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MANUSCRIPT

Social cognitive theory and women's career choices: an agent—based model simulation

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Abstract

An agent-based model is proposed and tested. This model aims to simulate agency as conceptualized in Bandura's (Am Psychol 37:122–147, 1982; Organ Behav Hum Decis Process 50:248–287; Annu Rev Psychol 52: 1–26) Social cognitive theory. Social cognitive theory has been used to explain the continued underrepresentation of females in certain fields, most notably fields that are associated with engineering and technology. The theory proposes that agents acquire information from four different sources, and then, through a process of reciprocal interaction, these agents develop their perception of self-efficacy. In this study, an agent-based model is used to model this interaction. The output from the simulation supports the validity of the model used and illustrates how agency "emerges" from the triadic interaction. The model successfully simulates several of the theorized aspects of social cognitive theory. The simulation results reveal that even small gendered differences can lead to female misrepresentation in certain fields. The model also shows that female discouragement plays a larger role than male encouragement in female underrepresentation. The implications of these results are discussed. Finally, the limitations of the model are discussed, along with directions for future research.

Keywords Agent-based models · Simulation · Social cognitive theory · Gender · Career choices

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1 Introduction

Female tertiary students now outnumber their male counterparts in many countries in the world. Data pertaining to U.S. colleges in 2015 show that females earn more than half of Bachelor's, Master's, and Doctoral degrees (Snyder et al. 2016). This same pattern is observed in most Organization for Economic Co-operation and Development countries (OECD 2019). Despite this, females continue to be underrepresented in certain fields (OECD 2019).

Today there exists a vast array of studies that seek to study why female students steer away from what is collectively called STEM fields: science, technology, engineering, and mathematics (Master et al. 2017; Schuster and Martiny 2017; Sáinz and Eccles 2012). This phenomenon is especially concerning since a significant number of studies have found no gender differences in mathematical abilities (Else-Quest et al. 2010; Hyde et al. 1990a, b; Hyde and Linn 2006; Lindberg et al. 2010). Some have argued that while the average performance of men and women in math might be comparable, men display a greater level of variation, causing them to be overrepresented in the highest percentiles (Ellison and Swanson 2010; Guiso et al. 2008). However, it has been shown that this variability is neither constant (Hyde and Mertz 2009) nor culturally indifferent (Feingold 1994), thus indicating that a better understanding of the wider social environment is necessary (Cheryan et al. 2017).

Given the above findings, researchers have tackled the question using frameworks that account for wider environmental factors that may affect career choices (Cheryan et al. 2017). One of the most dominant theories used to explain observed gender differences in career choices is social cognitive theory (SCT). SCT has received considerable support from empirical findings (Fouad and Santana 2017; Lent et al. 1987,2007). The purpose of this paper is to develop and test an agent-based model that simulates the triadic interaction process as conceptualized in Bandura's (1982, 2001) theory.

2 Literature review

2.1 Social cognitive theory

SCT offers a model that aims at describing gender development and differentiation (Bussey and Bandura 1999). The theory explains gender development in terms of a triadic reciprocal causation interaction (Fig. 1) between personal factors, behavioral patterns, and environmental events (Bussey and Bandura 1999, p. 685):

> The personal contribution includes gender-linked conceptions, behavioral and judgmental standards, and self-regulatory influences; behavior refers to activity patterns that tend to be linked to gender; and the environmental factor refers to the broad network of social influences that are encountered in everyday life.

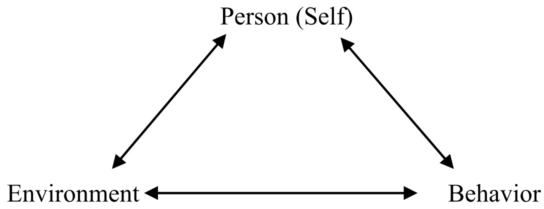


Fig. 1 Bandura's triadic reciprocal causation model

Therefore, SCT "subscribes to a model of emergent interactive agency," in which individuals are neither completely autonomous nor controlled mechanically by their environment (Bandura 2001, p. 4). Since the relationship between the individual and the environment is bidirectional, the concept of human agency plays a central role in the SCT. While the environment can limit the options available to an individual, humans have the ability to determine which part of the potential environment will actually be experienced (Zimmerman 1990), through what Bandura (1989) refers to as *selection processes*. These selection processes allow people to select and even construct their own environments. SCT distinguishes between the imposed environment, the selected environment, and the constructed environment. A potential environment can be selected through human behavior, while environments that do not exist as potentialities need to be constructed using generative efforts (Bussey and Bandura 1999).

Bandura (1977) argues that these selection processes depend on the individual's self-efficacy since people avoid activities that they believe, whether rightly or wrongly, exceed their capabilities, and they undertake activities that they believe lie within their capabilities. Thus, the issue is not one of efficacy, but instead, it concerns perceived self-efficacy, leading to the conclusion that perceived self-efficacy is the foundation of human agency and that self-efficacy is more critical than general outcomes expectations (Bandura 1982; Zimmerman 1990). A central tenet in perceived self-efficacy is the fact that it is domain-specific (Pajares 1996; Vogt 2008; Zimmerman 1990). Bandura (1986) has cautioned against using general and broad self-efficacy measures since individuals might have high perceived self-efficacy with regards to one task and very low perceived self-efficacy with regards to another. Thus, the number of different types of self-efficacy "is limited only by the possible number of behavioral domains that can be defined" (Betz 2004, p. 341).

Self-efficacy develops using information from four sources, and they are *performance achievements* (or enactive attainments), *emotional arousal* (or physiological state), *vicarious learning*, and finally, *social persuasion* (or verbal persuasion). As can be seen in Fig. 2, the environment continues to exert its influence because without some degree of environmental support, perceptions of self-efficacy cannot be sustained (Bandura 1986; Zimmerman 1990). Looking at Figs. 1 and 2, it is clear that the information sources fall broadly into the three elements of the triadic causation model (Litzler et al. 2014). Performance accomplishments

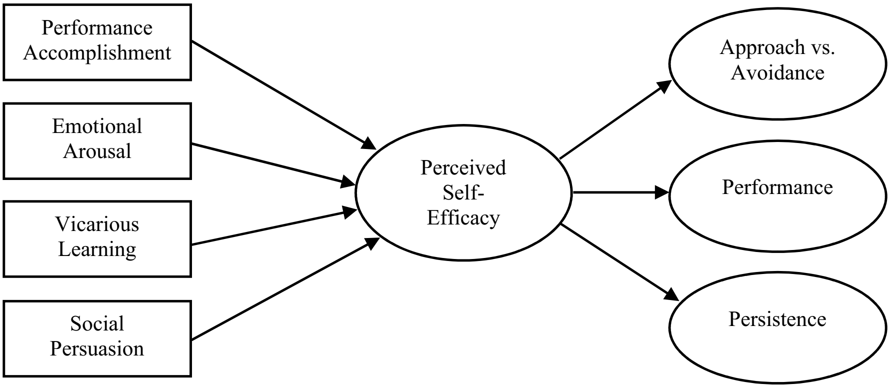


Fig. 2 Bandura's model of the sources of self-efficacy and the outcomes

are behavioral, vicarious learning and social persuasion are environmental, and emotional arousal is personal.

2.2 Career choices

SCT predicts that individuals will not consider occupations that they believe are beyond their abilities, no matter how attractive these occupations may be (Bandura et al. 2001). Thus, the theory predicts that females will avoid occupations that they are discouraged from engaging in through the sex-role socialization process (Betz and Hackett 1981). Betz and Hackett (1981) and Hackett and Betz 1981) were the first to use SCT to explain differences in career choices between males and females. They found that female college students displayed lower levels of self-efficacy for occupations traditionally held by males, while male students displayed equivalent self-efficacy for occupations that were traditionally dominated by males and those traditionally dominated by females. Crucially, while the differences existed in self-efficacy, there were no differences in English or math scores. Of central importance was the finding that self-efficacy expectations were a predictor of perceived career options, thus supporting the approach vs. avoidance consequence shown in Fig. 2. The other two consequences in the figure, performance and persistence, were also supported in other studies (Lent et al. 1984, 1986). In addition, Lent et al. (1987) found that self-efficacy was more useful than outcome expectations in predicting occupational preferences.

Bandura et al. (2001) identified three domains of personal efficacy: perceived academic self-efficacy, perceived social self-efficacy, and perceived self-regulatory efficacy. Path analysis revealed that while the children did not differ in their overall perceived academic self-efficacy, boys had a higher sense of self-efficacy for math, and higher levels of efficacy in science and technology. Girls, on the other hand, had higher levels of efficacy in educational and health-related fields. Other studies have also found that females have lower levels of confidence and self-efficacy in fields such as engineering (Cech et al. 2011).

Why do females report lower levels of confidence and self-efficacy in STEM fields? Fig. 2 indicates that there are four sources of information from which self-efficacy develops. As mentioned above, research has shown that there are no gender differences in grades, with regards to performance accomplishments. However, if many females avoid STEM fields, then these females will not get the chance to find out for themselves whether they are good at it or not, and they will not get the chance to master it since mastery requires several attempts (Bandura 1982). Thus, self-efficacy, it turns out, acts as a self-fulfilling prophecy (Betz 2004). With regards to emotional arousal, there is very strong evidence that females suffer from higher levels of math anxiety (Devine et al. 2012; Goetz et al. 2013), thus leading them to have more negative attitudes of it (Else-Quest et al. 2010). There is also evidence that this gap between females and males increased with age (Ceci et al. 2014; Hyde et al. 1990a, b).

With regards to the environmental information sources, there is reason to believe that the way that teachers and mothers interact with children is influenced by the child's gender (Gunderson et al. 2012; Simpkins et al. 2012), which in turn affects the child's achievements (Hill and Tyson 2009) and career choices (Bleeker and Jacobs 2004). In addition to the importance of engaging in the activities themselves, indirect sources are a very important source of information. Matsui et al. (1990) found that performance accomplishments and vicarious learning contributed to mathematics self-efficacy. As noted by Schunk and Pajares (2002), seeing similar others successfully perform a task will likely enhance an individual's belief in his or her own abilities at performing the same task. There is also strong evidence that gender differences exist here. As noted by Hackett and Betz (1981, p. 400),

> The sex-role socialization of females is less likely than that of males to facilitate the development of strong career-related self-efficacy expectations. In other words, women and girls in this society are either not encouraged or are actively discouraged from engaging in a variety of activities that serve to increase and strengthen expectations of personal efficacy.

Boys are more likely to be exposed to mechanical, scientific, and technical activities while growing up than girls (Betz and Hackett 1997). Tenenbaum and Leaper (2003) found that even when there were no gender differences in grades, parents were more likely to believe that science was both less interesting and more difficult for their daughters than for the sons. Data collected from the OECD (2015) also suggests that parents have higher expectations of their sons working in STEM occupations when compared to the same expectations with regards to their daughters.

3 Purpose of this study

The purpose of this study is to use agent-based modeling to simulate Bandura's triadic causation relationship between personal factors, behavioral patterns, and environmental events in the context of career occupation choices. Given that Bandura's model conceptualizes agency as a construct that emerges from the triadic causation model of interaction, agent-based modeling offers a suitable vehicle for simulation since the most distinctive feature of agent-based models (ABMs) is that they explicitly model interactions between different components (Gómez-Cruz Nelson et al. 2017). Unlike other modeling tools, ABMs do not attempt to model system-wide properties. Instead, ABMs model three components: agents, the environment, and the agent-agent and agent-environment interactions. Since the programming unit in ABMs is the individual, ABMs are most useful when agents are not homogeneous (Wilensky and Rand 2015). ABMs have been gaining in popularity over the years and have been used in a wide spectrum of disciplines including economics (Klingert and Meyer 2012), sociology (Fridman and Kaminka 2010), organizational behavior (Mozahem 2019), and political science (Kuznar and Frederick 2007).

In addition to developing the model, this study will verify the utility of the model by comparing the output produced with different theorized aspects of SCT. Once the validity of the model is established, using a series of what-if scenarios, this study will attempt to (1) shed light on the extent of discouragement that is needed in order to result in significant female misrepresentation in certain fields, and (2) investigate the effects of female discouragement has as opposed to male encouragement. Finally, reflecting on the model limitations, the study will propose several modifications that can be made in future iterations of the model in order to incorporate more complex elements of the environment as well as the decision making process of the individuals involved.

4 Description of the agent-based model

4.1 The model

Figure 3 shows the proposed model. Bandura et al. (2001) used principal component factor analyses to identify six factors that made up the structure of occupational self-efficacy. These factors were *Science-Technology Efficacy*, *Educational-Medical Efficacy*, *Literature-Art Efficacy*, *Social Service-Managerial Efficacy*, *Military-Police Efficacy*, and *Agriculture-Horticulture Efficacy*. The model presented in this paper includes the first four efficacies, which relate to career choices available to students in traditional universities. The *Military-Police Efficacy* factor includes the performance of military, police, and firefighting roles, while the *Agriculture-Horticulture Efficacy* factor includes occupational pursuits such as farming, raising livestock, and operating farm equipment. Both of these factors include occupations that are, in many instances, not found in traditional universities. Seeing that the purpose of this study is to develop a general agent-based model, the decision was made to exclude these two factors.

The model is built on the idea that there are different types of efficacies. As already stated in the literature review, self-efficacy is domain and task-specific in nature. Therefore, the model needs to allow for an individual's self-perception of self-efficacy to vary from one domain to another. In order to allow for this, the process of generating the self-efficacy for each category is completely random. This means that it is possible to have low self-perceptions in all categories, some categories, and zero categories. It is also possible to have a high self-perception in more

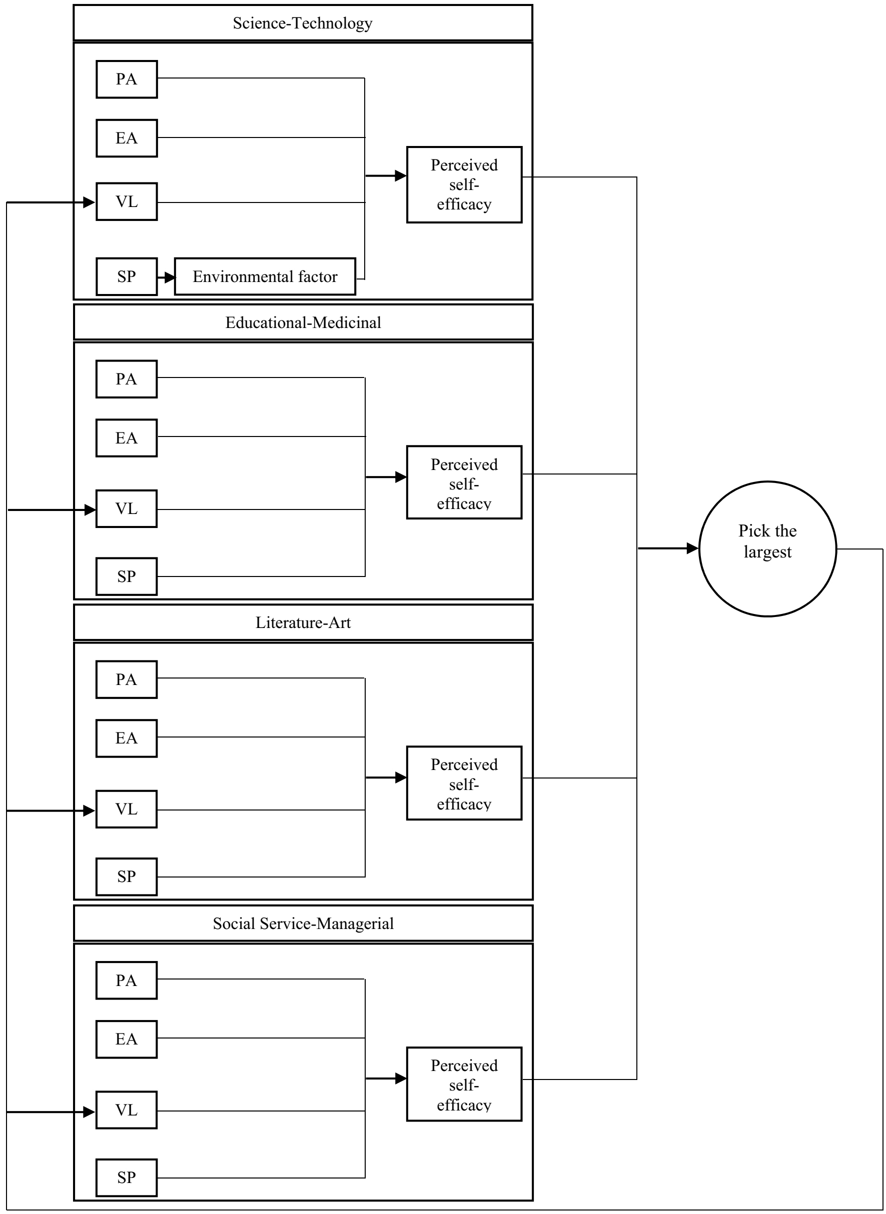


Fig. 3 The model

than one category. Each of the four categories has its own four sources of information, as stated in the literature review, and they are *performance achievements* (PA), *emotional arousal* (EA), *vicarious learning* (VL), and finally *social persuasion* (SP). This way, for example, an individual might be encouraged by her friends, parents, or teachers to pursue certain occupations, while being discouraged from pursuing other occupations. In addition, this same individual can have positive experiences about performing certain types of tasks, but not other tasks. Table 1 displays the variables that are included in the model, together with how the initial values are set.

The model starts with these four sources of information in each category. At each step, the program randomly assigns a number between zero and one to each of the 16 sources of information. The assignment of each number is independent of the assignment of other numbers. The *Perceived Self-Efficacy* in each category is then calculated as the sum of the four numbers associated with each of the four sources of information. Therefore, *Perceived Self-Efficacy* has a minimum value of zero and a maximum value of four.[1] Finally, the individual will pick the category in which he or she has the highest perceived self-efficacy.

The decision is then fed back into the model. Specifically, it is fed back into the *vicarious learning* source in each of the four categories. The reason for this is that the model takes into account the percentage of each gender in each of the categories. If the percent of males in a certain category is high, then this will act as "positive" information about the category for males, but not for females. This, however, does not mean that all agents have the same value for vicarious learning because the initial value, like the other three sources, is random. While it is true that all females might be exposed to the same percentage of males in engineering, it might be the case that a certain female has some successful female engineers in her family for example, while this might not be the case for other females. This is more clearly illustrated in the next section, which describes in a step-by-step approach what happens in each step of the program.

Looking at Fig. 3, it can be seen that the occupational category Science-Technology is different from the rest. Specifically, there is an *environmental factor* element. As already discussed in the literature review, a lot has been written about the underrepresentation of women in STEM fields. SCT has been employed to better understand gender-role development (Bussey and Bandura 1999). Since the assignment of values so far has been completely random, the *environmental factor* element was introduced to model the effect that the environment has on females in discouraging them from pursuing STEM-related occupations, while encouraging males to do so (Jacobs et al. 2005; Tenenbaum and Leaper 2003). Unlike all other values, the value of the *environmental factor* is not random. The program was run a number of times (described in detail below), each time varying the value of the *environmental factor*

[1] The 16 sources of information were modeled using a random uniform distribution instead of a random normal distribution because what is being modeled is not a characteristic of an individual. Instead, it is the characteristic of information that is received by an individual. The normal distribution would assume that the nature of the information will most likely be neutral (somewhere around the mean). Conceptually, this assumption is too restrictive. By using the random uniform distribution, the model assigns equal probabilities to all types of information. Self-efficacy, which is a characteristic of the individual, is calculated by adding the four sources of information. The sum of random variables that have a uniform distribution has an Irwin-Hall distribution, which converges to the normal distribution as the number of uniform variables being added increases. Therefore, by modeling the sources of information using a random uniform distribution, the simulation allows for any type of information with equal probability, while at the same time allowing for a normal distribution for self-efficacy.

Table 1 Variables included in the model

Variable	Meaning	Value
pa-science	Value of performance accomplishment in science-technology	Initially set using a random uniform distribution between zero and one
ea-science	Value of emotional arousal in science-technology	Initially set using a random uniform distribution between zero and one
vl-science	Value of vicarious learning in science-technology	Initially set using a random uniform distribution between zero and one
sp-science	Value of social persuasion in science-technology	Initially set using a random uniform distribution between zero and one
Efficacy-science	Self-efficacy in science-technology	Sum of the four sources of information in science-technology
pa-medicine	Value of performance accomplishment in educational-medical	Initially set using a random uniform distribution between zero and one
ea-medicine	Value of emotional arousal in educational-medical	Initially set using a random uniform distribution between zero and one
vl-medicine	Value of vicarious learning in educational-medical	Initially set using a random uniform distribution between zero and one
sp-medicine	Value of social persuasion in educational-medical	Initially set using a random uniform distribution between zero and one
Efficacy-medicine	Self-efficacy in educational-medical	Sum of the four sources of information in educational-medical
pa-literary	Value of performance accomplishment in literature	Initially set using a random uniform distribution between zero and one
ea-literary	Value of emotional arousal in literature	Initially set using a random uniform distribution between zero and one
vl-literary	Value of vicarious learning in literature	Initially set using a random uniform distribution between zero and one
sp-literary	Value of social persuasion in literature	Initially set using a random uniform distribution between zero and one
Efficacy-literary	Self-efficacy in literature	Sum of the four sources of information in literature
pa-social	Value of performance accomplishment in social services	Initially set using a random uniform distribution between zero and one
ea-social	Value of emotional arousal in social services	Initially set using a random uniform distribution between zero and one
vl-social	Value of vicarious learning in social services	Initially set using a random uniform distribution between zero and one
sp-social	Value of social persuasion in social services	Initially set using a random uniform distribution between zero and one
Efficacy-social	Self-efficacy in social services	Sum of the four sources of information in social services
Environmental-factor	The effect that the environment has on females in discouraging them from pursuing STEM-related occupations, while encouraging males to do so	Percentage with values that range from zero to 100

in order to investigate its effect on the results. It is important to note that the variable *environmental factor* affects only *social persuasion* in the *Science-Technology* occupational category. Parents, peers, and teachers are an important source of social persuasion information (Schunk et al. 2002). Therefore, the model aims at measuring the magnitude of encouragement/discouragement that would result in the significant underrepresentation of women in Science-Technology.

4.2 The program

Figure 4 presents an outline of the core code. Once the program is initialized, the only objects that are created are four nodes where each node represents one of the four occupational categories. When the program is executed, it goes through 700 steps.[2] In each step, two things happen. First, a new agent is created where the values of the sixteen sources of information are randomly assigned. The agent is assigned 16 different values between zero and one for each of the four sources of information in each of the four categories. The agent is then added to the pool of agents already existing in the program. The efficacy for each field is calculated as the sum of the four sources of information that correspond to that field. Once this agent has been added, all of the agents are asked to "update" their decision, which is the second thing that happens in the execution. Since the model utilizes a reciprocal causation interaction between the different sources of information, a choice is made randomly to determine which source will affect the other three in the current step. If the value of that chosen source is greater than or equal to 0.5, then the effect will be positive, i.e., the value of each of the other three sources is incremented by 0.1. Otherwise, the effect is negative, and the value of each of the other three sources is decreased by 0.1. If the chosen source is social persuasion, then the program factors in the effect of the environmental factor. For females, there is a decrease, while for males there is an increase. If the chosen source is vicarious learning, then the program factors in the current ratio of individuals of the same sex in the current field. After the values of the sources of information are updated, the values of the efficacies are also updated accordingly. Finally, the agent picks the occupational category in which he or she has the highest efficacy.

In what follows, a detailed step-by-step explanation is presented:

1. Create a new agent and assign 16 random numbers between zero and one inclusive to each of the sources of information.
2. Add the new agent to the pool of existing agents.

[2] In order to make sure that the system had reached a steady state by the time that 700 agents were created, a test run was executed where the percent of female agents in the science category was calculated at each step. This way, the percent change in this variable was calculated by finding the magnitude of the change in this variable in two consecutive runs. This was simulated 100 times, and the average over all runs of this variable was calculated. The magnitude of the averages of the percent changes in the first five steps were 100, 22.22, 17.91, 24.75, and 17.93. The magnitude of the averages of the percent changes in the last five steps were 0.91, 0.04, 0.274, 1.07, and 0.36. This clearly illustrates that the system had reached a steady state by the time that 700 agents had been created.

Setup:

1. Create four nodes that represent the four fields

Execution: Repeat 700 times

1. Create new agent:
   a. Create a node that represents the agent
   b. Randomly assign a gender to the agent
   c. Using a random uniform distribution between zero and one, set each of the sixteen sources of efficacy
   d. Calculate the four efficacies by adding the four sources for each occupational category

$$efficacy = pa + ea + vl + sp$$

2. Update self-efficacy for all currently created agents:
   a. For each efficacy:
      i. Randomly pick one of the four sources of efficacy
      ii. If the chosen source is social persuasion (sp), incorporate the environmental factor according to the gender of the agents
      $$\frac{d(sp)}{dt}\begin{cases} +(environmental\ factor), & male \\ -(environmental\ factor), & female \end{cases}$$
      iii. If the chosen source is vicarious learning (vl), incorporate the gender composition of the agents in the occupational category
      $$\frac{d(vl)}{dt}\begin{cases} +0.1, & ratio\ of\ same\ sex\ in\ major \geq 0.5 \\ -0.1, & ratio\ of\ same\ sex\ in\ major < 0.5 \end{cases}$$
      iv. Use value of chosen source to update the other three sources
      $$\frac{d(other\ sources)}{dt}\begin{cases} +0.1, & chosen\ source \geq 0.5 \\ -0.1, & chosen\ source < 0.5 \end{cases}$$
      v. Update the value of the efficacy to the sum of the four sources of information
      $$efficacy = pa + ea + vl + sp$$
3. For each agents, find the occupational category with the largest efficacy and attach the agents to that occupational category

Fig. 4 Code outline

3. Figure 1 summarized Bandura's triadic reciprocal causation model. In order to model this, and to allow behavior factors, personal factors, and environmental factors to influence one another, the agent generates a random integer between

zero and three. If the number is zero, the *performance achievements* (which is a behavioral component) will influence the other three sources. If the number is one, then *emotional arousal* (which is a personal component) will influence the other three sources. If the number is two, then *vicarious learning* (which is an environmental component) will influence the other three sources. Finally, if the number is three, then *social persuasion* (which is also environmental) will influence the other three sources. By "influence" I mean that if the source generates positive information about the category, then this positivity will spill over to the other sources. If, on the other hand, the source is generating negative information, then this will affect the remaining sources negatively. Since the determination of the source that is going to affect the other sources is completely random, and since each individual goes through this process at each step (since their introduction into the system until step number 700 when the program is terminated), the causation effect is triadic with each source affecting the others. This logic is implemented in the following way. For each occupational category, do the following:

a. Generate a random integer between, and including, zero and three.
b. If random integer equals zero, set *performance achievements* as the *anchor source.*

   Else-if random integer equals one, set *emotional arousal* as the *anchor source.*

   Else-if random integer equals two, set *vicarious learning* as the *anchor source.*

   Else-if random integer equals three, set *social persuasion* as the *anchor source.*
c. If the anchor source is *vicarious learning*, Calculate the percent of males and females "attached" to the category. If at least half of the agents in an occupational category are males, for example, then this information will have a positive effect on vicarious learning since male agents will observe other male agents attaching themselves to this category. If the percent is less than half, then this will decrease the value of vicarious learning:

   i. If the percent of male agents attached to the category ≥ 0.5, add 0.1 to the category-specific vicarious learning of all male agents.

      If the new value of vicarious learning for any male agent is now greater than one, set it to one (the maximum value of each source is one).
   ii. Else-if the percent of male agents attached to the category < 0.5, subtract 0.1 from the category-specific vicarious learning of all male agents.

      If the new value of vicarious learning for any male agent is less than zero, set it to zero (the minimum value of each source is zero).
   iii. Repeat (i) and (ii) for females

d. If the anchor source is *social persuasion,* the program incorporates the effect of the element environmental factors. As described above, this element represents the potential discouragement that females might be subjected to and the encouragement that males might receive, and it is modeled as a percentage. The higher the value, the more females are steered away from Science-Technology, and the more males are encouraged to pursue the same category. This is accomplished using the following logic:

i. Ask all male agents to increase their social persuasion value by the percent value of the environmental factor.
   If the new value of any of the sources is greater than one, set it to one (the maximum value of each source is one).
ii. Ask all female agents to decrease their social persuasion value by the percent value of the environmental factor.
   If the new value of any of the sources is less than zero, set it to zero (the minimum value of each source is zero).

e. Now I model the triadic interaction by allowing the *anchor source* to influence the other three sources:

i. If *anchor source* ≥ 0.5: add 0.1 to all other sources.
   If the new value of any of the sources is greater than one, set it to one (the maximum value of each source is one).
ii. Else-if *anchor source* < 0.5, subtract 0.1 from all other sources.
   If the new value of any of the sources is less than zero, set it to zero (the minimum value of each source is zero).

4. Now that the values of each source of information in each category have been updated, each agent calculates the new value of their perceived self-efficacy:

   a. Set perceived self-efficacy of each category to be equal to the sum of the four sources of information.

5. Finally, each agent "attaches" him- or herself to the category in which he or she has the highest perceived self-efficacy. The model allows agents to change their decision from step to step. An agent originally attached to one category, before the current step, might find that now, after updating his perceived self-efficacies, he has a better occupational choice. Therefore, the model takes into consideration the "persistence" outcome, which is illustrated in Fig. 2. The model also includes the "approach vs. avoidance" outcome, since the agent will avoid the category in which he has a very low perceived self-efficacy.

4.3 Simulations

The above model and program were implemented in Netlogo (Wilensky 1999), the most widely used agent-based modeling language. Figure 5 shows the user interface. There are four clusters of nodes in the figure. At the center of each cluster is a yellow node that represents an occupational category. The nodes connected to this central node are the agents, with blue nodes representing male agents and red nodes representing female agents.

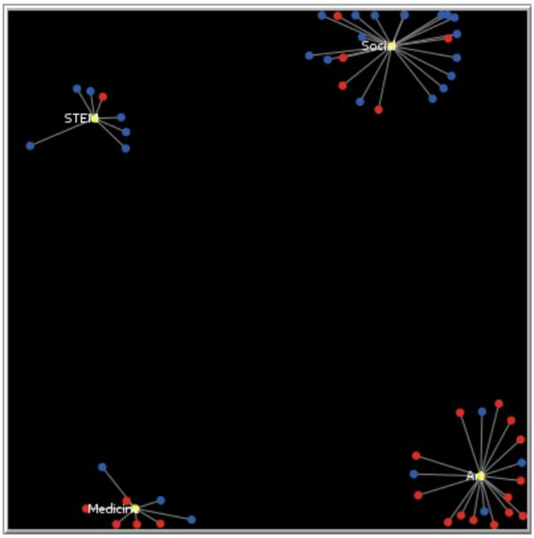


Fig. 5 The output screen

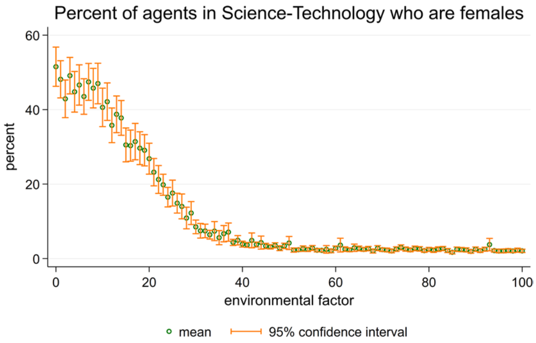
Each simulation run consisted of 700 steps. This means that each run was allowed to go on until 700 agents were created. The agent-creation process was random in that the model does not create 350 male and 350 female agents. Each gender had an equal probability of being created as the other. The first agent created remains in the system the entire run of the program, while newer agents spend less time. This way, the model allowed for more "experienced" agents. Each time the program ran a full simulation run, the following variables were collected:

- The value of the variable *environmental factor*.
- Percent of agents in each of the four occupational categories who were female.
- Percent of agents in each of the four occupational categories who were male.
- The initial value of each of the sixteen sources of information. These are the values that were assigned to each agent at the moment of his or her creation.
- The final value of each of the sixteen sources of information when the simulation run has ended.

As stated above, the variable environmental factor can take any value from zero to 100 inclusive. In the first run, the value was set to zero and subsequently increased by one. In the final run, its value was 100. Therefore, *environmental factors* took 101 different values.

The program ran 72 times for each value of the variable. Due to the randomness of the model, it is important not to rely on a single run, since events with a low probability can, and do, take place. The choice of the number of runs for each variable value is one of the most important considerations in developing agent-based models (Lee et al. 2015). Secchi and Seri (2017) have cautioned against using models that are underpowered and even models that are over-powered. To avoid the problems associated with each of these models, this study used the equation proposed by them

Fig. 6 Percent of agents in Science-Technology who are females



in order to calculate the optimal number of runs for each combination of values. Using a value of 0.1 for effect size, the corresponding number of runs turned out to be 72. This means that the entire program was run $101 \times 72 = 7272$ times. Since each value was run 72 times, it was possible to average the values of the returned variables and to create a confidence interval for each of the values.

The simulation ran for around 14 h on an Intel Core i5—2400 CPU @3.10 GHz. The output file contained 7272 records, each record pertaining to one full run.

4.4 Output

4.4.1 Females in Science-Technology

The first step in the output analysis is to look at the outcome variable of interest, the percent of agents associated with the Science-Technology occupational category who are females, and the variable that the program systematically varied, the *environmental factor*. Figure 6 displays the means and 95% confidence intervals. As expected, the larger the value of the *environmental factor*, the smaller the percentage of females. A value in the range of 10–20 for *environmental factor* results in a percent in the range of 40 to 26. Figure 6 also shows that the decrease is exponential with a much faster rate of decrease for small values of *environmental factor*. At a value of 30% for environmental factors, the percentage drops to below 10% and keeps decreasing.

The next step is to take a closer look at the *Science-Technology* occupational category. More specifically, it would be instructive to look at the characteristics of the agents that ended up in these categories. Figure 7 shows two graphs. These graphs show the values of *performance achievements*, *emotional arousal*, *vicarious learning*, and *social persuasion* for the females who end up in the category. The graph on top shows the initial values at the moment when the agent was created, and the graph on the bottom shows the final values when the simulation ended. All of these values are averages. It can be seen that initially, females needed to start with above the average (more than 0.5) values for each of the four sources when the variable *environmental factor* was close to zero. It can also be seen that by the end of the simulation, the values all increase to almost the maximum. This is due to the

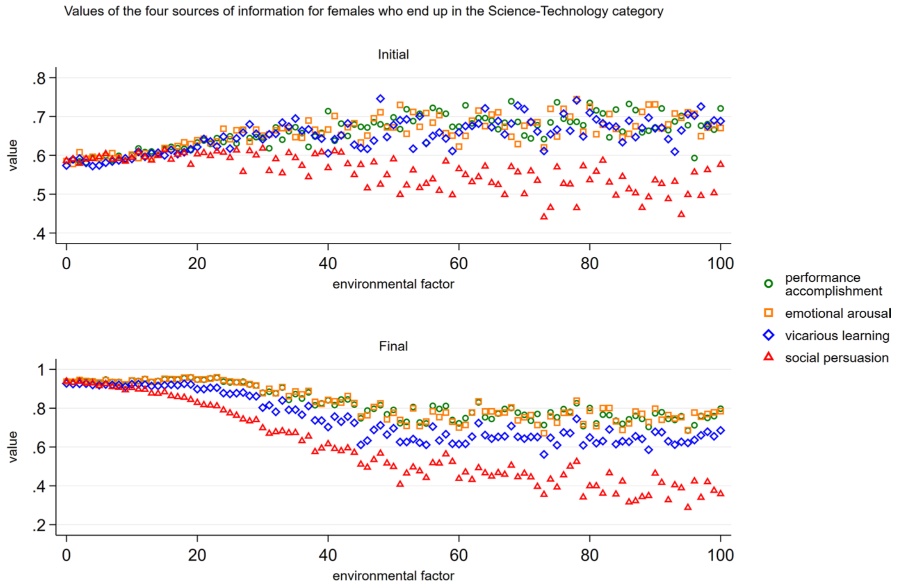


Fig. 7 Values of the four sources of information for females who endup in the Science-Technology category

reciprocal causation where each source feeds off the large value of the other sources. As the value of the environmental factor increases, females will have to start with higher values of the sources in order to offset the negative effect of the environment around them. This is true for all sources except *social persuasion*. For high values of environmental factor, the mean value of social persuasion for females that end up in the Science-Technology category is 0.5, which is the average for all agents, since the number was generated by a random-uniform distribution. Therefore, the more discriminating the environmental factors are, the less important their role becomes, and the smaller their effect, as can be seen from Fig. 6 above. It is important to note that the values in the top graph are initial values. This means that this is the randomly assigned value before the variable *environmental factor* comes into play. Finally, the bottom graph in Fig. 7 shows that the final value of *social persuasion* is slightly below 0.5, unlike the other sources.

Another point to note about Fig. 7 can be observed from the bottom figure, and it is that the value of *vicarious learning* is high (around 0.6) even when the variable *environmental factor* is large. Figure 3 shows that vicarious learning depends on the percent of same-sex agents in a certain occupation category. Figure 6 shows that the percent of agents in Science-Technology is very low when the value of *environmental factor* is high. Yet the bottom graph in Fig. 7 shows that the final value of *vicarious learning* for females in this category is high. How can that be? Female agents that end up in Science-Technology manage to maintain a high value of the variable despite the very small number of female agents in this occupational category. This emergent property of the model is a result of the triadic model that postulates that "People can exert some influence over their life course by their selection

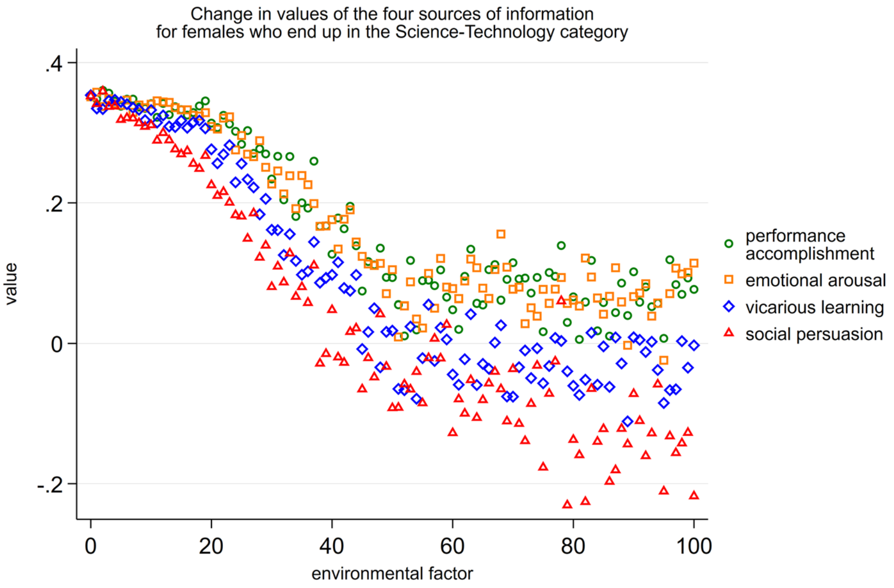


Fig. 8 Change in values of the four sources of information for females who end up in the Science-Technology category

of environments and construction of environments" (Bandura 1989, p. 1178). The model succeeds in modeling how "people construct their own career outcomes" (Lent et al. 2002, p. 255).

To visualize the power of the selection processes as illustrated in the model, Fig. 8 was produced. The figure shows the difference between the final mean and the initial mean of each of the four sources. Although the percentage of agents in Science-Technology who are females is less than 20 when the variable environmental factors is between 20 and 40, we see that the females who ended up in this category managed to increase the values of all four sources, since the difference which is represented in the graph is above the zero value. Even when the variable environmental factor is extremely high (greater than 70), the final values of *performance achievement* and *emotional arousal* are greater than the initial values, and this is what drives the females into this occupational choice. The model used does not differentiate between how *performance achievement* and *emotional arousal* are calculated, but it is important to note that the literature indicates that out of the four sources of information, performance achievement in the most potent (Lent et al. 2002). Therefore, even in a highly discriminatory environment (negative *social persuasion* and a very low percent of females agents in Science-Technology), a very small number of females manage to increase their personal factors and behavioral patterns while exercising some control over their environment. Hence, the model predicts that *performance achievement* becomes even more important with increasing discouragement.

With regard to females who end up in the other three categories, Fig. 9 shows their means of the initial values of the four sources of information regarding the

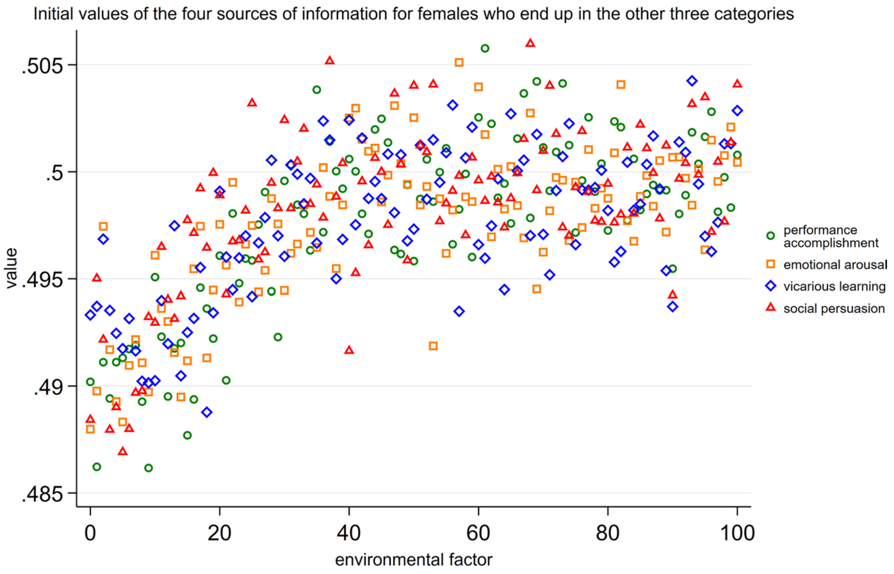


Fig. 9 Initial values of the four sources of information for females who end up in the other three categories

Science-Technology efficacy. The figure shows that the larger the value of *environmental factor*, the larger the initial values of the four sources of information. This increase in the means is due to the fact that females who start with higher values of the sources with regards to their efficacy in Science-Technology would end up picking another occupational category. Thus, the model also successfully simulates how women who might be mathematically capable end up choosing non-mathematics fields (Ceci et al. 2009).

4.4.2 Math anxiety

As noted in the literature review, females report a higher level of math anxiety, even when their grades do not differ from their male counterparts. Figure 10 shows the change (final minus the initial) in the value of *emotional arousal* for both males and females with differing levels of *environmental factor*. We can see that both males and females who end up in Science-Technology occupational roles manage to increase their emotional arousal, but females are less able to do so as *environmental factors* increases. Note that this figure shows that even when there is a discouragement for females, those that end up in the Science-Technology category still manage to increase the value of *emotional arousal*, but not as much as males, thus leading them to eventually have lower values. Therefore the model also succeeds in simulating the development of mathematical anxiety in females relative to males.

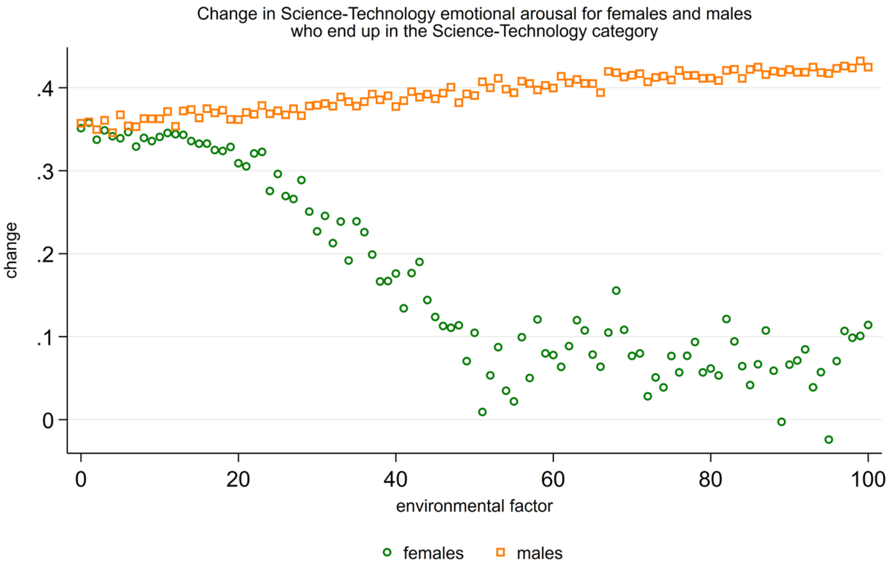


Fig. 10 Change in Science-Technology emotional arousal for females and males who end up in the Science-Technology category

4.4.3 Female discouragement vs. male encouragement

The simulation output in Fig. 6 shows how a small value of *environmental factor* can result in a large number of females avoiding Science-Technology occupations. This decrease is a result of environmental factors encouraging males while discouraging females at the same time. This raises the question as to whether the misrepresentation of females in Science-Technology occupational roles is due to the discouragement of females or whether it is due to the encouragement of males, which would lead to a decrease in the percent of female agents associating themselves with this particular occupational category. To test this, the model was run two more times, where in the first run the model only increased the value of *social persuasion* for males, without decreasing it for females, while in the second run the model decreased the value of *social persuasion* for females, without increasing it for males.

Figure 11 plots the percent of agents in Science-Technology in all three models for the sake of comparison. The output clearly shows that discouraging females is mostly responsible for the drop in their percent in Science-Technology. In fact, a comparison between the figures that were produced using the model that only included female discouragement and the figures that were produced using the model that included both male encouragement and female discouragement revealed that both sets of graphs were almost identical. Therefore, the simulation indicates that according to Bandura's model, self-efficacy depends not on what goes on with "other groups" of people, but what is happening with people who are similar to the individual. Indeed, in his paper, Bandura (1982, p. 126) describes vicarious experiences (or learning) as "Seeing similar others perform successfully..." In addition,

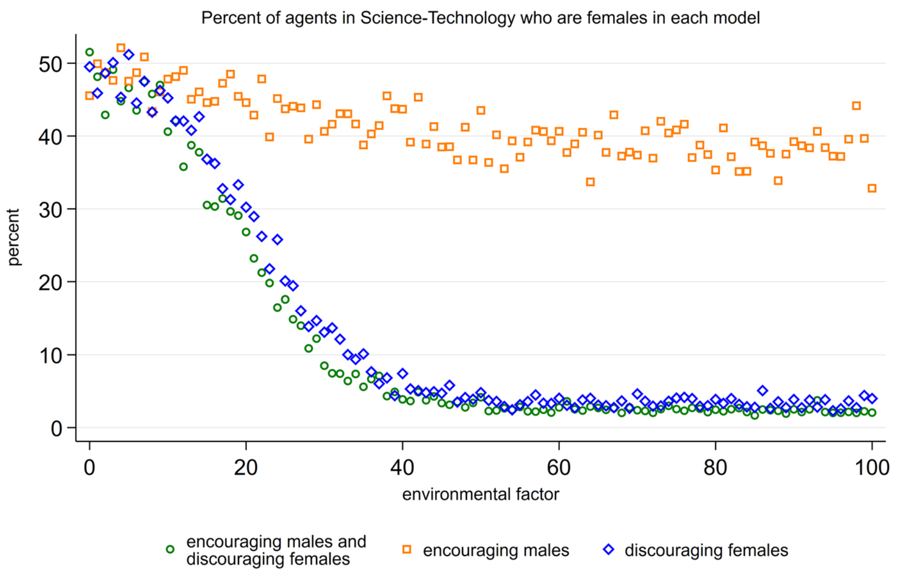


Fig. 11 Percent of agents in Science-Technology who are females in each model

Bussey and Bandura (1984) report that when children were exposed to male and female models, they modeled their behavior after the same-sex models. These findings are supported by the agent-based model simulation.

5 Discussion

ABMs are appropriate tools for studying processes that lack central coordination (Macy and Willer 2002). Career choices are such processes. ABMs allow researchers to convert theories into falsifiable hypotheses and to experiment with the theories by controlling certain elements of the theory while varying other elements (Conte and Paolucci 2014). This paper proposed and tested a computational model that follows Bandura's triadic causation interaction model. Bandura's model postulates that individuals base their choices on their perceived self-efficacy and that this efficacy is an emergent property from the interaction of personal factors, behavioral patterns, and the environment.

Before making sense of the implications of these results, it was necessary to test whether the proposed model mimics that which is being modeled, which in this case is social cognitive theory. The above results clearly show that the model successfully simulates several of the theorized aspects of social cognitive theory. Specifically, the output shows how math anxiety develops in females despite the fact that they might be performing well on the subject. The output also shows how a small number of females manage to exercise some control over their environment, thereby modeling how these females construct their own career outcomes (Lent et al. 2002, p. 255). The simulation results also support the notion that *performance achievement* is the most important source of information (Bandura 1989). Finally, the model also successfully simulates how women who might be mathematically capable end up choosing non-mathematics fields. All of the above findings support the use of the proposed model in simulating social cognitive theory.

Using ABM simulation, this study was able to study the characteristics of females who choose to enroll in Science-Technology occupation roles while varying the degree of social support that is received by these females. The results indicate that even a small amount of discouragement, such as a reduction of 10% in environmental support, can lead to considerable female misrepresentation. This is one of two main contributions of the simulation results. Research in educational psychology has uncovered that the expectations that parents have for their children differ according to gender (Tenenbaum and Leaper 2003). This line of research found that these gendered differences are large and significant (Bleeker and Jacobs 2004), even in developed countries (OECD 2015). The simulation results obtained in this study reveal that even small gendered differences can lead to female misrepresentation in certain fields. This means that to solve the problem of misrepresentation, gendered differences in environmental support need to be eliminated and not just reduced.

The second main contribution of this study relates to investigating the effect that female discouragement has as opposed to male encouragement. One of the many advantages of simulations is that they allow us to create "what-if" scenarios by controlling certain aspects of the environment. In this study, three different scenarios were tested. In the first, males were encouraged while females were discouraged. In the second, males were encouraged but females were not discouraged. Finally, in the last model, females were discouraged but the males were not encouraged. The results show that career choices are affected more by similar others rather than different others, again lending support to SCT. This finding has important implications for researchers as well as policymakers because it supports the notion that the solution to the misrepresentation of females in science and technology fields lies in focusing on females in and of themselves as opposed to focusing on how females are treated relative to males. The simulation results indicate that misrepresentation is not caused by relative differences between the two genders. Instead, it is caused by actively discouraging girls from entering such fields. The majority of research in social cognitive theory has concentrated on gender differences (Fouad et al. 2010). The result obtained here indicates that researchers would do well instead to concentrate on female discouragement in and of itself (Fouad et al. 2017, 2016). Possible solutions might include attracting women to science as well as supporting those already in science (Cronin and Roger 1999).

The simulation also showed how agency could be "grown" (Epstein 1999). The output clearly shows how, even under considerable social discouragement, a small proportion of the female population manages to maintain high levels of efficacy through selection processes, thus lending computational support to SCT. These selection processes allow agents to interact and to activate certain parts of the potential environment (Bussey and Bandura 1999). Social cognitive theory theorizes that self-efficacy is an emerges from the triadic reciprocal causation interaction between personal factors, behavioral patterns, and environmental events (Bussey and Bandura 1999). While many different aspects of social cognitive theory have been empirically supported (Fouad and Santana 2017; Lent et al. 1987, 2007), research has yet to shed light on how exactly does self-efficacy emerge from the aforementioned triadic interaction. The simulation results presented in this study provide computational support for this aspect of social cognitive theory.

6 Limitations and directions for future research

Like most studies, this study is not without its limitations. The primary limitation is that all models are "inherently incomplete depictions of the empirical world" (Wiseman and Gomez-Mejia 1998, p. 149). This is due to the fact that at some level, a decision has to be made about the level of complexity that should be included in agent-based models. As a result, a number of simplifications were made in the model used in this study. One such limitation is that the effect of time was not incorporated into the model. Research in educational psychology has found that gender differences in occupational choices develop overtime (Mozahem et al. 2018), and that the information received from the four sources of self-efficacy is mediated by the gender of children over time (Mozahem et al. 2020). These results support social roles theories that argue that males and females undergo different socialization processes and that these processes develop over time. As such, future research would do well to develop the model used in this study by incorporating the effect that time has on the development of self-efficacy.

A second limitation of the model is that vicarious experiences have been solely represented by the percentage of similar others in a similar field. Once again, this is a simplification because research has also found that females might choose to enter a certain field because a significant individual in her life is part of that field (Mozahem et al. 2019). In other words, not all similar individuals have a similar effect on the focal individual. As such, future modifications of the model might use a weighted function in order to account for the differing effects that some individuals may have on the focal person.

A third and final limitation of the model used is that the model only allows for varying the environmental component. Given that the main purpose of this study was to investigate the effect that this component had, the decision to limit the model in this aspect makes sense. However, future modifications of the model would be beneficial for both researchers and policymakers if they allowed for the varying of other components. For example, counseling might be used in order to decrease the math anxiety that is felt by the majority of females. In addition, the model can also be developed to allow for training programs that might affect performance accomplishments. It would be interesting to investigate whether the introduction of these elements would offset the effect of environmental sources such as social persuasion, and if so, to what extent.

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Compliance with ethical standards

Conflict of interest The author certifies that that he has no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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