Misperceptions and Realities: unraveling parenting norms through agent-based modeling

Andy Chen

MACS 30200 Final Project

Github repo: https://github.com/UC-MACS-30200/course-project-zhian21

University of Chicago

Dear Reviewers,

I am writing to provide an overview of the revisions made to my research proposal, in response to the valuable feedback received from Assignment 9 peer reviews and instructor comments. I appreciate the time and effort you invested in providing detailed and constructive feedback. Below, I summarize the main concerns and suggestions from the reviewers and outline the specific changes made to address each point.

Summary of Main Concerns and Suggestions:

- **1.** Lack of Abstract: Reviewers noted the absence of an abstract, which made it difficult to grasp the goal and scope of the project initially.
- **2.** Complexity of Design Concepts Section: The Design Concepts section was found to be challenging, particularly for readers unfamiliar with Agent-Based Modeling (ABM).
- **3.** Causal Claims: Concerns were raised about the appropriateness of making causal claims given the scope of the project.
- **4.** Definition of Social Norm: The need for a more explicit definition of social norms was highlighted.
- **5.** Source for Intensive Parenting Claims: A comment was made for sources or examples to support the claim about the idealization or overstatement of intensive parenting efforts.
- **6.** Survey Design Clarity: There was some confusion regarding whether the survey aimed to capture the norms students hold or those they believe are widely held.

Revisions Made

- 1. Inclusion of an Abstract: To address the first concern, an abstract has been added at the beginning of the proposal. The abstract succinctly outlines the objective, methods, and preliminary results of the study.
- 2. Clarification of Design Concepts Section: In response to the feedback regarding the complexity of the Design Concepts section, this part has been revised to include a more detailed explanation of Agent-Based Modeling (ABM) and its relevance to the study. A brief introduction to ABM, its purpose, and how it is used to simulate the spread of parenting norms among college students has been provided. This revision aims to make the section more accessible to readers who may not be familiar with ABM.
- **3.** Reframing Causal Claims: Acknowledging the concern about making causal claims, the discussion has been reframed around knowledge creation rather than causality. The revised

proposal emphasizes the generation of insights and understanding of the dynamics of parenting norms, rather than asserting causal mechanisms. This change aligns the claims with the project's scope and methodological capabilities.

- **4.** Explicit Definition of Social Norm: To address the need for a clearer definition, an explicit definition of social norms within the context of the project has been incorporated. The definition is now accompanied by specific examples to illustrate its application in the study. This addition ensures that readers have a clear and accurate understanding of the term used throughout the proposal.
- **5.** Source for Intensive Parenting Claims: In response to the request for sources or examples, references to relevant literature that discuss the idealization and overstatement of intensive parenting efforts have been included. These sources provide empirical support for the claims made in the proposal, enhancing its credibility and grounding the discussion in existing research.
- **6.** Clarification of Survey Design: To address the confusion regarding the survey design, it has been clarified that the surveys aim to capture both the norms that students hold and those they believe are widely held. This dual focus is now explicitly stated in the revised proposal, ensuring that the survey's objectives are clear to readers.

Abstract

This research project investigates the dynamics of misperceptions in parenting norms among U.S. college students through the use of agent-based modeling. Specifically, the study aims to elucidate how social learning strategies, demographic variables, and group sizes contribute to these misperceptions. Hypotheses include an increasing trend in parental investment, potential overestimation of such investment by students, and the influence of social learning strategies and social networks on these misperceptions. Despite limitations in capturing real-world complexities, the project employs a rigorous methodological approach, combining historical data analysis, surveys, and simulation modeling. Preliminary results indicate an upward trend in parental time investment in childcare and reveal the impact of different learning strategies on the dissemination of parenting norms. This research contributes to a deeper understanding of the perceptions and misperceptions of parenting norms among college students, offering insights into the broader implications of social norm dynamics.

Introduction

The complexity of human social learning

Social learning, as a pivotal evolutionary mechanism, significantly underpins the development and dissemination of complex cultural practices, technologies, and social norms, thereby facilitating the rapid adaptation of populations to changing environments (Kendal et al., 2018; Morgan et al., 2012; Whiten & van de Waal, 2017). This process, termed cumulative cultural evolution, is instrumental in the high-fidelity transmission of cultural knowledge across generations, markedly contributing to human ecological success(Henrich et al., 2016; Henrich & McElreath, 2003). It fosters the preservation and accumulation of cultural knowledge beyond the capabilities of individual learning, profoundly influencing a broad spectrum of daily activities and molding the intricate web of social and cultural practices that define human societies.

Despite its critical role, it is imperative to recognize that not all behaviors can be directly observed and internalized, presenting a notable challenge for accurate comprehension and assimilation of such behaviors. This underscores the complexity of social learning processes, particularly in the acquisition of social norms (Chung & Rimal, 2016; Legros & Cislaghi, 2020). According to Mackie et al. (2014), a social norm is constructed from the beliefs and desires of individuals within a reference group, where conformity to the norm is driven by empirical expectations (beliefs about what others do) and normative expectations (beliefs about what others think one should do). An illustrative example of this definition is evident in a case study on energy conservation in households. In this study, social norms were leveraged to influence behavior by disseminating information about the energy consumption patterns of neighbors. The researchers observed that households reduced their energy consumption when they believed that

their neighbors were also engaging in energy-saving behaviors, thereby aligning with the previous framework of empirical and normative expectations (Pavón et al., 2008).

These norms, primarily learned through observation and social interaction, are susceptible to misperception, a phenomenon where there is a discrepancy between the perceived and the actual behaviors and attitudes within a community, due to their inherent subtlety and the implicit nature of their transmission(Bursztyn & Yang, 2022; Mastroianni et al., 2022). Such misperceptions are further exacerbated in situations where direct observation is impeded, leading individuals to rely on second-hand information or biased narratives, thus magnifying the vulnerability of social norms to misperception (Bjerring et al., 2014; Miller & Mcfarland, 1987). This delineates the intricate challenges faced in accurately transmitting and adhering to social norms within human societies, highlighting the nuanced complexities inherent in the social learning processes.

Indeed, misperceptions are a widespread phenomenon across various domains, including politics, socioeconomics, education, and gender norms, reflecting genuine beliefs that significantly deviate from reality (Bursztyn & Yang, 2022). This prevalence is not merely a result of measurement errors but indicates a deep-rooted challenge in aligning individual beliefs with factual information (Lawson et al., 2021a). For example, in the context of gender norms, research has provided insights into the misperceived social norms regarding women's employment outside the home in Saudi Arabia. This study revealed a significant discrepancy: a majority of men privately support the notion of women working outside the home but substantially underestimate societal support for this idea (Bursztyn et al., 2020). This finding not only emphasizes the complexity of misperceptions but also illustrates how they can both influence and be influenced by social norms, cultural contexts, and individual experiences. Similarly, in the health domain, during the COVID-19 pandemic, a specific case study highlighted how misperceptions could distort understanding of societal norms and behaviors. It was found that individuals underestimated the extent to which others were complying with social distancing guidelines, potentially leading to lower adherence to such guidelines themselves (Cookson et al., 2021). This underestimation of compliance with health guidelines among peers illustrates the broader impact of misperceptions on individual and collective behaviors, often leading to suboptimal outcomes.

How misperceptions are "corrected"?

Building on the understanding of misperceptions across various domains, the Social Norms Approach (SNA) emerges as a strategic intervention designed to recalibrate these misperceptions, particularly those related to normative behaviors—actions deemed acceptable or typical within a community (Berkowitz, 2009; Cislaghi & Berkowitz, 2021). By providing accurate reflections of the behaviors and attitudes that prevail within a group, SNA aims to realign individual actions with these collective realities, thereby fostering healthier and more

socially responsible practices. For example, in the context of mitigating alcohol misuse among college students, SNA interventions have strategically disseminated data on the actual, often less excessive, drinking behaviors of their peers, with the goal of cultivating healthier drinking habits(Perkins & Berkowitz, 1986; Ridout & Campbell, 2014). Similarly, to bolster proenvironmental behaviors, SNA has been utilized to correct overestimations of peers' environmentally detrimental practices, thus promoting a more accurate perception of community norms regarding environmental stewardship(Huber et al., 2018).

However, the application of SNA comes with its own set of challenges and ethical considerations that warrant careful examination. The approach's success is heavily dependent on the accurate collection and interpretation of normative behavior data, a task that is inherently complex due to hard-to-measure norms (Burchell et al., 2013; Dempsey et al., 2018). This complexity raises concerns about the potential for misinterpretation of data, which could inadvertently normalize undesirable behaviors if SNA interventions are not meticulously designed and implemented. Moreover, the focus on adjusting individual behaviors to align with perceived group norms may overlook the rich tapestry of individual motivations and the impact of cultural diversity on behavior. This oversight could limit the effectiveness of SNA interventions across different demographic and cultural contexts. These considerations underscore the importance of a deep and nuanced understanding of social norms and the contexts in which they function. As such, when designing and implementing SNA-based interventions, it is crucial to navigate these challenges with precision and sensitivity, ensuring that the interventions are both effective and ethically sound.

Exploring the complex interplay between social learning and the spread of cultural norms, this research project seeks to deepen our understanding of the dynamics of misperception and its impact on individual actions. Specifically, the study aims to unravel how different social learning strategies, demographic and socioeconomic variables, and social group sizes contribute to the formation of misperceptions. This exploration is pivotal, as existing literature predominantly demonstrates the impact of misperceptions on behaviors without dissecting the underlying mechanisms that facilitate this process. By shedding light on these mechanisms, the project aims to generate valuable insights that could inform the design of social norm interventions, particularly for individuals more susceptible to misperceptions. Furthermore, the research will address the methodological challenges associated with data collection and the measurement of intervention effectiveness through the innovative use of agent-based modeling. This approach is instrumental in simulating the development of misperceptions and assessing the potential impact of interventions before embarking on empirical research. To ground this investigation in a concrete and culturally relevant context, the project will focus on parenting norms among U.S. college student populations. This specific demographic group offers a unique opportunity to examine how misperceptions influence behaviors within a well-defined cultural setting.

Hypotheses

The landscape of parental investment in the United States has seen a marked evolution over recent decades, characterized by a multifaceted approach that encompasses time, money, and adherence to intensive parenting norms. A significant trend observed is the increasing financial investment in children, with parents allocating larger shares of their income towards their offspring's upbringing, education, and extracurricular activities, reflecting heightened aspirations for their children's future success and well-being (Kornrich, 2016a). Concurrently, there has been a notable shift in the time investment by parents, with an uptick in the amount of time spent engaging in activities that promote the physical, cognitive, and emotional development of their children (Dotti Sani & Treas, 2016; Gimenez-Nadal & Molina, 2013). This shift towards more time-intensive parenting practices is indicative of a broader societal move towards what is often termed 'intensive parenting,' where the quality and quantity of time spent with children are seen as pivotal to their development (Lee, 2023). Moreover, the norms surrounding parental investment have also evolved, with a growing emphasis on ensuring that children not only achieve academically but also acquire a broad set of skills and experiences that are believed to be essential in today's competitive world. Hence, we first hypothesize that our findings will corroborate the increasing trend of parental investment in the U.S. population, especially in the time parents dedicate to their children's development. This expectation is grounded in the observed escalation of time spent on children's education and activities, alongside a notable rise in parental engagement in child-rearing practices that promote physical, cognitive, and emotional growth.

Given this evolving landscape, it is imperative to examine how these changing norms are perceived across different societal segments, particularly among students. This demographic, often not yet engaged in parenting themselves, derives their understanding of parental investment from indirect sources such as media, societal narratives, and observations of family and peers. This indirect exposure may skew their perception, leading to potential misinterpretations of the nature and extent of parental investments. In an era where 'intensive parenting' has become increasingly normative, there is a tendency for these efforts to be either idealized or overstated by those not directly involved in parenting activities. This phenomenon is supported by findings from studies on intensive parenting norms and their societal impact. For instance, research indicates that intensive mothering expectations, which are deeply ingrained in societal norms, often set unrealistic standards that can influence perceptions even among those not engaged in parenting (Forbes et al., 2020). Additionally, the visibility of intensive parenting in both social and traditional media, coupled with societal narratives that underscore the critical role of extensive parental involvement for child success, may contribute to these exaggerated perceptions (Chin & Phillips, 2004). Consequently, we hypothesize that U.S. students are likely to overestimate the current level of parental investment, particularly regarding the time parents dedicate to their children's development. This hypothesis is informed by the recognition that while intensive parenting practices are widely discussed and aspired to, their actual

implementation may not be as pervasive as perceived by individuals outside the immediate family context, leading to potential misconceptions among students about the average parental time investment in the U.S. population.

Lastly, the intricate dynamics of social learning strategies and the size of social groups play a pivotal role in shaping the misperceptions among students. If an individual's learning is heavily influenced by conformity bias, they are likely to adopt the most prevalent behaviors observed within their social circle, eschewing independent analysis in favor of mirroring the dominant parenting norms of their group (Kendal et al., 2018; Laland, 2004). This phenomenon underscores the significant impact of social learning strategies, where the frequency of certain behaviors within a group can dictate the norms that an individual chooses to adopt. Moreover, the application of these social learning strategies is intricately linked to individual demographic and socioeconomic variables. For instance, the educational gradient in parental time investment sheds light on the potential for class diffusion, suggesting that individuals with higher education levels may wield more influence in terms of norm spreading (Dotti Sani & Treas, 2016; Kornrich, 2016b). This interplay between social learning strategies, group size, and individual characteristics highlights a complex web of factors that contribute to the formation of misperceptions. Therefore, we hypothesize that students with larger social group sizes and those from lower household incomes and educational backgrounds are more susceptible to misperceptions. This hypothesis aims to unravel the nuanced ways in which social learning strategies, demographic factors, and socioeconomic variables converge to influence students' perceptions of parental investment norms.

Research Design

The research design of this project is structured to explore the dynamics of parenting norms among U.S. college students, focusing on the perception and misperception of these norms. The first component involves measuring existing parenting norms to establish a baseline, utilizing parents' time investment in childcare as a proxy for the intensity of parenting practices. This phase of the research design employs a dual-method approach for data collection. Initially, it leverages the American Time Use Survey between 2003 and 2022 to quantify the actual time investment by parents in childcare activities, providing a "true" baseline of parenting norms. For example, the participants are asked, "How long did you spend on activities related to household child's education", during a specified 24-hour period. Subsequently, the project modifies the survey questionnaire to gather data from a diverse sample of 1000 to 1500 U.S. college students, aiming to capture a wide array of demographic and socioeconomic variables. This innovative approach allows for the comparison of actual parenting norms with the perceived norms within the student community, thereby setting the groundwork for identifying potential misperceptions among this demographic group.

The second component of the research design focuses on measuring the perception of parenting norms among the same cohort of students. Specifically, we engage students in estimating their peers' beliefs about parenting norms, asking them to predict the level of agreement with certain statements within a hypothetical group of ten students. For example, we will ask "If we were to speak to 10 students, how many of them do you think would agree with each of these statements?" This technique, designed to assess whether students are likely to overestimate or underestimate these norms, serves as a pivotal tool for contrasting perceived norms against a "true" baseline derived from parental data. Such an approach not only facilitates the identification of potential misperceptions within the student population but also enriches our understanding of the discrepancies between perceived and actual parenting norms. This methodology, mirroring strategies employed in prior studies such as those examining women's empowerment in Saudi Arabia, underscores the utility of peer estimation in uncovering the nuances of social norm perceptions within specific demographic groups (Bursztyn et al., 2020). In short, the research begins with the American Time Use Survey data to establish a baseline of actual parenting norms based on parents' time investment in childcare. Following this, a modified survey will be administered to the U.S. college students to capture their demographic and socioeconomic variables and their estimation of parenting norms (self-estimation), facilitating a comparison between actual and perceived norms. Students will also be asked to estimate their peers' beliefs about parenting norms to identify potential misperceptions (peer-estimation). This methodology is informed by previous studies on social norm perceptions.

Table 1. Research Design Phases and Objectives

Phase	Description	Methods	Objectives
Phase	Measuring Existing Parenting Norms	Survey (2003-2022).	1. Establish a "true" baseline of parenting norms based on parents' time investment in childcare.
1		2. Modify the survey questionnaire to gather data from 1000-1500 U.S. college students.	2. Capture a wide array of demographic and socioeconomic variables and estimation of parenting norms to compare actual vs. perceived norms.
Phase	Measuring Perception of Parenting Norms Among Students	statements within a hynothetical	Assess whether students overestimate or underestimate parenting norms (peerestimation).

Phase	Description	Methods	Objectives	
	Simulating the Spread of Parenting Norms Using ABM	, ,	1. Simulate the spread of parenting norms among college students.	
11		demographic variables from the	2. Understand the dissemination of parenting norms and identify factors influencing these norms.	

Lastly, the project employs an agent-based model (ABM) to simulate the spread of parenting norms across the student population, taking into account the socioeconomic and demographic variables collected from the student survey. To comprehensively detail the use of Agent-Based Modeling (ABM) in simulating the dissemination of parenting norms among college students, we adopt the Overview, Design concepts, and Details plus Decision (ODD+D) protocol.

Overview

The ABM simulates the spread of parenting norms within a college student population, incorporating socio-economic and demographic data derived from student surveys. The primary focus is on norms related to time investment in parenting, exploring how these norms are communicated and adopted among individuals through different learning strategies.

Agents and their attributes and actions

The model only contains a single type of agent.

Agent: Parent

• Description:

o The agent represents a parent or a student in the model. The parent has a certain education level and is placed in a network, adopts a learning strategy, and invests time in their child. The parent can switch strategies based on certain thresholds.

• Attributes:

- Education Level (High, Medium, Low)
- Initial Time Investment
- Strategy (Individual Learning, Social Learning)
- Threshold

Child Outcome Score

Process Overview

1. Initial Setup:

- Agent Initialization: Each agent is assigned an education and income level (High, Medium, Low), a learning strategy (Individual Learning, Social Learning), and an initial time investment. Agents are also placed within a social network graph based on their education level.
- Network Creation: Separate network graphs are created for each education level, and agents are placed on nodes within these graphs. The networks are then combined into a unified graph (i.e., there are connections between agents from different education levels).
- Parameter Assignment: Each agent receives other parameters, such as thresholds for switching strategies and average node degree. These parameters vary based on the agent's education level.
- Optimal Time Investment: The model defines an optimal time investment value that maximizes child outcome scores.

2. Observation:

 Each agent observes the strategies and time investments of its peers within its network. They gather information about the time investments and corresponding child outcome scores of their neighbors.

3. Strategy Update:

- Individual Learning Agents: Agents using individual learning maintain their current time investment, as they rely on their own experience rather than peer influence.
- Social Learning Agents: Agents using social learning may adopt one of the following strategies:
 - Copying the Highest-Scoring Neighbor: The agent identifies the neighbor with the highest child outcome score and adopts their time investment.
 - Copying the Most Frequently Observed Strategy: The agent adopts the most common time investment observed among its neighbors.
 - Copying Randomly: The agent randomly selects a neighbor and adopts their time investment.

 After updating their time investment, agents recalculate their child outcome score based on how close their time investment is to the optimal value set in the model.

4. Time Investment Adjustment:

Feedback Loop:

- Assessment: Each agent calculates their child's outcome score based on their current time investment. This score is compared to the optimal score to determine the effectiveness of their investment.
- Positive Feedback: If the child outcome score is high (close to the optimal value), the agent receives positive reinforcement. The agent is likely to maintain their current time investment strategy.
- Negative Feedback: If the child outcome score is low (far from the optimal value), the agent receives negative feedback. This prompts the agent to reassess and potentially adjust their time investment strategy.

Strategy Switching:

- Discrepancy Threshold: If the agent's time investment significantly deviates from the optimal value, they may consider switching their learning strategy. Each education level (High, Medium, Low) has a specific threshold for what constitutes a significant discrepancy.
- Switch Probability: The likelihood of switching strategies when the discrepancy threshold is exceeded. This probability varies by education level:
 - High-Education Agents: Low switch probability, but sensitive to small discrepancies.
 - Medium-Education Agents: Moderate switch probability and thresholds.
 - Low-Education Agents: Higher switch probability, triggered by larger discrepancies.
- Execution: Agents exceeding the discrepancy threshold and within the switch probability will change their strategy to either individual learning or one of the social learning strategies. The new strategy is chosen based on predefined ratios specific to their education level.

5. Stop Conditions:

• The model will stop when all agents reach the maximum of child outcome scores (i.e., 20 points).

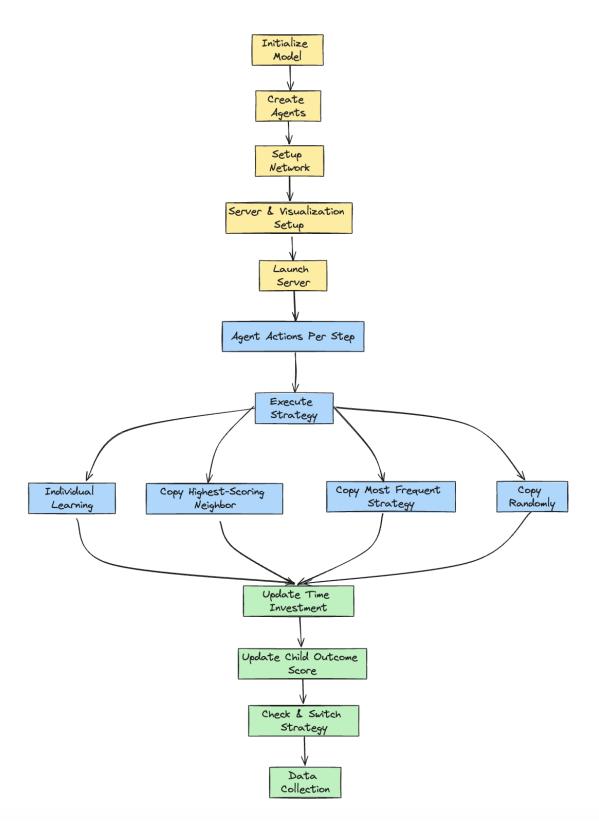


Figure 1. Flowchart of the Parental Learning Agent-Based Model (ABM) Process

Details

All of the parameters in the model are described in Table 2 below. The initial values of some parameters are empirically estimated, whereas others are decided based on informed guessing. For instance, the initial time investment and the education level ratios for parents from each different education level are derived from the data of the American Time Use Survey (ATUS) spanning 2003 to 2022. This setup aims to reflect realistic behaviors and social patterns, providing a robust foundation for simulating the dynamics of parental learning strategies.

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32 Low Rewiring Probability Float 0.1 Probability of rewiring connections for low education level agents	31	Medium Rewiring Probability	Float	0.5	Probability of rewiring connections for medium education level agents
	32	Low Rewiring Probability	Float	0.1	Probability of rewiring connections for low education level agents

Table 2. Parameters of the Parental Learning Model. This table outlines the various parameters used in the Parental Learning Model, including agent-specific attributes, model-wide settings, and network configuration parameters.

Preliminary Results

Figure 2 traces the evolution of parental time investment in childcare from 2003 to 2021, drawing on data from the American Time Use Survey to offer a quantifiable representation of parenting norms. The graph reveals a gradual upward trajectory in the average minutes parents dedicate to childcare per day, with the line indicating a notable increase from 2003's average of approximately 65 minutes to over 75 minutes by 2021. This trend underscores a shift towards more time-intensive parenting practices, reflecting broader societal movements towards

'intensive parenting,' where the quality and quantity of time spent with children are increasingly valued for their developmental benefits. The highlighted average of 70 minutes over the period serves as a baseline against which the year-to-year fluctuations can be assessed. These variations in time investment may correlate with shifts in cultural expectations, economic conditions, and changes in family structure that have influenced parenting approaches over nearly two decades. This longitudinal analysis forms the basis for investigating the alignment (or misalignment) between actual parental behaviors and societal perceptions of parenting norms among U.S. college students, exploring the potential misperceptions that may exist about the extent and nature of parental involvement in childcare.

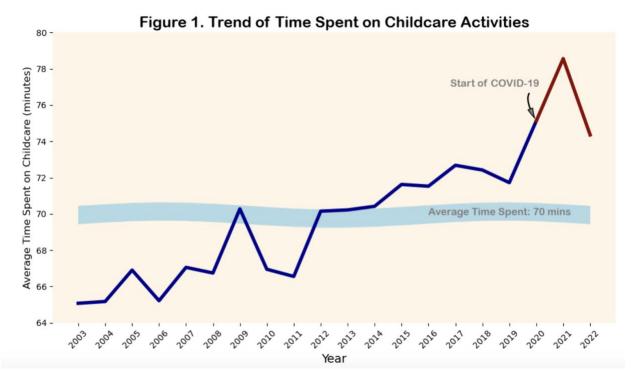


Figure 2. Trend of Time Spent on Childcare Activities

By default, our ABM model is configured using real-world data for initial time investment, with the assumption of high education level parents aligning closely with the optimal time value. This setup reflects empirical findings, showing that high education level parents not only invest more optimal time in their children but also have a higher individual learning ratio and fewer connections with their surroundings compared to parents from lower education levels. The network graph on the left IN Figure 3 illustrates these interactions, with node colors indicating education levels (darkslategray for high, cadetblue for medium, and paleturquoise for low) and node sizes representing time investments. The right panels track the progression of average child outcome scores and the number of social learning agents across different education levels over 50 steps.

The top right chart in Figure 3 illustrates that high education level parents quickly achieve optimal child outcome scores, stabilizing at the maximum score of 20 early in the simulation. In contrast, medium and low education level parents gradually improve their child outcome scores, taking longer to reach stability. Meanwhile, the bottom right chart shows the dynamic shift in the number of social learning agents over time. High education level parents maintain a low number of social learning agents, reflecting their higher reliance on individual learning. In contrast, medium and low education level parents exhibit more significant fluctuations in social learning agents, indicating a greater reliance on social learning strategies.

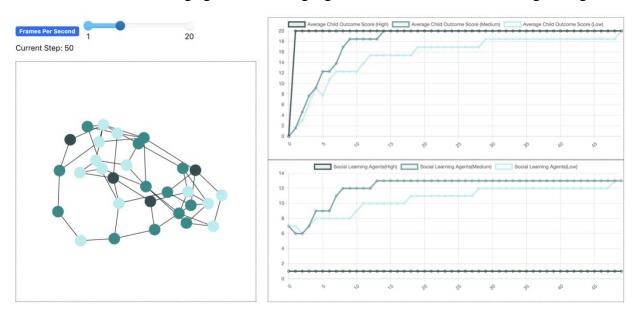


Figure 3. Simulation Results under Default Settings

Evaluation

The preliminary results demonstrate that the project's innovative methodology, combining empirical data collection with agent-based modeling, has successfully addressed its primary objectives of exploring the dynamics of parenting norms among U.S. parents and college students and the potential misperceptions therein. Specifically, the trend of time spent on childcare activities, as depicted in Figure 2, provides a tangible baseline of actual parenting norms, which is crucial for assessing the effectiveness of the ABM in simulating the spread and adoption of these norms within the student population. The ABM simulations, detailed in Figure 3 further elucidate how different learning strategies—Frequency Dependent Learning, Success Base Learning, and Random Copying—affect the dissemination and adoption of intensive parenting norms, offering insights into the mechanisms through which perceptions and misperceptions of norms are formed and altered.

However, our model incorporates several simplifying assumptions that may limit its ability to fully capture the complexities of real-world parenting norms. First, the model includes only one type of agent, representing parents, and does not consider the roles of other influential actors such as family members, educators, or peers. These additional agents play crucial roles in shaping child outcomes and parental strategies. Their absence in the model limits its comprehensiveness and fails to account for the broader social dynamics that influence parenting practices.

Furthermore, the setup for the social networks in the model is less than ideal. Due to the restrictions of the Mesa library, the social networks of different education levels are interconnected. This interconnectedness does not accurately mimic real-world scenarios, where social barriers often exist between parents of different socioeconomic statuses. These barriers can significantly influence social learning and the adoption of parenting practices. The model's inability to represent these social divisions may limit its ability to accurately simulate the spread and influence of intensive parenting practices within distinct social groups.

Proposed Timeline and Feasibility Assessment

This project embarks on a comprehensive exploration of parenting norms among U.S. college students, structured over a carefully planned timeline to ensure both methodological rigor and practical feasibility. The initial phase of the project, spanning one month, is devoted to analyzing historical data on parenting norms from the American Time Use Survey for the years 2003 to 2022. This crucial step establishes a reliable baseline for understanding changes in parenting norms over time, utilizing historical data analysis techniques validated in prior research to lay a solid foundation for the study (Craig, 2011; Dotti Sani & Treas, 2016; Gimenez-Nadal & Molina, 2013). Following this, the project allocates four months to the revision and administration of a survey questionnaire to a targeted sample of 1000 to 1500 U.S. college students. This sample size is chosen based on considerations of convenience, resource constraints, and the ease of obtaining Institutional Review Board (IRB) approval, a common prerequisite for research involving human subjects in academic settings. The synergy between the analysis of historical data and contemporary survey methods mirrors best practices in social science research, enhancing the project's methodological soundness (Kilgallen et al., 2021; Lawson et al., 2021b).

Subsequently, the next five months are dedicated to the development, testing, and refinement of an Agent-Based Modeling (ABM) simulation. This simulation, informed by socioeconomic and demographic data from the student surveys, aims to model the dissemination and adoption of parenting norms. ABM's utility in simulating complex social interactions and norm transmission has been well-documented in similar investigations, making it a pivotal tool for uncovering the dynamics behind parenting norm spread among college students(Conte & Paolucci, 2014; Liang et al., 2022; Zia et al., 2019). The project's final phase, lasting four

months, focuses on data analysis, the dissemination of findings, and preparation for publication. This timeline aligns with the standard processes of similar studies, providing sufficient time for a thorough analysis and the peer review process.

The project's design draws on methodologies that have been effectively applied in related fields, enhancing its feasibility and potential for significant contributions to the understanding of parenting norms. By addressing potential challenges, such as the limitations inherent in self-reported data and ensuring a robust comparison of perceived norms against established baselines, the project is well-positioned to offer insightful findings. Moreover, the inclusion of various social learning strategies in the ABM simulations enriches the analysis, offering a nuanced understanding of the factors influencing the spread of parenting norms among U.S. college students. This comprehensive approach, coupled with the project's methodological rigor and strategic planning, underscores its potential to advance the field of social science research on parenting norms.

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