Decoding the STEM Gender Gap: Understanding the Factors at Play

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1 Introduction

In recent years, **women's under-representation** in science, technology, engineering and math (**STEM**) fields has gained widespread attention in public, academic and policy circles. Beyond being a barrier to the equality and justice of our society, this marginalization is becoming problematic from a **strategic** point of view too: many of the world's most pressing challenges require interdisciplinary solutions rooted in STEM, to which women would bring new perspectives and approaches.

To help address this increased demand, widespread efforts have encouraged women participation in STEM fields (e.g. the *Girls Who Code* organization); although notable, such efforts would be bolstered by an awareness of the backgrounds, characteristics and personality traits of students who choose these paths to begin with.

A wealth of research has demonstrated that student **background characteristics** shape men and women's plans to enroll in STEM majors, although in different ways and amounts: in this project, some of these factors are applied to model the dynamics of a **population** of female and male individuals interacting, studying, being influenced by their environment and finally choosing whether to pursue a STEM career or not.

The main goal is exploiting simulated data to understand the **interplay** between these factors, and possibly bring new **insights** to light.

2 Model

Given the need to gather insights into the impact of the individual's environment in his or her decisions, an **agent-based** modeling was chosen. In particular, each agent represents a person with the following attributes.

- A **gender** (female or male). In the initial population, we assume it to be assigned with a uniform (0.5) probability.

- A **binary** value associated to each of the **BIG Five**[3] **personality traits**. The Big Five, also known as the Five Factor Model (FFM) or the OCEAN model, is a widely recognized framework in the field of psychology for understanding personality traits. It categorizes personality into five broad dimensions.

  - **Openness**, reflecting an individual's openness, curiosity and willingness to explore new ideas and experiences.
  - **Conscientiousness**, referring to the degree of organization, responsibility and self-discipline an individual possesses.
  - **Extraversion**, i.e. the extent to which a person is outgoing, energetic and socially oriented.
  - **Agreeableness**, or an individual's tendency to be compassionate, cooperative and considerate of others.
  - **Neuroticism**: also known as *emotional stability*, this trait refers to the extent of emotional instability or reactivity an individual experiences.

  Despite the traits being defined as a continuum in the original model, in our simplification they are binarized to 1 if the corresponding trait is more present than not (e.g. an agent will have *neuroticism* property set to 1 if emotionally unstable, 0 if emotionally stable).

  The attribution of traits to the initial population was chosen to reflect real world one. For what concerns openness and conscientiousness, each individual has a uniform (0.5) probability to be assigned to the trait or not. Since extraversion appears to be more common than introversion [7], a probability of 0.6 was fixed. Finally – provided that women tend to score higher than men on neuroticism and agreeableness [5] – female agents were set a probability of 0.6 of having these two traits, as opposed to male 0.5.

- A **maximum number** of closed friends, sampled from a **Poisson** distribution of $\lambda = 5$ if the agent is extrovert, of $\lambda = 3$ if he or she is introvert.

- A **math score**, which starts at 0 and is developed during the simulation.

- An **interest**, which can be *Art*, *Social* or *Science*.

  The interest is initially assigned based on **personality traits**. If the agent has the **conscientiousness** trait, a goal-oriented attitude is assumed to guide him/her to the *science* interest. On the other hand, **agreeableness** is assumed to indicate a *social* interest and finally **openness** to favour an interest in *art*. If the agent possesses more than one of these traits, the interest is sampled from a uniform distribution of the corresponding ones. If he or she does not possess any of the traits, it is again a uniform distribution, but on all possible interests.

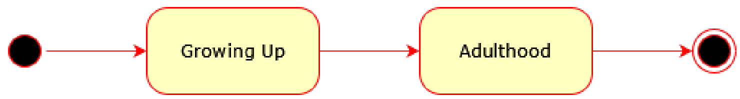


Figure 1: Statechart representing the two main states of the agent during simulation.

- A boolean value indicating whether the individual has chosen a **STEM career**, always false at the beginning.
- A boolean value defining whether the person has a **parent** with a STEM career, always false in the first generation of agents.
- A number indicating the **generation** the agent belongs to, starting at 1.

While some attributes stay fixed, many of them can change during the course of the simulation, as the agent passes through the states shown in Figure 1.

During the **growing up** phase, the agent attends **school**, **socializes** and exchanges **interests** with his/her connections.

During **adulthood**, he or she chooses a **career** and a long-term **partner** with whom eventually **reproducing**.

The passage time from first to second state is given in years and sampled from a *Discrete Uniform Distribution* in the range $(10, 13)$, i.e. from the mandatory school years to the end of italian high school.

In this context, it is important to notice that – by considering only these two phases – this model could be understimating childhood and parental influence, reducing it to personality and the presence of a STEM career in the family.

The two states are articulated in more complex substates having their own transitions, which are described in the following sections.

Growing Up

Figure 2 shows the substates of *growing up*.

The initial state is the **learning** one, during which agents eventually increment their **math score**. Specifically, the score is increased each time the agent enters the *learning state*, with a starting probability p of 0.2, incremented by

- 0.2 if the agent has the *conscientiousness* trait, reflecting higher diligence and responsability;
- 0.2 if the agent is interested in *science*.

The probability p is decremented by 0.2 if the agent possesses the *neuroticism* trait: this condition is aimed at highlighting the importance of *self efficacy* – defined as *the belief in one's capabilities to organize and execute the courses of action required to produce given attainments* [1] – in the developement of math abilities [11]. In turn, increasing math abilities tends to improve *self-efficacy*, in a way that is – however – different for women and men: at the same levels

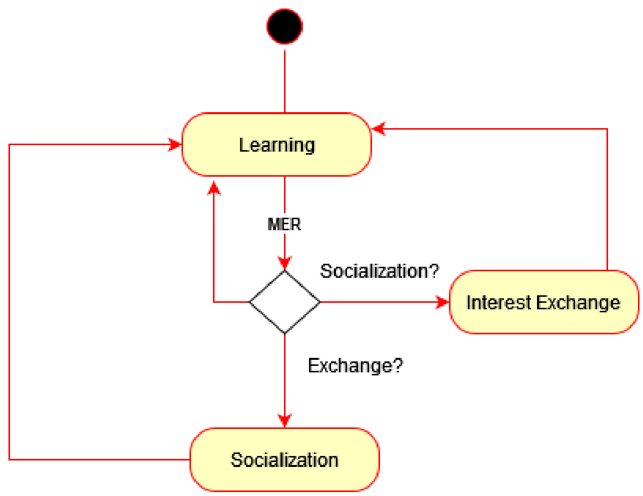


Figure 2: Statechart representing the internal working of the *Growing Up* substates.

of observed ability, girls' mathematics ability beliefs under challenge have been found markedly lower than those of boys [8]. To reflect this process, assuming a relative small impact of math score on *neuroticism* as a whole – the *neuroticism* trait has a probability of 0.01 for women and of 0.04 for men to be set to 0 if the math score is increased.

After a time – expressed in months – that depends on a *Month Exchange Rate* parameter (MER in Figure 2) the agent can switch to one of the two other states, i.e. *interest exchange* and *socialization*.

In the **socialization** state – entered with a probability of 0.6 by extraverted agents and of 0.3 by introverted ones – the agent reaches another random agent, which has a certain probability p of becoming one of his or her closed friends. More precisely, $p = 0.2$ if the two agents have the same gender, and $p = 0.1$ otherwise; this difference is introduced to reflect the gender bias in selecting friends during adolescence [2], which may create echo chambers from the interests point of view. If the friend is accepted but the agent's maximum number of friends is reached, he or she is disconnected from a random friend to be able to add the new one.

When the *socialization* state is not reached, the **interest exchange** state is activated with a probability of 0.1 for extroverts and 0.2 for introverts: during this state, the agent sends a message (containing his or her interest) to a random connected agent. If an agent receives this message while he/she is in the *learning* state, with a probability of 0.03 the original interest is substituted in favour of the received one.

At the end of one of these two states – or if none is activated – the agent gets back to the *learning* state.

In all the *growing up* substates, the agent is under the influence of the **media** agent, possessing the following attributes.

- A **media bias**, intended as a value between 0 and 1 that, if higher than 0.5, favours men interest in science and otherwise women's.
- A **media influence**, i.e. a value between 0 and 1 indicating the percentage of population which is assumed to receive the message.

Once a year – value chosen to counter-balance the broadcast power – the media agent sends messages encouraging the *science* or *social* interest in an audience that depends on its influence and bias. More precisely, the **audience dimension (AD)** is sampled from a Binomial distribution of parameters

$$n = \frac{\text{population size}}{2},$$

$$p = \text{media influence}.$$

Thus – given $AD \sim \mathrm{Binomial(n, p)}$ – the male gender is selected with a probability corresponding to **media bias** for receiving *AD science* messages; the other gender receives *AD social* messages. This way, according to the *media bias*, one gender has a higher probability to be directed towards *science* than the other. This dynamic was lately introduced in the model to emphasize the importance of **role models**, which has been identified as one of the most impactful propagators of gender bias in STEM [10].

Adulthood

Figure 3 shows the internal work of the *adulthood* state.

The first phase is the **career choice**: this is the central component of our simulation, when the agent decides whether pursuing a STEM career or not.

Similarly to what happens with the math score increment, the probability p of choosing a STEM career starts at 0.2 and can be incremented by

- a value between 0 and 1 depending on the *math score influence* parameter, if the agent's math score is higher than the average math score obtained by the population after education;
- a value between 0 and 1 depending on the *science influence* parameter, if the agent is interested in science;
- a value between 0 and 1 depending on the *family influence*, if at least one of the two parents has a career in STEM (it has been shown [9] that this factor plays a role in the decision to pursue a STEM major).

The probability p can also be decremented by

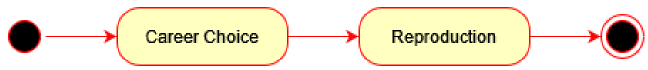


Figure 3: Statechart representing the internal working of the *Adulthood* substates.

- a value between 0 and 1 depending on the *social influence* parameter, if the agent is interested in *social* (literature has documented the negative effect of social activist orientations on students' STEM-related decisions, especially among women [4]. In [9], decomposition analysis showed women's relatively stronger social activist orientation serving as one of the key explanations for the gender gap in computing);
- a value between 0 and 1 depending on the *art influence* parameter, if the agent is interested in *art*;
- a value between 0 and 1 depending on the *neuroticism influence*, if the agent has the *neuroticism* trait.

Once the career is chosen, after a time in years sampled from a Uniform Discrete Distribution in the range $(1, 5)$, the agent chooses a random **partner** of the opposite sex he or she is already connected to and the **reproduction** phase starts. Each couple generates a **number of children** that is sampled from a Poisson distibution of $\lambda = 2$: to-be-generated children are handled with a queue system that contemplates a delay in months computed as

$$\max(9,\ d),$$

with $d \sim \text{Normal}(21,\ 3)$.

The assignment of personality traits from second generation on follows a slightly different procedure than the first generation, since it considers the possible inheritance of personality traits [6]. In a rough simplification, the inheritance is modeled as follows.

- For each trait, the agent has a 0.2 probability of inheriting it. If the trait is inherited, the mother's or father's one is taken with uniform probability; if it is not, the assignment works as for the first generation (so gender and population differences are kept).
- The generation is incremented by one with respect to parents'.
- If at least one of the parents has a career in STEM, the children's **family in STEM** attribute is set to 1.

After the reproduction phase, both parents are removed from the population and children reach the *growing up* state.

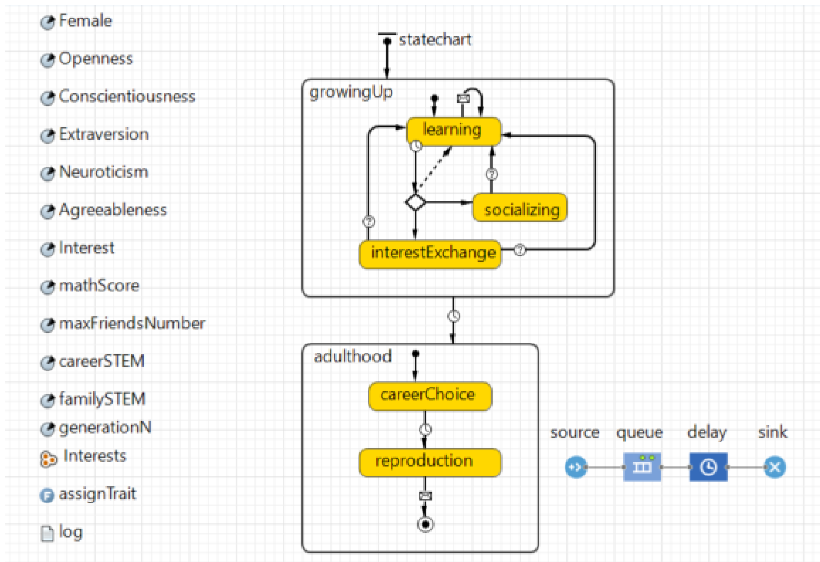


Figure 4: States of the `Person` agent in AnyLogic.

3 Implementation

The implementation of the model was performed using the AnyLogic Simuation Software [12]. The software – and in particular the `Agent Palette`, containg agent-based modelling components – provided an intuitive interface and the necessary tools to directly translate the model for active simulation.

The dynamic of **state transitions** follows the rules described above: the logic of the `Person` agent can be seen in Figure 4.

Agents' **parameters** are expressed in form of **boolean values** for what concerns all personality traits, `familySTEM` and `careerSTEM`. `Interests` are coded as a shared collection of strings from which the string `interest` parameter is selected, while `mathScore` and `maxFriendsNumber` are defined as integers.

Personality traits, `mathScore` and `familySTEM` are initialized at agent creation, while `maxFriendsNumber` and `interests` are assigned at the beginning of the `growingUp` state to guarantee proper attribution in generations following the first. In this context, exploiting the `Standard agent contacts network`, each agent is initially connected to its neighbors, included in a distance range of 40; this represents a first network which is later expanded in the `socializing` state.

Agents communicate between each other by sending messages to other random connected agents; actions characterizing the states are performed as coded entry actions at state entrance. The `media` agent – whose simpler logic is displayed in Figure 5 – sends messages to people in the `learning` state when reaching the `broadcast state`, triggered at the rate defined before.

At the moment of the partner choice in the `reproduction` state, a new

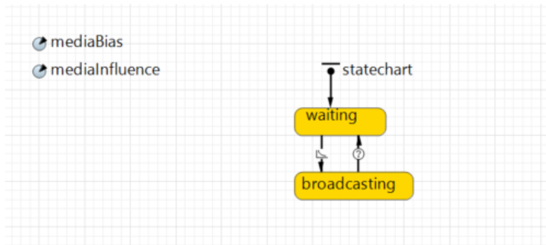


Figure 5: States of the `Person` agent in AnyLogic.

one-to-one connection called `partner` is activated.

In the `reproduction` state, a coordination with the `Process modelling library` makes it possible to model the queuing of to-be-generated children: specifically, each of the children is injected in the `queue` shown in Figure 4 and enters it through the `source` component; the delay is modeled by the `delay` component of capacity 1 and, once completed, the new agent is created after entering the `sink`, where eventually inherited traits are assigned. The process is further synchronized to the `Person` agent by the sending of a message indicating that all the elements in the queue have been processed – message that also triggers the transition to the final state.

The overall **interface** of the simulation can be seen is Figure 6. Here the first bar chart from left – updated month by month in simulation time – shows the number of agents by **interest**. The three pie charts show, respectively, the percentage of people choosing **STEM** against not choosing it, the **gender gap** and the percentage of people from each **generation** at the given moment. The last bar chart shows the frequency of different **personality traits**.

At the top, simulation **parameters** can be customized and direct effect can be visualized both on the charts and on the agents' representation below.

The simulation starts with an initial population of **500 agents** and ends when the **fourth generation** is reached, i.e. stops the analyisis at the third one.

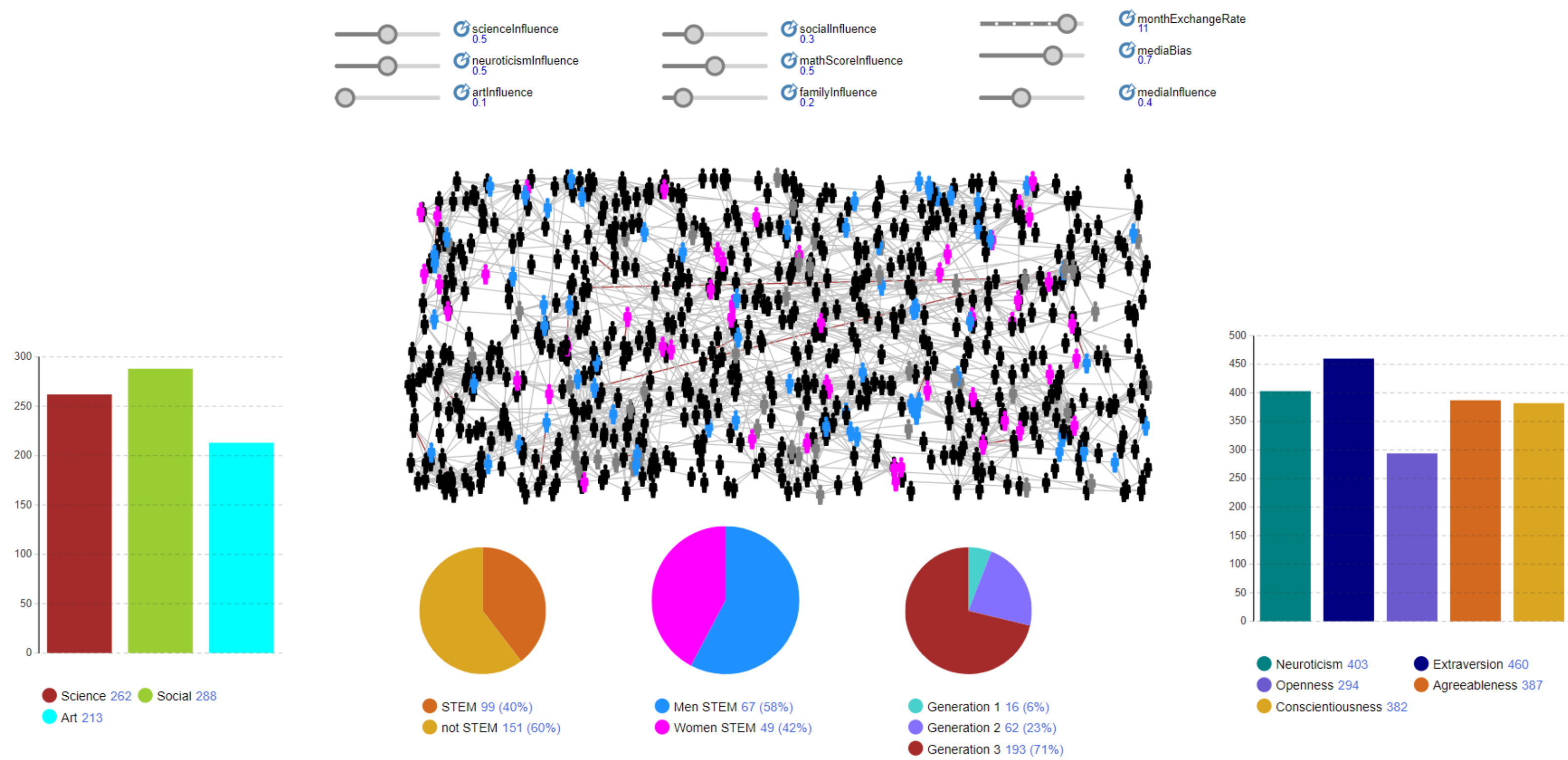


Figure 6: Model interface.

4 Experimental analysis

For experimental analysis, AnyLogic **parameter variation** function was exploited. This function makes it possible to automatically run the model multiple times with different combinations of parameters, to assess the effects of parameters change.

More specifically, the following values of parameters were tried, running 20 simulations for each combination:

- `socialInfluence`: 0.1, 0.4, 0.7;
- `mathScoreInfluence`: 0.1, 0.4, 0.7;
- `neuroticismInfluence`: 0.1, 0.4, 0.7;
- `monthExchangeRate`: 6, 9, 12;
- `mediaBias`: 0.5, 0.7, 0.9.

The other parameters (`artInfluence`, `familyInfluence`, `scienceInflence` and `mediaInfluence`) were kept fixed at 0.1, 0.2, 0.2 and 0.4 respectively.

The subset of varation parameters was chosen for two main reasons.

1. Literature has identified them as the most **significant** in motivating both gender gap and the decision to pursue a STEM major in general.

2. Those are the parameters on which it appears more **realistic** to intervene: while it seems hard to think of changing women's personality biases, it looks more doable to revise the image STEM majors give, for example highlighting their applications in social matters, or encouraging female role models and confidence in math abilities.

The main metric chosen to evaluate the system was the actual **gender gap**, i.e. the percentage of women choosing a career in STEM with respect to all agents that end up pursuing it. Given the presence of stochastic variables, we consider the mean percentage obtained in each iteration (i.e. a combination of parameters), computed over all the 20 replications.

The average percentage across all simulations is 45%, which is higher than expected, but can count as a baseline in which no specific reason to choose a STEM career is selected. The starting gap is likely due to gender personality differences and to the fact that we are considering media bias going from 0.5 to 0.9, meaning media is unbiased (0.5), biased (0.7) or strongly biased (0.9) in favour of men in all simulations.

Table 1 shows the mean percentage of women choosing STEM careers, when again computing the mean of simulation runs having the specified value for the parameter of interest.

Table 2, on the other hand, contains the correlations between the parameters of interest and the percentage of women choosing a STEM career.

The parameter showing the highest correlation – in absolute terms – is `mediaBias`: broadcasting the social and science iterests, it strongly influences which agents are going to be interested in the latter. As we can visualize from Figure 7a, science interest rates start similar for men and women and linearly increase and decrease respectively as `mediaBias` progresses. This has a big impact on the gender gap, since agents interested in social aspects are penalized twice in STEM career choice: because they are not interested in science, and because they are interested in social matters themselves. This dynamic is linked to the negative correlation with `socialInfluence`, which is milder because the larger diffusion of the *agreeableness* trait makes social interest prevalent among men too.

The other parameter controlling diffusion – namely the `monthExchangeRate`, i.e. the rate in months at which socialization and interest exchange happen among agents – shows a weak positive correlation instead, meaning that women STEM percentage weakly increases as social exchange decreases. Figure 7b shows the progress in terms of number of people interested in science as social exchange becomes more rare: we can see that – for both genders – the metric is decreasing. This trend is due to a collateral factor: by reducing social exchange we are also minimizing socialization, a key component leading to partner choice and reproduction, thus reducing population in general. The mild correlation with gender gap might be caused by the fact that in the model women are more likely to form bounds and exchange interests with other women: in a context of high media bias, encouraging social exchange might act as an echo chamber.

Interestingly enough – although the average math score reached by women is lower than men's (3.57 against 3.90) – `mathScoreInfluence` shows a positive correlation with women STEM percentage. This can be explained in terms of interaction with other factors: when high, the math score influence mitigates the effect of other more polarized properties, such as the imbalance in science interest and neuroticism. The variance of average math score among women and men across simulations is in fact 0.91 and 1 respectively, making it easier to convey `mathScoreInfluence` in favour of women, expecially when considering that the influence is applied when agent's math score is higher than average. Additionally, the math score increase is favoured by the *conscientiousness* trait, which is not polarized between men and women.

The `neuroticismInfluence`, on the other hand, has the second highest absolute correlation with women STEM percentage, this time negative: the average number of women having the *neuroticism* trait across simulations is 409 (as opposed to men's 356); this difference is due to initial personality traits in the population, only mitigated by trait inheritance and – with a very low probability – math score increase.

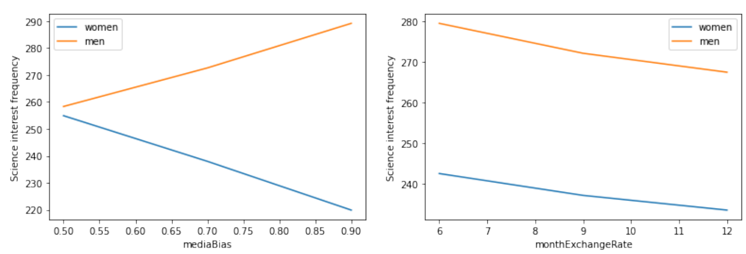
Although systematic, this analysis has the limitation of putting together many combinations of parameters that are counterbalancing themselves. Also looking at Table 1, we can notice that single factors are having a marginal impact on the overall gap, while it also seems important to address the measurable differences obtained when specific combinations of parameters are set. This analysis cannot be exhaustive by nature, and is demanded to the pecu-

socialInfluence	0.1	47%
	0.4	45%
	0.7	45%
mathScoreInfluence	0.1	45%
	0.4	46%
	0.7	47%
neuroticismInfluence	0.1	47%
	0.4	46%
	0.7	45%
monthExchangeRate	6	45%
	9	46%
	12	46%
mediaBias	0.5	47%
	0.7	46%
	0.9	44%

Table 1: Percentage of women in STEM based on selected parameters.

	Correlation
`socialInfluence`	-0.31
`mathScoreInfluence`	0.37
`neuroticismInfluence`	-0.42
`monthExchangeRate`	0.15
`mediaBias`	0.61

Table 2: Correlation between parameters and the percentage of women choosing STEM careers.



(a) `mediaBias` (b) `monthExchangeRate`

Figure 7: Science interest freqency in men and women as `mediaBias` and `monthExchangeRate` increase.

liar interests for which simulation data is analyzed. We here experiment four scenarios:

1. **First scenario**: we assume a high `neuroticismInfluence` (0.7) and the

highest `mediaBias` (0.9). Keeping all other parameters variable, the average women STEM percentage across simulations results to be 43%.

2. **Second scenario**: if we keep the parameters as they are in the first scenario, but fix a low bias in not choosing STEM careers if interested in social aspects, the percentage grows to 45% even when keeping media hugely biased in favour of men.

3. **Third scenario**: in the context of the second scenario, fixing a `monthExchangeRate` of 6 – thus encouraging a high social exchange – reduces the women percentage to 44%.

4. **Fourth scenario**: starting from the third scenario, lowering the media bias to 0.7 and not fixing a high `neuroticismInfluence` increases women STEM percentage to 46%.

Conclusions

We conclude that – in modeling the STEM gender gap – a complex interplay of factors must be considered. Personality differences are having an impact that can most strongly be mitigated by media influence, due to their broadcasting power. Furthermore, when media and culture are hugely biased, social exchange can become a double edged sword.

A necessity of finding ways to lower women's lack of confidence in their computing and math abilities emerged. The low impact of school in increasing it – modeled as the low probability (even lower for women) of setting the *neuroticism* trait to zero – ended up being the second most important factor propagating the STEM gender gap.

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