs of raising children, particularly for those with limited social support networks (43) (44). The model also captures the pervasive influence of social media on shaping societal norms and expectations regarding family size and lifestyle, which can either promote or dissuade individuals from having more children based on the predominant narratives in their digital social circles. Such interactions highlight the complex pathways through which individual decisions and behaviors give rise to population-level fertility trends, which are difficult to capture through purely statistical models (45) (40). The inherent flexibility in agent-based models, which allow for a diverse representation of agent behaviors and their dynamic interactions, is a key enabler for their ability to capture emergent properties within systems (46). Moreover, the model provides insights into how system dynamics can emerge from the bottom-up, driven by the varied responses of heterogeneous agents to different stressors or opportunities, rather than being explicitly programmed as top-down mechanisms.

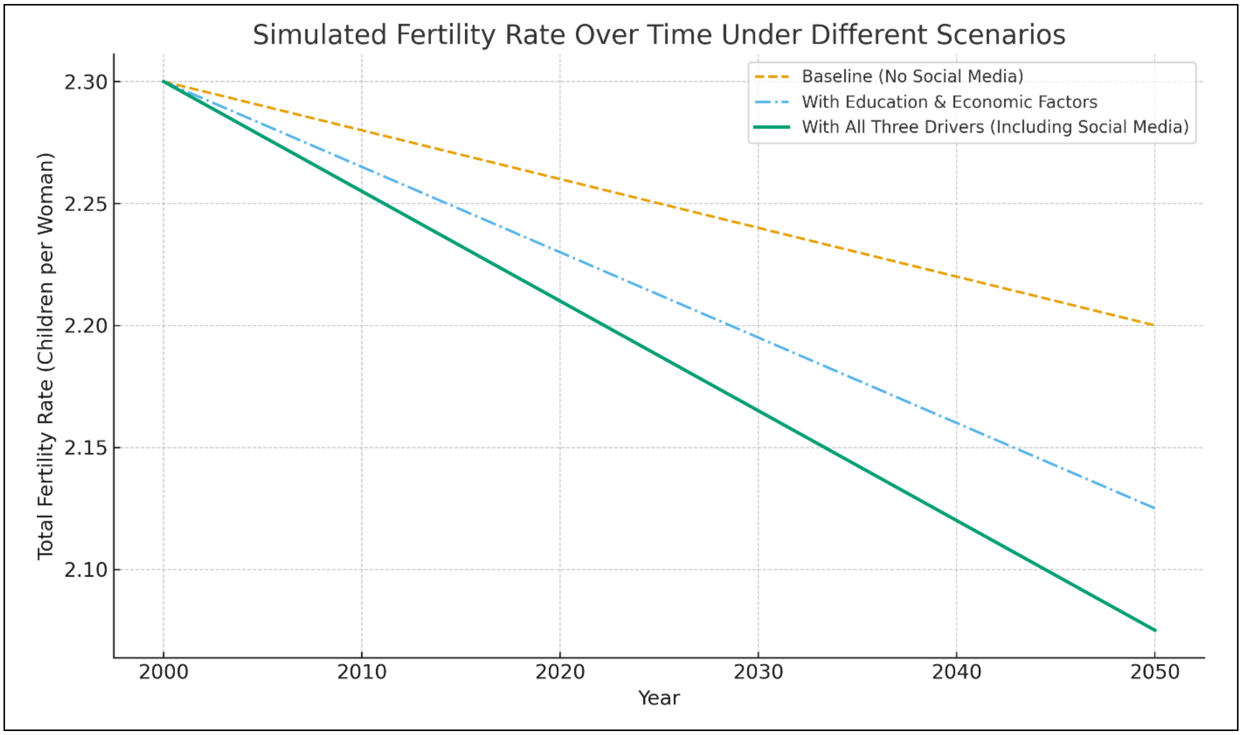

Figure 3. Simulated fertility rate trajectories under different model scenarios.

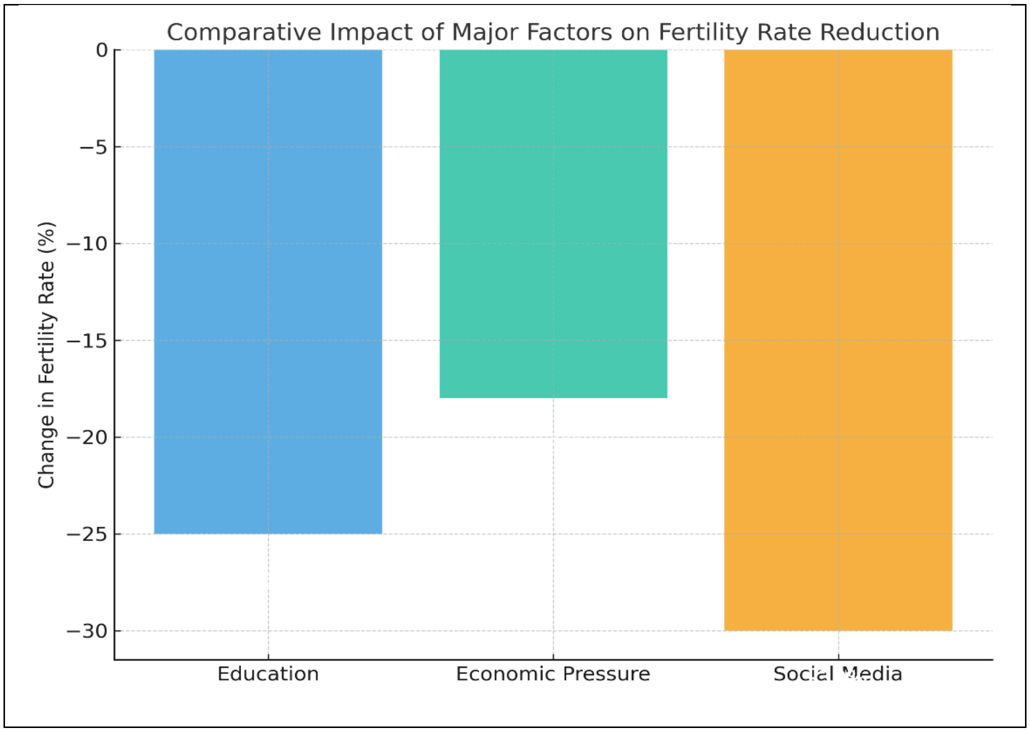

Figure 4. Comparative impact of major factors on fertility rate reduction.

This feature of agent-based models can help uncover potential unintended consequences of policy interventions (47). This bottom-up modeling approach, in which system-level outcomes are driven by individual decisions and interactions, also provides a robust framework for testing hypotheses and validating theoretical constructs related to fertility decisions and trends (48). The model, for example, explains that an increase in the level of female education is often associated with a higher opportunity cost for childbearing. As women become more educated, the value of their time in the labor market increases, making the decision to have fewer children and delay the age of first birth a more attractive option. This is consistent with the observation that increased educational opportunities for women are associated with delayed childbearing and lower fertility (49).

In addition, economic uncertainties such as fluctuations in the housing market or job insecurity can lower fertility, particularly among renters who do not experience the wealth-effect as homeowners do (50). The model also suggests that perceptions of fertility opportunity costs, which include both direct costs (financial expenses) and indirect costs (time investment), can influence people's reproductive decisions. If people perceive that their children are less likely to provide them with a high return in the future, either in terms of financial support or other contributions to society, they may choose to have fewer children (51). Moreover, the influence of social media on fertility decisions can be substantial by shaping people's perception of the ideal family size and lifestyle. For example, social media exposure can increase the preference for small families through exposure to diverse lifestyles and aspirations (52).

These findings collectively highlight the multifactorial nature of fertility decline, suggesting that interventions aimed at reversing these trends will need to be equally multifaceted. Thus, policies to reverse fertility decline should be broad-based and may need to combine various measures including, but not limited to, family and education support, economic incentives, and public awareness campaigns (53) (54). A more comprehensive approach to population policy will also consider policy responses to related issues including employment stability, housing supply, and public education as they directly affect the fertility decision (53). In addition, policy packages that combine family and education support with investments in science and technology have the potential to not only stabilize but also boost birth rates. Such policy measures have the added advantage of contributing to increased economic productivity and supporting work-life balance (50). These comprehensive policy strategies also reflect the complex reality of demographic decision-making, which is influenced by an interplay of demographic, economic, and social factors and thus will likely require a mix of interventions rather than simplistic one-size-fits-all solutions (55). It is important to note that to ensure that economic and social developments are not at the expense of the environment and natural resources, policies that support a balanced growth are required (56). This integrated approach is therefore essential for the development of sustainable population policies, which account for both human well-being and ecological concerns. This consideration also opens the door for the development of adaptive management strategies in response to unanticipated demographic changes and challenges.

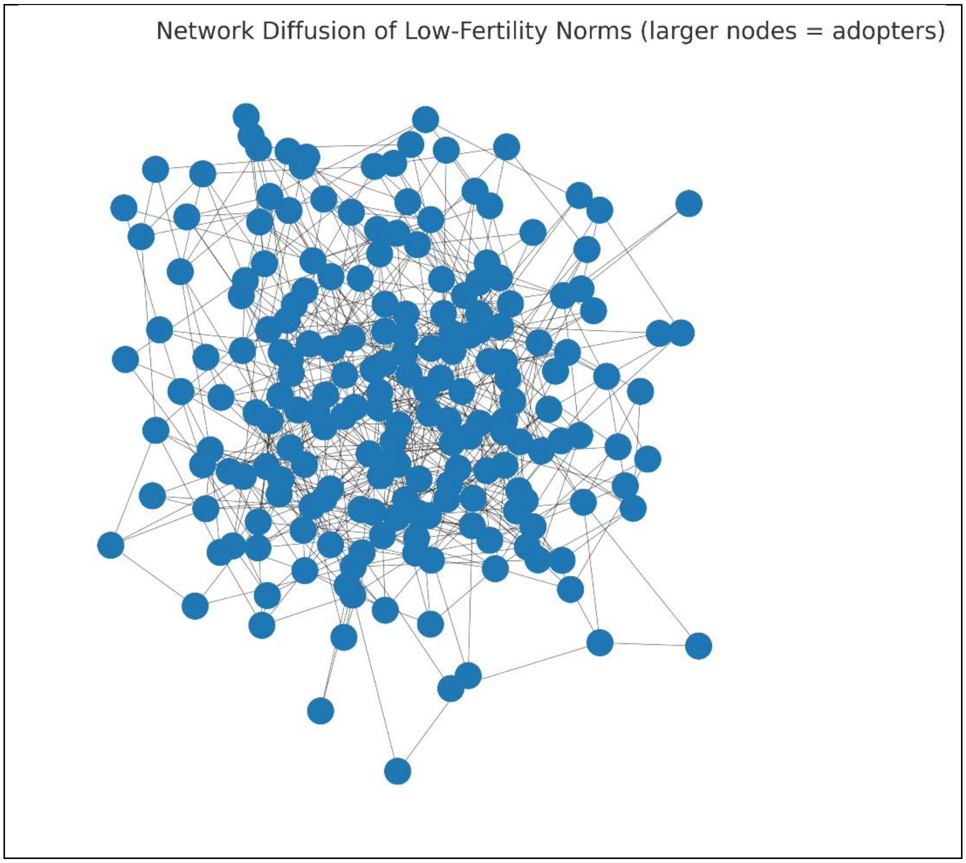

Figure 5. Visualization of social network diffusion of low-fertility norms among agents.

This integrated framework therefore provides a more comprehensive lens for evaluating the effectiveness of various population policies in achieving the desired demographic outcomes and their impact on ecological systems. The model also reveals the impact of varying socio-economic conditions on the emergence and consolidation of regional demographic divides. It shows how differences in fertility rates can become entrenched under different socio-economic conditions (57). As a result, policy responses to low fertility rates may need to be localized, as a one-size-fits-all approach may be ineffective, or even counterproductive in areas with different social, cultural, economic, and other background conditions (58) (59). These localized differences in fertility rates, which can be driven by idiosyncratic factors, including unique values and institutions, and community-specific infrastructure, further highlight the need for targeted policy responses that take into account subnational demographic variations (60). For example, pronatalist policies, as shown in the previous discussion, must be carefully designed to ensure they do not inadvertently contribute to existing societal inequalities or ignore the needs of other segments of the population, such as older adults, within the ongoing demographic transition (61). The delicate balance between addressing low fertility rates and ensuring social equity and cohesion also highlights the need for an integrated policy approach that takes into consideration the potential intergenerational effects of population policies on different population groups. This integrated approach is also more likely to be more sustainable, as it will ensure that measures to boost fertility rates are also designed to be supportive of the wider community.

Table 3. Sensitivity analysis showing fertility rate response to parameter changes.

Scenario	Change in Social Media Influence	Change in Economic Pressure	Resulting Fertility Rate
Baseline	0	0	2.3
+10% Social Media	+0.10	0	1.9
+10% Economic Pressure	0	+0.10	2.1
Combined Increase	+0.10	+0.10	1.7

DISCUSSION

The present study employs an agent-based model to explore the multifaceted drivers of fertility rate decline, integrating the influences of education, economic pressures, and social media within a dynamic simulation framework. This methodology affords the exploration of the aggregate-level or system-level phenomena, which emerge from the interactions of multiple heterogeneous agents, each with distinct behavioral rules, as outlined in reference (62). In the context of fertility trends, this means observing how micro-level interactions, like individual education levels affecting career choices and, in turn, family planning, can lead to macro-level demographic patterns, demonstrating the concept of emergence (bottom-up) in complex systems (63) (64). An important aspect of this model is its ability to capture the non-linear dynamics often present in such systems, where certain thresholds and feedback loops can significantly amplify or dampen the effects of external shocks or policy measures (62). For instance, the model can simulate how a sudden economic downturn or a policy change, such as a new child benefit scheme, might affect fertility rates differently based on the current state of other interacting factors within the model.

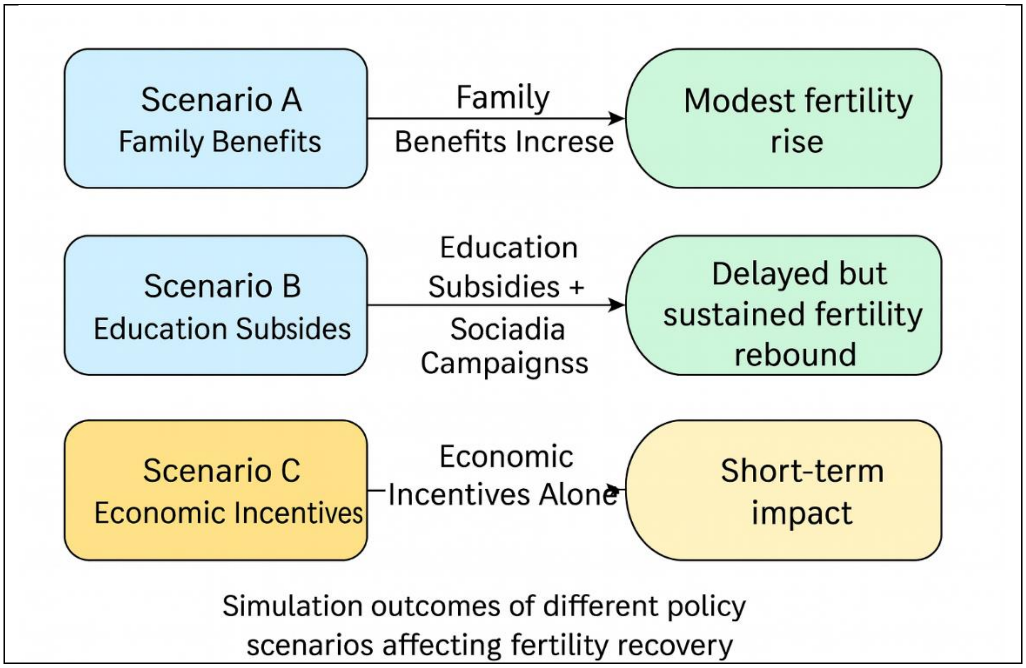

Figure 6. Simulation outcomes of different policy scenarios affecting fertility recovery.

Additionally, the model reveals that the delayed effects of educational attainment and shifting social media norms regarding family size and work-life balance contribute to a significant inertia in fertility rate adjustments. This inertia makes it challenging for policy interventions to effect quick changes in fertility rates, as the decisions made by individuals based on past states of the system take time to manifest at the population level. This aspect of the model underscores the importance of long-term strategic planning and policy adaptability, rather than short-term reactive measures, in effectively managing demographic trends. By providing a detailed understanding of these dynamics, the agent-based model offers valuable insights for policymakers in anticipating potential unintended consequences and refining intervention strategies to achieve the desired demographic stabilization or growth.

Moreover, beyond just predicting the outcomes of policy changes, the model can be used to test various scenarios and combinations of interventions, allowing policymakers to proactively evaluate different policy mixes and identify strategies that are robust across a range of possible future states (37). This is particularly useful for designing demographic policies that are resilient to rapid societal and technological changes, offering a clear advantage over more static predictive models. The dynamic interplay of individual decision-making and the emergent system-level phenomena captured in the model highlights the complexity of fertility dynamics, where there is no straightforward functional relationship between the underlying socioeconomic determinants and observed fertility outcomes (62). Instead, as in the real world, the model shows that heterogeneous agents, each acting on locally available information and individual preferences, generate complex, often unpredictable demographic patterns (63) (64).

This is further corroborated by observations in micro-landscape interventions, where individual-level manipulations lead to varied macro-level responses, underscoring the need to consider individual-level heterogeneity in population models (8). Additionally, this behavior is consistent with findings that deviations from the economic optimum in agent decisions, which may be significantly influenced by social factors, can accumulate over time, thereby affecting large-scale, behaviorally realistic models, such as those used in land use change (65). This generative ability, in the sense that the simulation can explain or generate novel structures and outcomes for which there is no specific rule, is an important feature of agent-based models. It allows for the testing of hypotheses about complex systems that would be very challenging, if not impossible, to do with traditional statistical methods (37). This is particularly true in the domain of fertility and population dynamics, where the interplay of individual decisions, informed by a myriad of factors including education, economic conditions, and social media, leads to complex, non-linear, and emergent system-wide outcomes that cannot be easily deduced by simply aggregating individual-level data (38). The knowledge gained using the approach described here may be also valuable for a better understanding of how a particular outcome, such as societal breakdown, can develop from individual actions – a situation that is difficult to capture using equilibrium-based modeling (65).

This type of response transition (from micro- to macro-level, from individual agent to individual agent interactions up to large groups and their reactions to the environment) highlights the complex processes that occur as individuals act in the face of environmental challenges, not always being intuitive (66). Agent-based modeling is used for such purposes as it can mimic individual behaviors in socio-environmental systems (67) (68). Agent-based models work from the bottom up in that the behavior of the system or model emerges from the characteristics and interactions of the agents themselves, and do not require agents to be homogeneous and systems to be characterized by group-level characteristics (69). This approach allows researchers to build in the heterogeneity of individuals, households, and neighborhoods that represent these individual attributes and decision-making processes, and to track them over time (70). In particular, the refined way in which social media was incorporated in the model shows the important role of this information transmission pathway for how fertility preferences are both formed and change in different age and social groups. Namely, while social media was treated in other models, this study incorporated the detailed mechanisms by which social media influence changes in fertility preferences, and also its transmission from one agent to another. In addition, it is explicitly captured here that social media influence different age and social groups in specific ways and that this influence, including how and when fertility preferences change, also differ across different social groups. These intricate differences are important to be able to capture when investigating how complex social interactions can be used to influence fertility, and here an agent-based modeling approach with a multi-agent-based model can help understand such influence (24).

In fact, agent-based models can realistically represent different behavioral rules and interactions among agents in a system that mirror those in real-world, complex social systems and provide a rich source for analyzing these and other similarly complex socio-demographic phenomena (37). This is a particular strength of agent-based models over many other models of complex social systems in that the macro-level patterns emerge from the micro-level interactions, and this is not easily simulated with an aggregate model (24). Non-linear relationships and feedback loops can be built into an agent-based model and result in the realistic representation of important aspects of a social system (71). This approach also provides a rich source for exploring how policy and management interventions at one scale in a system will lead to a variety of outcomes at another scale in the system, and these outcomes may be different than what one might expect from intuition. This is an important strength of an agent-based modeling approach and highlights the need to understand systems at all scales. Agent-based models, with their ability to simulate individual-level behaviors and their interactions, are particularly suited to understanding how micro-level processes aggregate to produce macro-level outcomes (72) (73).

This includes understanding the complex ways in which social media can impact fertility intentions, as these social networks provide a platform for creating communities and sharing globalized ideas, norms, and values, which can then influence individual and group behaviors (52). This is especially true for social media, which have become one of the most popular forms of media across the world, particularly among young adults, and these platforms also are being used to spread a wide range of ideational influences associated with fertility transitions (74). Finally, only an agent-based approach can capture the dynamic and evolving nature of social media influence, as the “infection probabilities” are not static, but can themselves change as users engage with media or as social media platforms evolve over time (75). In this way, such models provide the ability to analyze the potential impact of specific digital trends or viral content on fertility decisions across different subpopulations, an understanding of which would not be possible with traditional demographic models. This capability is also important for the identification of tipping points in demographic transitions that are likely to be impacted by rapid technological and social change. The coupling of agent-based modeling to real-world data in this case, especially as it is being done here with regards to the relationship between social media use patterns and demographic trends, can be a powerful way to confirm and calibrate such complex simulation models, and in turn, allows for the creation of more accurate models that can help predict changes in fertility rates under a wide range of socio-economic and technological scenarios.

CONCLUSION

In conclusion, agent-based modeling can capture the emergent properties from local interactions and behavior of individuals which other statistical analyses fail to capture (2). Agent-based models can effectively analyze how the intricate relationships and changes in interactions between people's values and perceptions which are driven by numerous internal and external factors, most recently social media, ultimately aggregate to changes in fertility patterns at the population level (76) (52) (4). They can also effectively simulate the diverse and adaptive behavior of heterogeneous agents in dynamic systems to predict outcomes like a negative correlation between population growth and per capita wealth which may make policies designed to impact fertility rates ineffective (2).

In addition, they can model confounding latent variables, like the time-varying effects of levels of education and deprivation, to help to better understand how small perturbations in factors can move populations into tipping points of a fertility transition (1). Agent-based models can also represent individual choice and decision-making which can be used to model how different policy levers, like free access to education or financial incentives, might affect fertility decision-making in different population subgroups (7). Machine learning can also be used in conjunction with agent-based models to more accurately predict individual-level outcomes by classifying, combining and inferring missing data (77). This can be used to allow for the design of policy tools that can more quickly adapt to population changes and unpredicted outcomes (54) (78). This improved capacity to more accurately predict individual-level outcomes can also help to design more effective, person-centered designs for both contraceptives and contraceptive programming (11). In addition, because agent-based models formalize relationships into algorithmic formats they are uniquely able to represent more behavioral realism, including various forms of bounded rationality and the social networks which influence the spread of information, norms and behaviors (79). Thus, agent-based models have the potential to be used to help policymakers to plan for the long-term implications of current population changes and potential policy levers that can be used to intervene to help to ensure a sustainable population. (54)

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