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Practicing Theory Building in a Many Modelers Hackathon: A Proof of Concept

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Scientific theories reflect some of humanity's greatest epistemic achievements. The best theories motivate us to search for discoveries, guide us towards successful interventions, and help us to explain and organize knowledge. Such theories require a high degree of specificity, which in turn requires formal modeling. Yet, in psychological science, many theories are not precise and psychological scientists often lack the technical skills to formally specify existing theories. This problem raises the question: How can we promote formal theory development in psychology, where there are many content experts but few modelers? In this paper, we discuss one strategy for addressing this issue: a *Many Modelers approach*. *Many Modelers* consists of mixed teams of modelers and non-modelers that collaborate to create a formal theory of a phenomenon. Here, we report a proof of concept of this approach, which we piloted as a three-hour hackathon at the Society for the Improvement of Psychological Science conference in 2021. After surveying the participants, results suggest that (a) psychologists who have never developed a formal model can become (more) excited about formal modeling and theorizing; (b) a division of labor in formal theorizing is possible where only one or a few team members possess the prerequisite modeling expertise; and (c) first working prototypes of a theoretical model can be created in a short period of time. These results show some promise for the many modelers approach as a team science tool for theory development.

Keywords: modeling, formal theory, theory development, hackathon, team science, education

Introduction

> *Scientific theories are our most important epistemic achievements. Our knowledge of individual pieces of information is little compared to theories such as general relativity and evolution by natural selection that shape our understanding of many different kinds of phenomena.*
> Thagard (1988, p. 33)

> *There is nothing as practical as a good theory.*
> Lewin (1943, p. 118)

Theories are among science's crowning achievements (Thagard, 1988). Theories motivate us to search for discoveries, guide us towards successful interventions, and help us to explain and organize knowledge (Borsboom, 2013). Mature theories are specific on what should or should not happen under various conditions. This specificity makes it possible to link theoretical propositions (e.g., how mass curves space) to empirical consequences (e.g., the bending of starlight that passes our sun). Results from experiments that are in line with theories do not mean that these theories perfectly predict all real-world consequences. Instead, success means that the links between inputs and consequences are clear and observable. Thus, it is not surprising that mature, successful theories are expressible in mathematical terms (e.g., general relativity, population dynamics). Mathematics, and also computational rules, enable a high degree of precision and help to overcome the ambiguity of natural language. Many successful theories are captured in *formal models*[1] that take environmental circumstances as inputs and provide outputs which, as empirical consequences, can be observed and tested (e.g., the pressure P exerted by a gas given a certain volume V, temperature T, universal gas constant R, and mass of the gas n according to the ideal gas law $PV = nRT$).

Currently, in psychological science, there is a dearth of mature, precisely-specified theories (e.g., Borsboom et al., 2021; van Rooij and Baggio, 2021). Typically, psychological theories are narrative natural-language descriptions based on implicit assumptions about nature Fried, 2020; Robinaugh et al., 2021. Their lack of specificity allows one to derive a broad range of potentially contradictory predictions. For instance, Harris (1976) demonstrated that cognitive dissonance theory as described by Brehm and Cohen (1963)could be formalized such that three conflicting consequences could be derived, two of which contradicted Brehm and Cohen's expected predictions (see Appendix A).

Given their scientific value, many scientists have argued for the need to formalize theories in psychology (e.g., Fried, 2020; Robinaugh et al., 2021). However, psychologists currently face substantial challenges in developing more formal theories. One challenge is that developing formal models of theories requires considerable effort and resources.

In the development of psychological theories, there is often a gap between verbal theories and formalized models. This gap may contribute to the lack of reproducibility in psychological research (van Rooij & Baggio, 2021). Verbal theories describe phenomena in words but often lack the precision and clarity of formal models, which can be tested and validated empirically. In contrast, formal theories are mathematically explicit, allowing for predictions to be made, which can be compared to data. However, formalizing theories requires technical skills (e.g., programming, differential calculus)[2]. This raises a key question: How can theories become more formalized in a field where there are many content experts but few modelers?

In this paper, we provide one answer to this question using a *Many Modelers* approach. In Many Modelers, mixed teams of modelers and non-modelers are tasked to create a formal theory from verbal theory to explain a phenomenon. Here we report a proof of concept[3]. We show that the participating psychologists that have never developed a formal model before can (a) become excited about formal modeling and theorizing through hacking; (b) a division of labor in formal theorizing could be possible where only one or a few team members possess the prerequisite modeling expertise; and that (c) first working prototypes of a formal model of a theory can be created in a short period of time. In what follows, we describe the setup of the hackathon, the modeling results and experiences, and a reflection on the outcomes of the hackathon. This paper is concluded with a discussion of the results, critical reflection, and some speculations for further investigation.

The Many Modelers Approach

In Many Modelers approach, several teams of scientists work to formalize the same theory. Teams are given a verbal theory to formalize and a phenomenon that the theory should explain. Teams are asked to develop a model that (a) incorporates the principles or

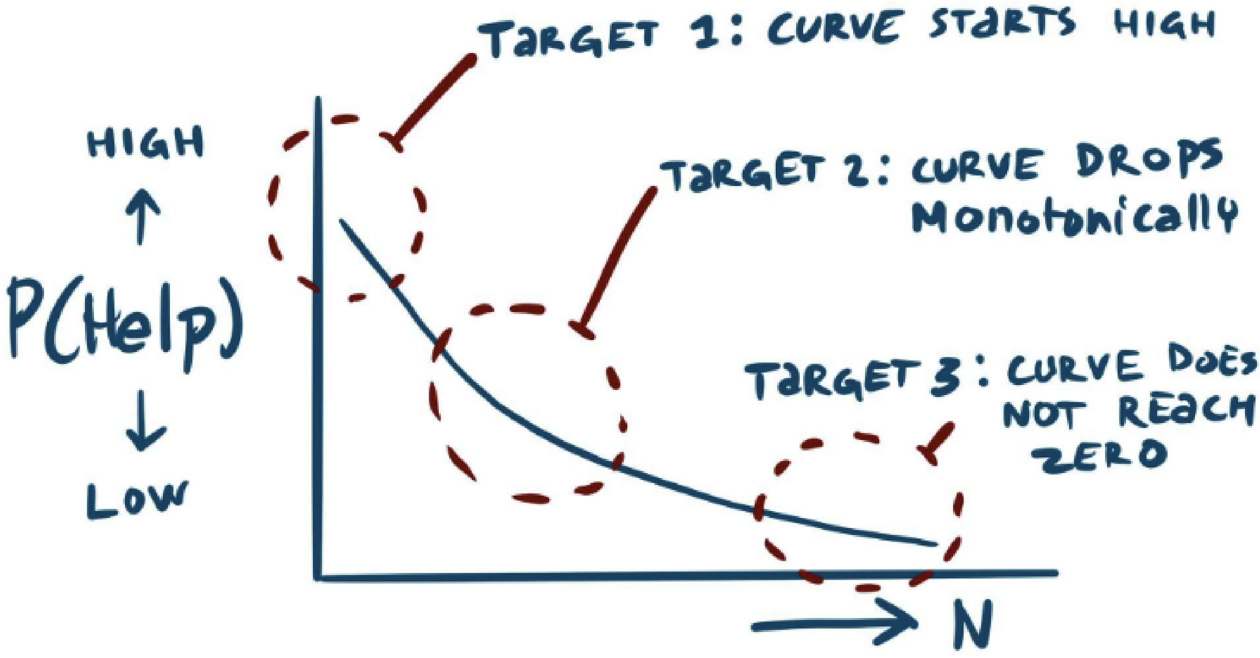
[1] *With a formal model we mean an abstracted and/or idealized representation (e.g., of the solar system) that consists of mathematical equations or computational rules. Please note that we do not equate formal models with theories.*

[2] In which many psychologists lack training (e.g., Robinaugh et al., 2021)

[3] The results and experiences of a three-hour hackathon hosted at SIPS 2021 conference (Society for the Improvement of Psychological Science, 2021).

Figure 1

The data pattern representing The Bystander Effect phenomenon and the three relevant components (targets) of this pattern.



mechanisms expressed in the theory and (b) can produce data (e.g., through simulation) that resembles the phenomenon to be explained. We developed this approach based on the Theory Construction Methodology (TCM; Borsboom et al., 2021) and *productive explanation* (van Dongen et al., 2022). In the TCM, empirical phenomena (e.g., the placebo effect) are interpreted by data patterns (e.g., a distribution), which are explained by a theory (i.e., a set of conjectures about nature). That is, in a world where the theory is true, these phenomena would be expected to exist (for further details, see Borsboom et al., 2021). Productive explanation further clarifies whether a theory explains a given phenomenon. A theory *explains* a phenomenon when a formal model (an expression of the theory) produces the data pattern that represents the phenomenon (see van van Dongen et al., 2022).

Developing formal models that bridge theory and data was the focus of the Many Modelers hackathon. Teams were provided with a verbal theory and a phenomenon that was purported to be explained by the theory. Teams then had to develop a model that incorporated all conjectures and mechanisms and that could qualitatively resemble the patterns of the provided phenomena. Our project was an empirical attempt to evaluate whether teams of scientists, most without relevant modeling experience, could formalize psychological theories.

This approach used tools that utilize programming and calculus skills, but offers its use for universal and is flexible for various scientific analysis. Programming data generating models and modeling dynamical systems was attempted to be embedded within empirical sciences.

Preparation

The setup of the project consisted of the theory material, a description of the phenomenon, and a user manual. A week before the event, we published the user manual (Appendix B) and verbal theory (Box 1) on an OSF project dedicated to this hackathon (https://osf.io/9pdbJ/). The phenomenon was made available to the participants at the start of the hackathon.

We chose the bystander effect as the phenomenon to be explained, as it is a well-known psychological phenomenon for which many verbal theories exist (Fischer et al., 2011). We provided a short description of the phenomenon (see Box 1) and a visualization of the data pattern representing the phenomenon. The visualization indicated the phenomenon's three relevant components (see Figure 1). The participants' goal was to qualitatively reproduce the provided graph that included all three components (modeling targets). The only constraint was that their model must embody the components of the theory that were provided. Box 2 described the provided theory, extracted from *The unresponsive bystander: Why doesn't he help?* by Latané and Darley (1970).

Box 1. The phenomenon and modeling targets given to the modelers.

The bystander effect
The bystander effect is the social-psychological phenomenon wherein individuals are less likely to help a victim when there are a larger number of other people present. This phenomenon to be produced by your model can be separated into three components or targets:

1. Without other people present, the tendency (probability or frequency) that a person helps a victim is high.
2. The tendency of helping decreases monotonically with the number of other people (bystanders) present.
3. The tendency of helping a victim never drops to 0.

Setup of the Hackathon

At the start of the hackathon, we briefly introduced the Many Modelers hackathon, TCM, and productive explanation. We then provided the participants with the phenomenon to be explained. We then assigned participants to teams, and teams were given two and a half hours to complete their model. After the allowed time, we reconvened and discussed the results and experiences of the teams.

The Modelers

The hackathon took place online at the SIPS 2021 conference on Friday 25 June 2021. Participants were given the option to register in advance if interested. In total, 36 people participated. Because mathematical and computational modeling requires substantial expertise, we ensured that each team contained at least one person with modeling experience. We took an inventory of the participants with modeling experience at the start of the hackathon and allocated a person with modeling experience to each team.[4] All other participants were randomly and evenly distributed. In total, we had six teams with six members. One team included two modelers; all the other teams included one modeler.

Output

The main intended output of the hackathon was one formal model per modeling team. Teams had 150 minutes to complete their model. Because we expected this time to be insufficient for all teams to develop and code a model, we provided teams with a description and example of pseudocode (Appendix C) and recommended teams to start programming their model after they created sufficient pseudocode. We instructed participants to focus on developing a pseudocode implementation of their model due to time constraints.

After 150 minutes, all teams completed a pseudocode version of their model. Furthermore, two teams completed the additional step of translating the model into actual code so that it reproduced the bystander effect data pattern. We also asked teams to keep a logbook during the hackathon and report their modeling experience afterwards. Below, we provide a summary of the methods and the descriptions of the teams' modeling experience. The teams' descriptions of their models can be found in Appendix D. Logbooks and code can be found in the online supplementary materials at https://osf.io/9pdbJ/. [5]

[4] Modeling expertise was defined as "having previously been the lead on a project where the aim was to build a computational or mathematical model of behavior, cognition, or culture (i.e., if your only modeling expertise is with statistical models, for this hackathon, this would not qualify as sufficient modeling expertise)."

[5] We did not verify modeling expertise beyond a single self-assessment question concerning fit with the definition of modeling expertise. After the hackathon was concluded, participants were asked to evaluate their modeling expertise on Dreyfus and Dreyfus (1986) expertise scale. All participants that signed up as modelers self-identified as competent, proficient, or expert; all non-modelers self-identified as novice or advanced beginner.

Box 2. The verbal theory of group helping behavior

Group influence on (helping) behavior
We, humans, are social beings and have a tendency to help others that appear to need assistance. Furthermore, we also perform tasks for which we feel responsible without an immediate personal payoff. For instance, we may throw trash in a bin while taking a stroll or put an article of clothing back on its original rack when we decide not to buy it.
Such helping behaviors are common but not without exceptions. Latané and Darley (1970) identified three psychological processes that they hypothesize to affect helping behavior:

1. **Diffusion of responsibility.** This refers to the reduction in felt responsibility when other people are present and/or also working on the same task. The more people around, the less personal responsibility individuals will feel.

2. **Evaluation apprehension.** This refers to the fear of being judged by others when acting publicly. In other words, individuals fear making mistakes or having others judge their actions as inadequate. This fear makes people more reluctant to take action in critical situations.

3. **Pluralistic ignorance.** This occurs when a group of individuals remains trapped in supporting a norm, belief or behavior that no or only a few group-members privately support. This state is upheld because everyone acts in support of the norm, belief or behavior due to the false belief that everyone else supports the norm, belief or behavior; when in fact, (almost) no one does.

Models summary

Of the six teams, four created pseudocode of their model, while the remaining two (Teams 4 and 6) even programmed their model in R (R Core Team, 2021). The models programmed in R produced patterns similar to Figure 1 when data was simulated from them. We can consider these two models working prototypes, because data can be simulated from these models and the pattern that these data show resembles, qualitatively, the data pattern that represents the bystander effect phenomenon. Apart from Team 4, all teams attempted to incorporate the psychological processes that comprised the given theory (see Box 1). In addition to modeling the psychological processes, some teams included extra elements in their model. Team 1 added components to capture social norms, particularities of the situation, and people's beliefs. Team 3 added a parameter to indicate the gravity of the situation, components to account for individual differences, and a variable for people's assessment of the seriousness of the situation. Team 5 added components to incorporate people's predisposition towards helping others. Team 6 added an additional empirical finding as an extra constraint.

Various approaches were used to formalize the verbal theory (Box 1). Teams 1 and 5 used acyclic causal diagrams, where the verbal theory's psychological processes act on each other to cause the bystander effect (see Figures D1 and D5 in Appendix D). Team 2 envisioned the psychological processes as linear functions of the people present (which are supposed to combine to produce the phenomenon). Team 4 opted against modeling the psychological processes in a way that is representative of mechanisms with people, opting to specify the effect of bystanders on the psychological processes as exponential functions (e.g., felt responsibility to help $= 1/n^x$, for $x > 0$) and the probability of helping as a quotient of these functions. Similarly, Team 6 modeled the psychological processes as logistic and exponential functions that in combination produced the phenomenon. Team 3 modeled the theory as an exit control loop that began with a victim's initial need for help, with the need for help increasing with every run of the loop and terminating when a person's assessment of the situation reached a certain threshold. For further details, see Appendix D or the online supplementary materials at https://osf.io/9pdbJ/.

Modeling experiences

The workshop provided many unique experiences and lessons learned. Each team was given a chance to express their experience in their own words. The next subsections were written by the members of the team in question, and, apart from some minor edits, are expressed in their own words.

Team 1

The modeling experience for our team allowed us to experience the modeling process first-hand. The mixed group (one person with more modeling experience and others with less or no experience) was useful to get a good balance of technical and conceptual work. We, the members of Team 1, tried to come up with mechanistic explanations based on the verbal theory provided.

As none of us had much experience with the R programming language at the beginning of this process, we were hesitant to include more and more nodes, variables, and models in our model. However, we had to keep the desire to include more and fewer nodes and variables in our model in check and instead limited ourselves to a few that seemed especially informative.

Team 2

The majority of group members were modeling beginners; thus, the modeler also posed as a teacher to introduce some considerations necessary to start the process. While we, the members of Team 2, were not able to finalize our model, the whole group experienced the hackathon as a valuable learning experience for how to even approach a modeling project. At first, we considered a variety of model types including an agent-based model with binary outcome (yes/no to help), which we rejected based on the hackathon's aim. We proceeded from a more theoretical perspective, spending most of the time on operationalizing the psychological constructs of the theory and how they would relate to the number of bystanders and the probability to help. Given the limited time, our model could not be finalized during the hackathon; thus, we could not evaluate whether it would produce output matching the description of the phenomenon. Yet, the experience was valuable and enjoyable, taking away some of the fears of modeling we had. However, having some basic foundational knowledge of the modeling process (e.g., general steps and considerations), which most of us were only introduced to here, could have allowed for a more productive session. Finally, combining the thoughts and efforts of the various groups seems to be a fantastic way of making scientific progress collectively.

Team 3

We found that developing the pseudo-code and discussing among team members really helped sharpen our mental picture of how the bystander effect unfolds. This was partially because writing pseudo-code actively enforced certain steps (i.e., first we had to think about the involved parameters, then think through how they change one after the other) and uncovered areas where theoretical precision was lacking. The collaboration throughout our team also allowed us to appreciate how the different teams scaled the degrees of freedom that the verbal theory left us with. As the familiarity with effects from similar phenomena varied throughout our team, we think it would have been helpful if the process had been accompanied with a set of parameters that were a priori defined by an expert. The transition from theoretical work to detailed code, using different programming languages, was instructive as well. It emphasized attention to detail (such as ensuring that the program does not run infinitely) and strengths of each team member in organizing specific branches of the model. Overall, the approach made it clear which concepts needed to be refined, but it also highlights which pieces of information are needed to create robust models, which could guide future empirical studies.

Team 4

We, the members of Team 4, thought that this is an instructive approach to learn about: (a) challenges in modeling by exposing how different assumptions can affect results, (b) identifying relevant variables and their functional interplay, (c) how/if different models place emphasis on different aspects of the phenomenon, and (d) if modelers can reproduce an effect without deep familiarity with the phenomenon. We started with defining the input variables of the model function that are necessary to reproduce the effect. Next, we discussed how to combine those variables in a function to produce the targeted relation between number of bystanders and probability of helping. During this, we faced several challenges. First, the concept of pluralistic ignorance was difficult to define and model. Second, we discussed other factors that seemed likely to have an influence on the effect, but we were not certain how and if we should include them. Finally, as we are not experts on the bystander effect, we did not know how the factors of our model compare in strength. In general, we decided to value simplicity without sacrificing functionality; including as few factors as possible and leaving the weights equal, but potentially flexible as additional free parameters.

Team 5

We thought it was challenging to work on a problem without expert domain-knowledge and with people with different backgrounds and experience in modeling. It took time to come to a shared understanding of the phenomenon and the components, and to decide whether to model an individual or a group. Nonetheless, we came up with pseudo-code for a potential realization of the bystander effect. Many details of the model remain open. We have not specified the functional forms of individual traits or the equation for the probability of helping that includes all individual variables. Our next step would be to read more about the bystander effect and to look for similar, existing models to specify our functions. We realize that our model is extremely simple. For example, it does not assume interactions between bystanders and does not track how behavior within one individual may change with other bystanders joining, leaving, or helping. Despite these limitations, it would be interesting to see to what extent our simple model can reproduce empirically observed patterns of the bystander effect. Ultimately, we believe that modeling psychological phenomena, such as the bystander effect, is a team science task. Ideally, empiricists with domain knowledge and theoreticians with modeling experience would work side-by-side. Theoreticians can push empiricists to be specific about their variables and assumptions. Empiricists can push theoreticians to build a model that is 'complex enough' to learn something valuable about the phenomenon. Such synergies between empiricists and theoreticians could accelerate progress in psychological research.

Team 6

Our team, Team 6, differed in modeling expertise and familiarity with the bystander effect and accompanying theories. No team member had expertise with the bystander effect specifically, and two team members had some mathematical modeling and programming experience. We first discussed the phenomenon and agreed on an interpretation. The bystander effect as a single phenomenon can be modeled with a vast range of different models. To limit the range of possible models, we identified additional relevant phenomena to model (i.e., in addition to the data pattern provided in Fig. 1). However, constructing the model based on a better knowledge of the literature and considering the strength of evidence that supports the existence of the phenomena would have led to more confidence in the final model as an accurate representation of the bystander effect. Regarding the hackathon experience, some of us found it difficult to translate the verbal phenomenon into a testable model, and others found that modeling only one phenomenon (without further constraints) was ineffectual given the large degrees of freedom. Working interactively in a Google doc and a shared screen in Zoom worked well. Parallel working phases during which one member drafted R code, another worked on the visualization of the model, and others worked on the Google doc at the same time also worked well.

Summary of the experiences

The experience reports from our hackathon reveal several messages. Participants with limited technical background enjoyed being part of a modeling group. The hackathon helped these participants to see formal modeling as less intimidating and increased participants' curiosity about rigorous theoretical work. Several teams reported that going through the process of formalizing a verbal theory opened their eyes to the problem of vagueness in existing psychological theories[6]. Many modelers' projects appear to provide a useful teaching tool for first experiences with modeling. See Table 1 for an overview of the lessons learned.

The experience reports also provide clues for how to ensure that first experiences are positive. (a) Reserve time and resources for teams to get to know one another and the material. When team members are unfamiliar with one another, a shared understanding seems lacking. Considerable time is required to interpret concepts and processes in a way that all team members can agree on. Giving groups' time to prepare — via group discussion, reading material, and interaction with content experts — could smoothen the subsequent modeling process. (b) Provide a minimum skeleton appears useful to get teams started. Making pseudo code or a similar product available gives structure and a place to start from. Providing more than one phenomenon to explain (i.e., produce) could constrain the number of modeling choices and could provide additional guidance for the modeling team. There may also be cases where certain components of the verbal theory have been previously specified (i.e., formalized) in other theories[7]. Having a small number of pre-formalized theory components can add to the modeling skeleton that teams can start with. (c) Provide rudimentary modeling knowledge to participants. If time and resources are available, modeling novices could be familiarized with modeling possibilities and the most customary jargon and concepts in a short preparatory lecture or hand-out.

Reflection on the Hackathon

After the hackathon, participants were asked to evaluate the division of labor in the teams and assess their personal change in enthusiasm for formal modeling. Regarding the division of labor, non-modelers responded that, despite the difference in expertise (power imbalance), they experienced the work as collaborative and felt that they could contribute to the model development. This was corroborated by the modelers. It seems that in none of the teams the modeler dominated the team or was considered to take undue credit. Furthermore, participants were asked to rate their change in interest in or enthusiasm for formal modeling on a five-point Likert scale ranging from 1 "it greatly decreased"

[6] We acknowledge that the vagueness in psychological theories is not necessarily caused by a lack of skills or education. It is plausible that publishing and career incentives make it advantageous for researchers to be strategically ambiguous in their formulation of theories, hypotheses, and research goals (Frankenhuis et al., 2022).

[7] Of course, provided that these theories have been extensively and successfully tested.

Table 1

Lessons learned

Lesson	Description of the lesson
Influence of assumptions	Our attempt at modeling exposed how easily different assumptions can influence the output of the model.
Identifying variables and relationships	It was instructive to practice the identification of the relevant variables (e.g., number of bystanders) and their relationships (e.g., linear, u-form, exponential, etc.).
Dependence on subject knowledge	It was instructive to see whether we could reproduce the effect without substantial subject knowledge of the effect.
Team science	Team science, the collaboration of individuals with different expertise and skills, can accelerate scientific progress.
Explanation and understanding	We learned and started to think more about what it means for a theory to explain a phenomenon. Getting hands-on experience with how the epistemological pieces (phenomena, empirical and simulated data, statistical patterns, formal theory, formal model) can fit together improved our understanding of how theories could explain phenomena, made transparent by formal modeling and data simulation.
Expandability	Spelling out the involved variables highlighted areas in which additional factors, such as interindividual differences, could be added to the model.

to 5 "it greatly increased." Of the 22 participants that responded, only three remained unmoved (scored a 3), while everybody else's enthusiasm increased (scored a 4 or 5).

Two additional comments are worth making in terms of the hackathon organization. The first comment concerns how or where to incorporate domain expertise. As stated in Section 2.1, the "bystander effect" phenomenon was selected because we expected it to be well known and an explanatory verbal theory existed. We expected this to reduce the requirement of explicit domain expertise for the modeling teams. In response to our query about possible causes of the reported limited specificity that could be reached with the models, the modeling teams indicated that, though the instructions were clear enough, they had been hampered by the vagueness of the theory. This could be mitigated by having at least one team member with additional domain knowledge to fill in any gaps. Alternatively, such domain knowledge could also be incorporated into the materials provided to the participants (e.g., point (c) above). Both are viable solutions, though we expect that the latter will result in lower diversity between the models that the teams create. Additionally, low levels of domain knowledge in the teams or the material could also be a boon: the creativity of the teams could in such a case be less hampered by conventions and other restrictive ways of thinking about the topic.

The second addition concerns the hackathon's time limit. Only three hours were available for the hackathon. If the results and the modeling experiences are any indication, this is an insufficient amount of time for getting to know your teammates, familiarizing yourself with the material, and adequately formalizing the theory (point (a) above). As a solution, we could emulate the setup of most many-analysts projects and let teams organize and model in their own time. We expect that such an approach would benefit the quality of models that the teams will create. At the same time, if the main goal is to make formal modeling more accessible and increase enthusiasm for it, rather than generating high-quality models, the limited hackathon format may suffice. These goals could be potentially served even better in an in-person rather than online format. Keeping this in mind could be of benefit when designing future many modelers projects and/or conducting further investigation into this approach.

Conclusion

In this paper, we reported our Many Modelers hackathon hosted at the SIPS 2021 conference. If better scientific theories through formal modeling can help to improve psychological science then more psychologists need to have the skills to develop such formal theories. Our proof of concept suggests that (a) a Many Modelers approach can be useful for getting psychologists enthusiastic about formalizing theories and interested in acquiring modeling skills; (b) first attempts at such theoretical models can be developed in a relatively short period of time; and (c) it is possible for teams of psychologists to develop formal models of theories even if not all team members possess modeling expertise.

One long standing challenge in building formal models of psychological theories is that psychological science degree programs (from undergraduate to graduate school) do not typically include training in theoretical modeling. This stands in contrast to training in statistical modeling, which is well-integrated into many programs across all fields of psychology. Given burgeoning interest in formal theoretical modeling (e.g., Fried, 2020; Guest and Martin, 2021), we believe that a variety of creative approaches are needed to address this gap.

As a proof of concept, this report provides modest evidence for the utility of a team-based approach for developing formal models, while also raising important questions. If more psychologists become enthusiastic about theoretical modeling and interested in acquiring modeling skills, how should this training unfold? What specific skills are needed for psychological scientists to feel confident in formal modeling? Should education in psychological science be adjusted to provide a more rigorous mathematical and programming background to facilitate modeling work? How should this be accomplished (e.g., additional undergraduate mathematics course requirements, elective graduate school options, summer workshop programs)? Such shifts, though potentially difficult to implement, could represent a new direction for the field of psychological science, and could help psychologists to produce strong, specific, testable theories for pressing problems, ranging from cognitive processes to social dynamics, psychopathology, and beyond.

To moderate our optimism, we want to add some critical reflection and speculation. Firstly, as one of our reviewers noted, an obstacle on the road toward formal psychological theories could be our limited ability for proper, precise, and/or direct measurement. For instance, the theory we used contained the components “diffusion of responsibility”, “evaluation apprehension”, and “pluralistic ignorance.” None of these have a fixed definition, operationalization, or measurement procedure. However, this does not have to be a barrier that prevents fruitful theorizing. Precise measurement would offer clear guidance on how to formalize and incorporate something like “pluralistic ignorance” in a model. We expect that the absence of such measurement does not preclude formalization, but would allow for a plurality of formalizations, something hinted at by the models created during this hackathon. Such formalizations might even, in turn, inform further investigation and measurement development.

Secondly, while dedicating attention to formal modeling in psychology curricula might be advisable, its implementation will likely be impeded. Many contributors to this project have been involved with teaching psychology in numerous departments across the world. We share the general experience that a substantial percentage of psychology students have difficulties with math and we can expect that many will dread the thought of having to acquire the additional skills required for mathematical and computational modeling (Carpenter & Kirk, 2017; Mulhern & Wylie, 2004, 2006). In general, psychology programs are perceived to be (much) less mathematically demanding than physics, chemistry, computer science or bioengineering programs[8]. Thus, there might be good arguments to reserve room in psychology curricula for formal modeling, but if a sizeable percentage of psychology students can be convinced to take these courses remains to be seen. However, if the many-modelers approach proves viable, then only a few might be enough to foster productive formal theory development.

Thirdly, while proposals for reorganizing psychology departments to include theory-formation training are appealing (e.g., Borsboom et al., 2021), implementing such training might ultimately prove difficult in countries in which well-funded research industries simply do not exist. In such countries, psychology is, due to economic constraints, almost entirely limited to educating applied psychologists. Furthermore, researchers in many developing countries face additional difficulties due to, for instance, recurring political involvement in science education (e.g., rejecting the theory of evolution; Abbott, 2013; David & Bálint, 2018) and the incentive structures that favors quantity over quality (e.g., researchers get paid per publication; Chawla, 2020). Issues such as these are bound to set constraints on transcultural generalizability of the initiative for more rigorous theory development. International many-modelers collaborations, as described in this proof-of-concept, could allow researchers to skirt these economical and political constraints.

Finally, we want to offer a last point of speculation. Though the assessment of the models was beyond the scope of this proof of concept, we can offer two promising avenues for future many-modelers projects to incorporate such assessment. First, the robustness or sensitivity of the models could be assessed by simulating data from the model over a wide variety of parameter

[8] However unpleasant this thought may be for the computationally-minded teachers and researchers in psychology.

settings and evaluating how often the statistical pattern is produced that represents the phenomenon. Second, hold-out phenomena could be used. After the modeling teams have succeeded in creating a model that produces the required data patterns, one or more additional phenomena are provided that should also be accommodated. In this case, the merits of the models can be assessed in terms of changes to the model necessary to accommodate these new phenomena – the fewer, the better.

In conclusion, we hope that our pilot project helps to move psychology towards more formal modeling. We look forward to seeing others host their own Many Modelers projects to both formalize theories and inspire researchers' interest in theoretical modeling.

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Author Contributions

The conceptualization was done by NvD and LT. The preparation and organization of the hackathon was done by NvD, AF, JdR, LT, SW, and DB. The modeling during the hackathon was done by AG, AR, JA, (Team 1); DG, EA, AK, YSL (Team 2); JF, JH, JMR, YS (Team 3); AGK, YO, MJ, AS, AK, AD (Team 4); NW, HKP, MAW (Team 5); and ŠB, NAT, FS, SJG (Team 6). The original draft, except Section 2.4.2 and Appendix D, was written by NvD. The original draft of Section 2.4.2 and Appendix D were written by the respective modeling teams. Review and editing of the manuscript was done by all authors. We recognize Jonas Haslbeck for making considerable contributions to the organization of the hackathon and the content of the manuscript.

Open Science Practices

This article is theoretical and does not include any data and was not preregistered, therefore is not eligible for Open Science badges. The entire editorial process, including the open reviews, is published in the online supplement.

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Appendix A

Formalization of the cognitive dissonance theory

Here we provide the formalization of the cognitive dissonance example discussed in the introduction. Part of the verbal theory of cognitive dissonance theory was described by Brehm and Cohen (1963) as follows:

> *The amount of dissonance experienced by the person depends on the ratio of dissonant to consonant elements, where each element is weighted according to its importance to him. ... In sum, the magnitude of the dissonance experienced depends directly on the number and/or importance of dissonant cognitions relative to the number and/or importance of consonant cognitions* (Brehm and Cohen, 1963, p. 5).

From which they 'derive':

> *[W]ith the relative attractiveness of the two alternatives held constant, the more attractive they both are, the greater is the magnitude of the dissonance* (p. 6).

The original expected consequence of cognitive dissonance theory was that when the relative attractiveness of two options, one chosen and one rejected (e.g., vanilla and chocolate ice cream), was held constant but both options were more attractive in absolute terms (e.g., both made with higher quality cream), then the magnitude of a person's cognitive dissonance should increase (Brehm and Cohen, 1963, p. 6). Harris (1976) showed that, according to this theory, there are three ways that the absolute attractiveness of the options could be increased while the relative attractiveness remains unchanged:

1. Increase the positive attributes of both options in equal amounts (e.g., higher quality ingredients).
2. Decrease the negative attributes of both options in equal amounts (e.g., lower quality ingredients).
3. Increase the positive attributes of the chosen option and reduce the negative attributes of the rejected option by the same amount.

According to the theory, these manipulations result in increasing dissonance (A), decreasing dissonance (B), and leaving cognitive dissonance unchanged (C), while only the first option is consistent with the expectation made from the verbal theory.

Harris (1976) demonstrated this through formalizing the given cognitive dissonance theory. Concretely, he showed that one can formalize the first quote, for the special case of equally important cognitions as

$$d = f(n_c + n_u)/(n_c + n_u),$$

where d is the magnitude of the distance; n_c, n_u represent the number of positive and negative features of the chosen (c) and rejected (u) alternatives, and f represents any monotonically increasing function of n (Harris, 1976, p. 213). Brehm and Cohen (1963) provided no definition of "relative attractiveness" and "the more attractive they both are" (total attractiveness). Thus, Harris (1969) employed Greenwald's (1969) different rating of relative attractiveness, which he formalized as

$$a_c \times (n_c + n_u), \quad a_u \times n_u, \quad \text{or} \quad (n_c + n_u)/(n_c + n_u).$$

If this formalization is incorporated in the definition of d, this yields

$$d = f[n_c + n_u, a_c]/(n_c + n_u).$$

In this case, Harris (1976) considered $a_c = (n_c + n_u), (n_c + n_u)$ as plausible formalization of the total attractiveness of the chosen and rejected alternatives. However, in this formalization of the cognitive dissonance theory, a_c can be increased while n_c remains constant by:

(A) increasing n_c and n_u by the same amount, increasing d;

(B) decreasing n_c and n_u by the same amount, decreasing d;

(C) increasing n_c and decreasing n_u by the same amount, leaving d unchanged.

Appendix B
User Manual

Dear modelers,

Thank you for participating in the Many Modelers hackathon at SIPS 2021! This document presents a brief overview of what to expect during the session.

Why?

Many psychological theories exist, but their scope, assumptions, and explanatory power are often unclear. One way to evaluate a theory is to build a formal model and observe if the model can produce relevant phenomena. However, verbal theories can often be formalized in many ways. By working in teams of many modelers we can illuminate the many possible formalizations to see which produce the expected phenomena and how they do so (and have some fun as well)!

When?

The hackathon takes place via Zoom on the 25th of June from 8:00 till 11:00 CEST. The Zoom link for the hackathon can be found on our Landing Page

What?

During this hackathon, you and other teams of scientists will formalize the same theory. Every team gets the same theory (which is available at our OSF folder) and phenomenon that the theory purports to explain (which will be presented at the beginning of the hackathon). You will have approximately 2 hours to work towards a computational or mathematical model of the theory. In the last half hour of the hackathon, we will reconvene to give teams the opportunity to discuss their work and evaluate whether their formalization produces the phenomenon (i.e., shows behavior that is qualitatively similar to the specifics of the phenomenon).

We know two hours is a very short time for developing a full fledged and working model! Our recommendation is therefore to focus on writing some pseudocode describing what you want the model to look like before programming the actual model (see example of pseudocode). This will help ensure that all teams will have something to show for their work. Each team will be assigned a Google Doc (accessible via the OSF folder) in which this pseudo-code / model description can be added. For the actual model, you are free to use any programming language and software. We kindly request to share a copy of your model (finished or unfinished) or make it accessible to us if stored online.

How does it end?

We leave half an hour at the end of the hackathon for a brief evaluation. The (first few) teams are asked to briefly present (max 5 minutes, 0-3 slides):

1. what they did;

2. what the challenges/problems were they faced; and

3. their model or what their model (should) look(s) like.

These presentations might spark questions and discussions, which we will go into as long as there is time. We would like to plan a longer debriefing and evaluation session after SIPS. If you want to be present at this post-SIPS session, make sure that we have your email address (by filling out the registration form).

Deliverable(s)?

We don't know how this hackathon will go and if this many modelers approach is viable for developing formal theories. It could be that this hackathon proves interesting enough to write a paper about. If this is the case, all contributing teams will be invited as co-authors if they allow their model and documentation to contribute to the paper and be made publicly available. Details about this will be provided after SIPS.

If you have any questions:

1. Before the Hackathon starts: please contact nnnvandongen@gmail.com. Also, please join our SIPS 2021 Slack channel (#7a_many-modelers) for easy communication between participants.

2. During the hackathon: use the chat in the Zoom session.

We are looking forward to meeting you all!

Best,

The Many Modelers team

Appendix C
Pseudocode

Pseudocode is used to describe an algorithm or function step by step without taking into account the syntax of any specific programming language. The example underneath shows a pseudocode of a model in which a person tries to maximize positive outcomes (in any given time frame) by always choosing the action with the highest expected reward.

Input: The set of actions a person can take
Output: Actions taken over the specified time frame

```
# Initialize expectations
expected_outcome = 0 * length(actions)

While time > 0:
    selected_action = which action
        max(expected_outcome)

    # If more actions have a maximum
        value, select at random
    if length(selected_action) > 1:
        random selected_action

    # Observe outcome by drawing from
        the probability distribution
    # of the selected action
    outcome = sample from
        P(selected_action)

    # Update expected outcome
    prediction_error = old expected
        outcome - outcome
    new expected outcome = old expected
        outcome + prediction error

    save selected action

return(selected actions)
```

If preferred, you could also use a flowchart as a graphical alternative to the pseudocode described above.

Appendix D
Models descriptions

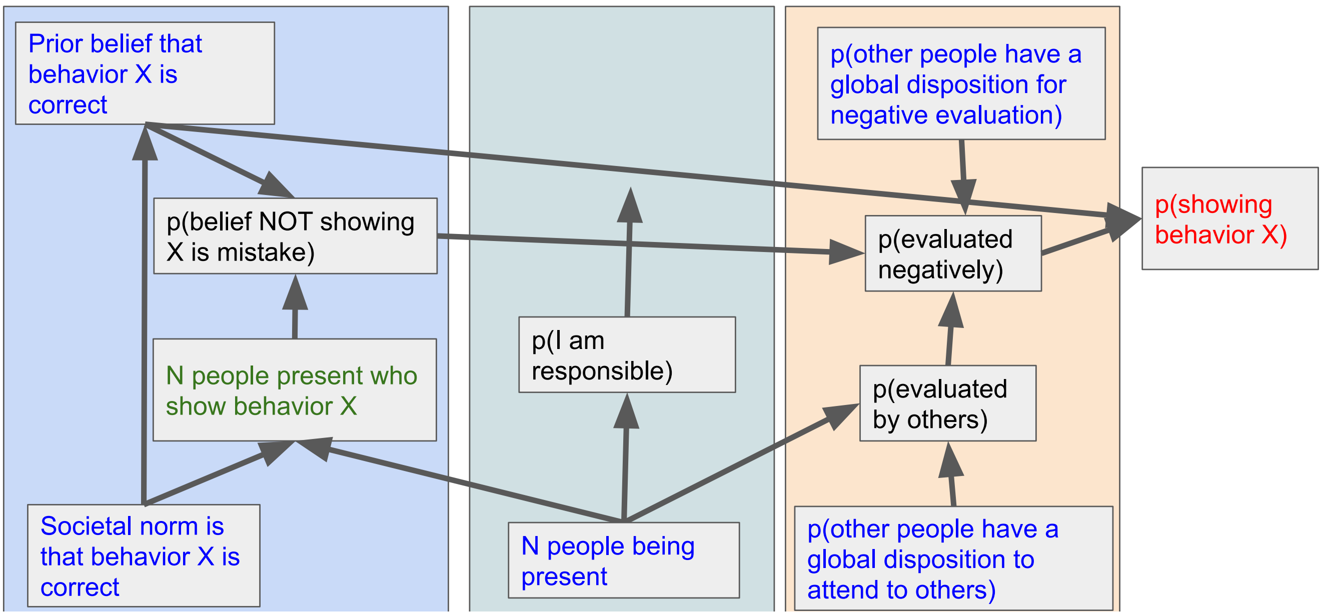
Team 1

We started from the inputs (number of people present), outputs (probability of helping), and the three underlying psychological processes proposed by Latané and Darley (1970):

1. Diffusion of responsibility (a person feels less responsible if more people are around);
2. Evaluation apprehension (a person does not worry about incorrect behavior per se, but whether it is discovered and judged negatively);
3. Pluralistic ignorance (a societal norm might hardly be endorsed and thus not visible in people's actual behavior).

Figure D1

Graphical representation of the model developed by Team 1.



We then identified additional variables that should play a role in bringing about these processes — some of them describing society at large (i.e., is behavior X a societal norm?), some describing the particular situation (i.e., How many people present show behavior X?), and some describing stable, "trait-like" beliefs held by the person in question (i.e., Do people pay attention to what others do, in general? Do people evaluate others negatively, in general?). Finally, we postulated "state"-like beliefs that the person holds in the particular situation. These beliefs correspond to the three psychological processes proposed by Latané and Darley; they are influenced both by the circumstances and the person's trait-like beliefs.

Our model represents psychological variables with nodes. Nodes are connected via edges representing causal influences. Each node has a certain "intercept" as its starting value before considering the influences by other variables — e.g., a high general belief that one will be negatively evaluated by others. Beyond this intercept, incoming edges determine the degree (slope) by which a node's overall value will be affected by the values of other nodes, similar to a regression. All belief variables can have values between 0 and 1, meaning that the sum of all inputs needs to be transformed, e.g., via a beta distribution or softmax.

In conclusion, we believe that our model produces the bystander effect and features the three psychological processes provided in the instructions. We started implementing the model in computer code in R, but did not finish.

Team 2

Our model considers a situation where one person suddenly requires help in a public location with *N* other people present. The effect that an increasing number of people decreases one's probability to help is called Diffusion of Responsibility (direct effect of *N*).

Next, we identified the main aspect of Evaluation Apprehension to be the "Fear of Making Mistakes" (FoMM), which we defined as an individual trait parameter (FoMM). It describes a particular individual's tendency to be afraid of interpreting the situation incorrectly and acting needlessly or even making it worse. We would expect this fear to intensify with increasing numbers of people around (e.g., FoMM*N).

Lastly, we discussed Pluralistic Ignorance to be the experience of group pressure. However, we considered that an individual's susceptibility to conform to other people's actions, i.e., the Need to Conform (NtC) to not helping, maybe the more suitable term. This parameter would also increase with the number of other people not helping (e.g., NtC*N).

Each of these parameters would contribute negatively to one's own probability to help. Although we operationalized the hypothesized effects, we did not succeed in combining them into a model within the given time frame.

Team 3

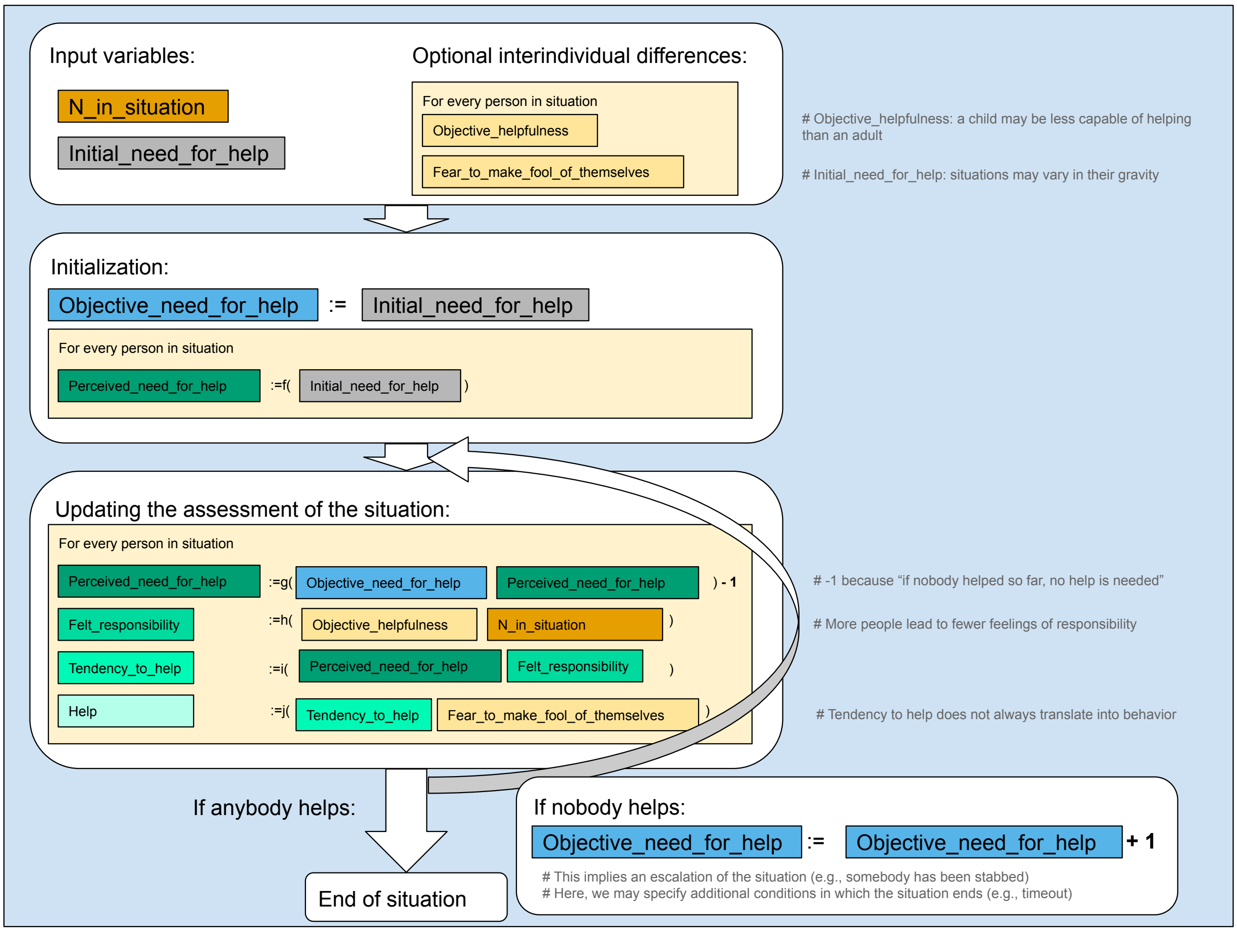
To develop our model, we first considered which parameters would be necessary to capture the relevant features of a bystander situation. Discussing our assumptions about what it would take for this situation to take place made us consider parameters beyond those directly specified in the bystander effect theory. As we were specifically interested in how the dynamics unfold over time, we decided on a model that allows us to assess these changes over time. Once we had settled on a set of parameters, we wrote simple pseudo-code that conceptualizes the model and would help us to implement it.

As input parameters, the program needs to know the number of potential helpers (N_in_situation, see also Figure X) as well as the initial gravity of the situation (Initial_need_for_help). For each helper, we also added some input parameters to allow for interindividual differences – these should not matter for producing the general pattern, but we thought adding them would be fun. The program first initializes some variables to get going. Then, it enters a process that may be repeated multiple rounds. Every potential helper updates their assessment of the situation (Perceived_need_for_help) in a manner that ensures some stability over time, and sensitivity to changes in the objective situation, but also some continuous decrease over time ("nobody has helped so far, so there's probably no need for help"). Every helper also has a certain Felt_responsibility, which importantly is a function of N_in_situation (ensuring diffusion of responsibility). Perceived_need_for_help and Felt_responsibility are translated into a dichotomous decision (Help). If nobody helps, the gravity of the situation (Objective_need_for_help) increases and every helper re-assesses the Perceived_need_for_help.

To actually produce the bystander effect, we would need to additionally specify the functions linking the variables–for example, Felt_responsibility needs to be at maximum if only one person is around (N_in_situation == 1) and then asymptotically drop towards some minimum

Figure D2

Graphical representation of the model developed by Team 3.



as N_in_situation approaches infinity. Two team members started to program the model (one in R, the other in Matlab) although we ran out of time at that point.

Team 4

We used an as-if model whose transformations from input to output variables do not relate to psychologically meaningful processes. We predicted that the subjective norm and the felt responsibility of helping others would contribute to helping. We further predicted that felt responsibility decreases exponentially with the number of bystanders n. Finally, we predicted that both factors would add up to the value of helping:

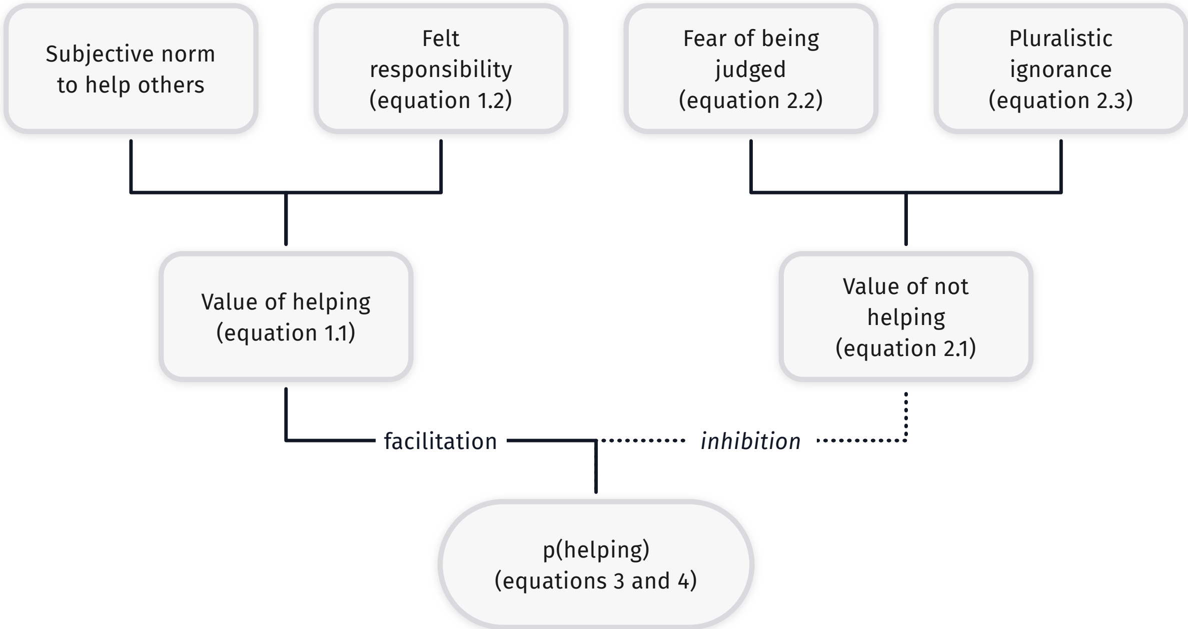
Value of Helping:

$$\text{value of helping} = \text{subjective norm to help others } + \text{felt responsibility to help } (n) \tag{D1}$$

$$\text{felt responsibility to help } (n) = \frac{1}{n^f} \tag{D2}$$

Figure D3

Graphical representation of the model developed by Team 4.



where $f > 0$ is a free parameter that determines the slope of the exponential function.

We further predicted that the sum of the fear of being judged and pluralistic ignorance would determine the value of not helping, and that both factors would increase exponentially with n:

$$\text{value of not helping} = \text{fear of being judged}\ (n)\ + \text{pluralistic ignorance}\ (n) \tag{D3}$$

Fear of being judged and pluralistic ignorance:

$$\text{fear of being judged}\ (n) = n^{j} \tag{D4}$$

$$\text{pluralistic ignorance}\ (n) = n^{i} \tag{D5}$$

where $j > 0$ and $i > 0$ are free parameters that determine the slope of the exponential function.

The probability of helping is the value of the action of helping divided by the sum of the values of helping and not helping:

$$\text{value of not helping} = \text{fear of being judged}(n) + \text{pluralistic ignorance}(n)$$

To deal with potentially negative numbers for values, we extend this formula to:

$$p(\text{helping}) = \frac{\text{value of helping}}{\text{value of helping} + \text{value of not helping}} \tag{D6}$$

The model has been implemented in R (R Core Team, 2021). The arbitrary values of 2 for the subjective norm and 0.3 for f, j, and i yielded a bystander effect as desired.

Team 5

Each individual has an initial inclination to help (i.e., a prior probability of helping) and three traits which alter their probability of helping: the feeling of personal responsibility, the fear of being judged by others, and the belief about whether others are likely to help or not. The probability of helping is positively associated with the feeling of personal responsibility and negatively associated with their fear of being judged (Figure 1). We assume that the feeling of personal responsibility decreases with the number of bystanders and that the strength of this association is moderated by the individual's belief about whether anyone else is likely to help. The higher this belief, the more steeply the feeling of responsibility declines with the number of bystanders. Finally, we assume that the fear of being judged increases with the number of bystanders.

Based on this setup, we can study how an individual's probability of helping changes as a function of the number of bystanders and different trait levels. Specifically, we could explore different levels of the feeling of responsibility (e.g., low, high, or moderate) in combination with different functional forms of the decline (e.g., linear or nonlinear). For example, we could compare two individuals that both experience that their feelings of responsibility linearly decline with the number of bystanders. However, one individual may show a higher average feeling of responsibility than the other. We could also explore different levels of the belief about whether others are likely to help and the average fear of being judged. As with the feeling of responsibility, we can explore different ways in which fear increases as a function of the number of bystanders. Based on our pseudo-code, we expect that our model would reproduce the bystander effect and yield insights into the extent to which this effect depends on an individual's trait levels. We would implement our model in R or Python.

Team 6

To build the initial model, we used the programming language R (Version 4.1.1; R Core Team, 2021) and a simple mathematical function that would result in the mathematical properties corresponding to our interpretation of the bystander effect. Based on a finding from the literature on the bystander effect (Grofman, 1974), we further specified that the overall probability of at least one person helping should remain approximately constant when keeping all other characteristics of the situation unchanged (an additional effect). The initial model thus specified the probability of a bystander helping as, where n is the number of bystanders and Panyone is the probability that at $1-\left(1-P_{\text{anyone}}\right)^{\frac{1}{n}}$, one person would help in the situation, which is determined by the features of the situation, characteristics of the involved individuals, etc. The proposed model successfully reproduces the bystander effect as well as the additional effect we introduced to limit the range of possible models. We next incorporated two variables into the model which represent psychological processes assumed to influence P_{anyone}: the felt responsibility and the fear of negative evaluation. We chose plausible functional relationships of these variables with other variables. For example, we used an exponential function for the felt responsibility and a logistic function for the fear of negative evaluation (for details, see Figure 1). When we fully programmed the model, we were able to verify that it produced the desired bystander effect, and plausible values for the assumed internal psychological variables.

Figure D4

Graphical representation of the model developed by Team 5.

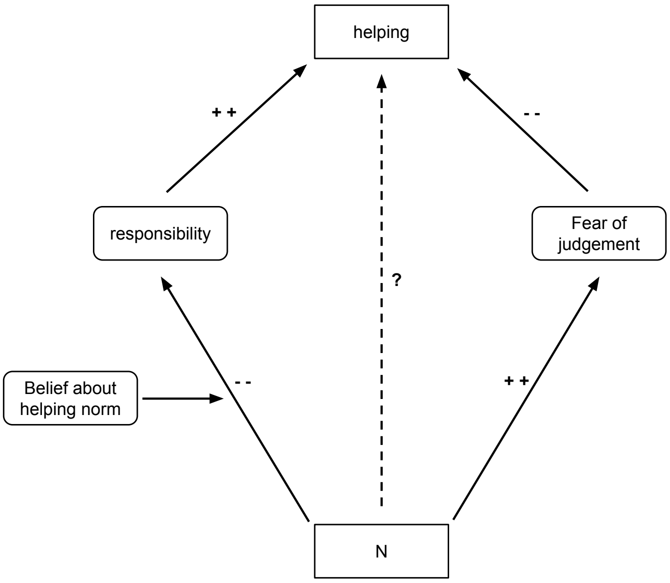


Figure D5

Graphical representation of the model developed by Team 6.