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Moving alcohol prevention research forward—Part II: new directions grounded in community-based system dynamics modeling

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ABSTRACT

Background and aims Given the complexity of factors contributing to alcohol misuse, appropriate epistemologies and methodologies are needed to understand and intervene meaningfully. We aimed to (1) provide an overview of computational modeling methodologies, with an emphasis on system dynamics modeling; (2) explain how community-based system dynamics modeling can forge new directions in alcohol prevention research; and (3) present a primer on how to build alcohol misuse simulation models using system dynamics modeling, with an emphasis on stakeholder involvement, data sources and model validation. Throughout, we use alcohol misuse among college students in the United States as a heuristic example for demonstrating these methodologies. **Methods** System dynamics modeling employs a top–down aggregate approach to understanding dynamically complex problems. Its three foundational properties—stocks, flows and feedbacks—capture non-linearity, time-delayed effects and other system characteristics. As a methodological choice, system dynamics modeling is amenable to participatory approaches; in particular, community-based system dynamics modeling has been used to build impactful models for addressing dynamically complex problems. **Results** The process of community-based system dynamics modeling consists of numerous stages: (1) creating model boundary charts, behavior-over-time-graphs and preliminary system dynamics models using group model-building techniques; (2) model formulation; (3) model calibration; (4) model testing and validation; and (5) model simulation using learning-laboratory techniques. **Conclusions** Community-based system dynamics modeling can provide powerful tools for policy and intervention decisions that can result ultimately in sustainable changes in research and action in alcohol misuse prevention.

Keywords College drinking prevention, complex systems science, computational modeling and simulation, participatory research, policy, system dynamics modeling.

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INTRODUCTION

This is the second of two papers advocating for a paradigm shift in alcohol prevention research. These papers seek collectively to: (1) introduce how complex systems perspectives can address some of the limitations of current alcohol prevention research; and (2) provide readers with a basic understanding of computational modeling methodologies, grounded in alcohol misuse among college students in the United States, demonstrating their potential for alcohol prevention research and action.

Alcohol misuse continues to represent a significant health and safety challenge [1–4]. While alcohol misuse has received much research attention, the bulk of current approaches—grounded in risk-factor epidemiology and linear causality—have targeted proximal and low-leverage factors [5–7], typically overlooking interacting factors, such as macrosocial, spatial and temporal considerations. While these approaches have generated modest successes, they have generally failed to reverse population-wide trends and, in some cases, exacerbated the problems they intend to solve [8–10].

To generate breakthroughs in alcohol prevention, a paradigm shift is necessary [11]. In particular, holistic approaches grounded in complex systems perspectives are warranted [12]. Embracing complex systems perspectives will provide greater understanding of the factors contributing to alcohol misuse, and consequently equip alcohol prevention research and interventions more effectively. A complex systems paradigm, which conceptualizes alcohol misuse as a complex adaptive system and allows for the application of computational modeling methodologies, has the potential to lead to scientific and practical breakthroughs [11,13,14]. Unfortunately, complex systems approaches are underutilized and often poorly understood in alcohol prevention research. Therefore, our objectives are threefold: (1) to provide an overview of computational modeling, with an emphasis on the foundational properties and mechanics of system dynamics modeling (SDM); (2) to explain how community-based SDM can forge new directions in alcohol prevention research; and (3) to present a primer on how to build alcohol prevention models using SDM, with an emphasis on stakeholders, data sources and model validation. We use alcohol misuse among college students in the United States as a heuristic example for demonstrating these methodologies. We also include supplementary materials pertaining to college drinking, consisting of two heuristic concept models (Supporting information, Concept models S1 and S2), a walkthrough and simulation results for these two models (Supporting information, Appendix S1) and a spreadsheet with model parameters (Supporting information, Table S2), to which we reference and direct the reader at various points in this paper. The figures and supplementary materials discussed here were developed using Vensim software [15].

COMPUTATIONAL MODELING AND SIMULATION

Problems which function as dynamically complex systems, such as alcohol misuse [11,12,14], require the design and development of mathematical representations (i.e. formal models) to characterize the systems' processes most effectively [16]. Generally referred to as computational modeling and simulation techniques, these approaches allow researchers and stakeholders to experiment with and test intervention scenarios and their consequences over time, which can greatly inform intervention decisions [12,17]. These computational formalisms are especially relevant for alcohol prevention research, given that drinking behaviors are often resistant to interventions that seek to prevent alcohol misuse [11,18,19]. This so-called 'policy resistance' [18] generates a discouraging illusion of intractability. Dynamic modeling methodologies offer means to overcome policy resistance. Diverse modeling techniques (i.e. agent-based modeling, SDM) have been utilized to study complex systems among various health-related domains, including obesity [20], chronic disease [21], illicit drug use [22] and health-care [23].

While a discussion of the array of modeling methodologies is beyond the scope of this paper, herein we delve into SDM—a dynamic modeling approach particularly useful in delineating critical underlying drivers in drinking prevention. SDM is a top–down aggregate modeling approach that captures non-linear relationships between components of complex systems with time horizons that can extend far beyond those feasible in traditional prevention research. A core assumption of SDM is that the causes of a problem are endogenous—that change over time occurs within the system due to feedback effects and circular causality—although initial stimuli may be exogenous [24]. Thus, SDM frames system behavior deliberately as a consequence of system structure and not external forces [24].

SDM simulates a series of mathematical equations [25]. Below is an example of a SDM equation from Fig. 1 (Supporting information, Concept model S1), where the number of occasional drinkers in a given month t (O_t), is:

$$O_t = O_{t-1} + pAI * A_{t-1} - pOD * O_{t-1} - pOI * O_{t-1} + pRD * R_{t-1} - pLCO * O_{t-1},$$

where:

- pAI = the probability that abstainers will escalate in a given time-period (here, 1 month);
- A_i = number of students abstaining in month I;
- pOD = the probability an occasional drinker will de-escalate (become an abstainer) in a given time step;
- pOI = the probability an occasional drinker will increase their drinking;
- pRD = the probability that a regular drinker will de-escalate their drinking;
- R_i = the number of regular drinkers at time I; and
- $pLCO$ = the probability of leaving college for an occasional drinking in a given month.

Using both concept models in the supplementary materials (Supporting information, Concept models S1 and S2; also included here as Figs 1 and 2), we demonstrate here how SDM is grounded in stocks, flows, auxiliary variables and feedbacks loops [26]. The first concept model (Fig. 1 and Supporting information, Concept model S1) presents what stocks and flows may look like in the context of college drinking. The number of people in each stock (e.g. 'abstainers') is analogous to prevalence and determines the current state of the system at any point in time. Flows (e.g. 'students initiating drinking') are analogous to incidence and determine changes to levels of stocks over time [27]. The dynamic interplay between stocks and flows dictate inertia, delays and other sources of disequilibrium [27].

The second supplementary concept model (Fig. 2 and Supporting information, Concept model S2) presents what stocks and flows, together with auxiliary variables and

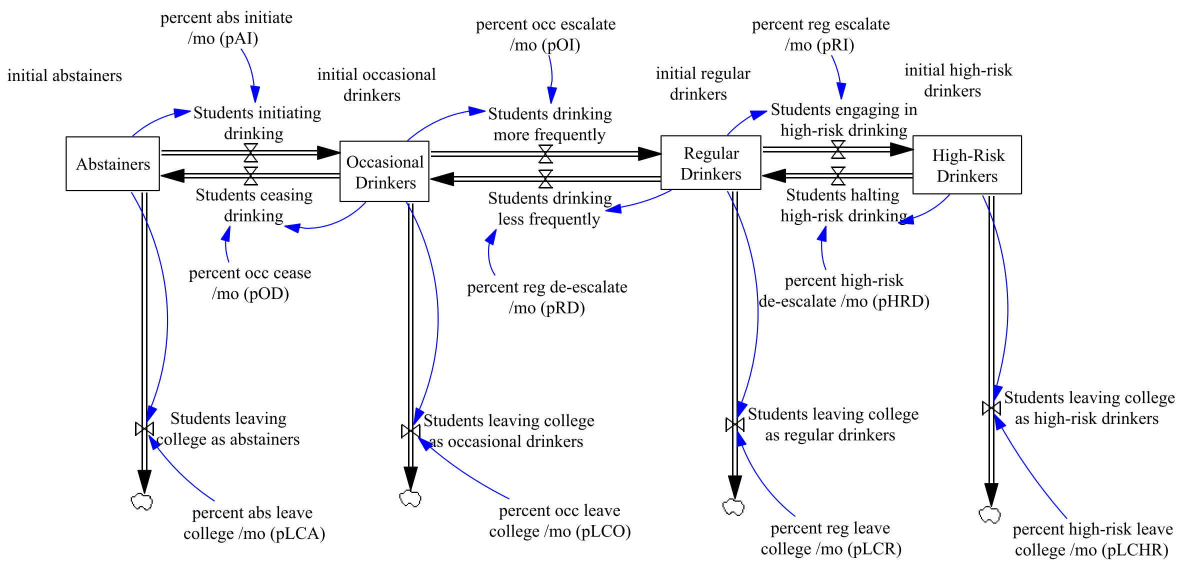

Figure 1 Basic stock and flow structure of alcohol misuse in college environments. [Colour figure can be viewed at wileyonlinelibrary.com]

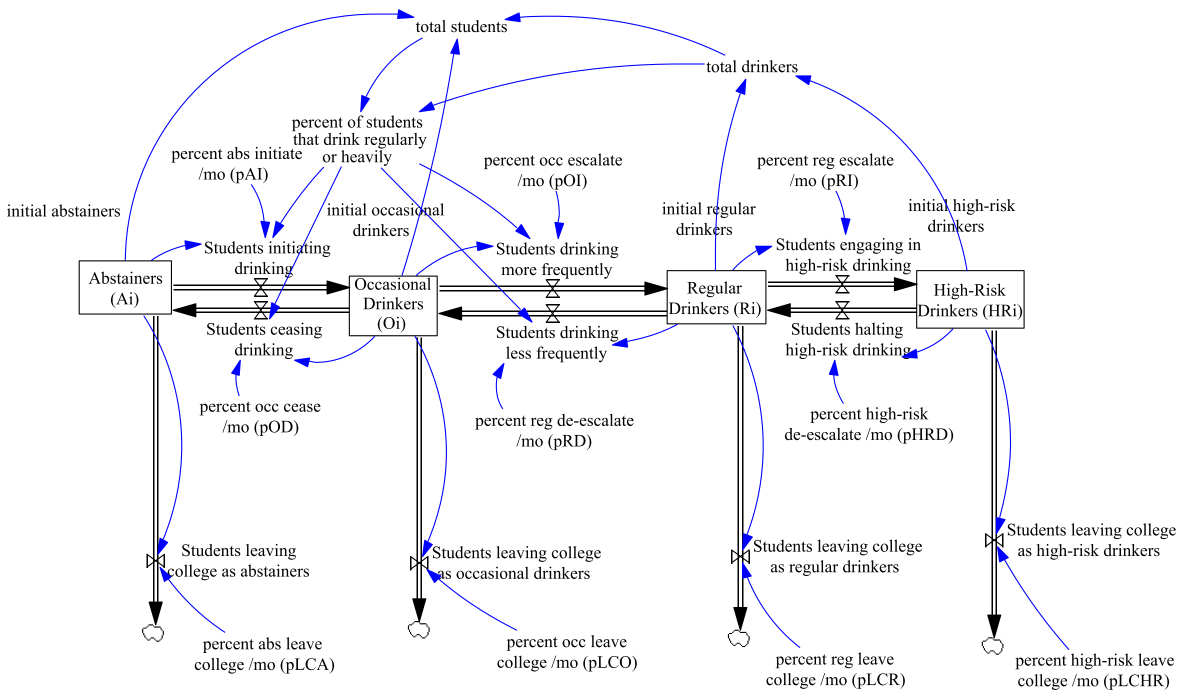

Figure 2 Basic stock and flow structure of alcohol misuse in college environments, with system feedback. [Colour figure can be viewed at wileyonlinelibrary.com]

feedback loops, may look like in the context of college student alcohol misuse. Auxiliary variables (e.g. 'total students') represent causal factors and can be embedded in powerful causal pathways which generate chains of 'ripple effects'. These chains are represented in SDM by feedback loops, which are where a path begins at any factor, moves from link to link and returns to the original factor. For example, in Fig. 2 (Supporting information, Concept model S2), a feedback loop operationalizing peer influence of abstainers on occasional drinkers is as follows: 'abstainers', to 'total students', to 'percentage of students who drink regularly or heavily', to 'students ceasing drinking' and back to 'abstainers'. Thus, through the lens of SDM, system structure is defined by its feedback structure, where causal factors are connected by arrows, with annotations about polarities and time delays [28]. Ultimately, feedbacks determine system behavior and constitute key factors contributing to an outcome [28].

SD models are deterministic and can be presented as both diagrams and mathematical equations, similar to causal inference approaches. However, SDM differs in a number of fundamental ways from these other techniques. For example, a core purpose of SDM is to elicit and build confidence in hypotheses and theories about how structural factors (or 'mechanisms') influence outcomes (e.g. college student drinking) [27]. This focus on structural mechanisms distinguishes SDM from other causal inference approaches as these models, including those based in the general linear model (GLM), are oriented toward goodness-of-fit and primarily isolate relationships between hypothesized causal factors and outcomes by controlling for confounding variables [19,29]. In contrast, SDM incorporates an array of factors holistically to explore how interrelationships within the system generate the mechanisms relevant to outcomes of interest [28]. This emphasis on structural mechanisms allows for testing multiple hypotheses simultaneously [30] through the use of model simulation [31]. The iterative model validation in SDM allows researchers to generate hypotheses which evolve concurrently with the SD model (i.e. 'dynamic hypotheses') [32–34]. Finally, the causal loop diagram (CLD) of SDM contrasts in several key ways with diagrammatic techniques such as directed acyclic graphs, with perhaps the most important being that CLDs incorporate feedback loops deliberately and incorporate the influence of time, which are reflected in time delay notations and expressed in underlying model equations [28,35].

COMMUNITY-BASED SDM IN ALCOHOL PREVENTION RESEARCH

SDM improves our ability to determine what forces shape alcohol misuse over time, their inter-relationships and how diverse factor configurations govern the dynamics of the system [27]. Through its emphasis on stocks, flows and feedbacks, SDM provides a detailed map of causal relationships between factors that affect system dynamics, and uses quantitative and qualitative modeling principles to conceptualize the underlying feedback loop structure and simulate the repercussions of potential decisions over long time-frames that would be pragmatically impossible to explore using traditional approaches.

Community-based SDM, using group model-building (GMB) approaches, can be used to generate impactful models. GMB methodologies were developed because of the importance of building models and conducting simulations with stakeholders that leverage the diagramming conventions of SDM. GMB is an iterative process in which 10–12 stakeholders reach consensus under the direction of facilitators and modelers [36–39]. Community-based SDM applications have resulted in refined procedures for conducting GMB exercises for maximum efficacy [36,40–42]. Detailed documentation, providing walkthroughs for the design of GMB sessions, is readily available [39,40,43], and an active community of GMB experts continue to refine and disseminate best practices.

Applied to college student alcohol misuse prevention research, GMB would be used to deconstruct alcohol misuse and identify optimal prevention strategies. The GMB team would be comprised of stakeholders representing government, law enforcement, school, community and businesses; experts in alcohol prevention and public policy; and modelers and facilitators [39]. Participants' experiences and interests in mental models of the problem at hand would be expected to reflect diverse (possibly conflicting) views on the etiology, perpetuation, exacerbation and potential solutions. These differences are ultimately beneficial, as: (a) divergent perceptions, strategies and alternatives will be challenged to reach consensus on shared mental models [42]; (b) a common language will emerge to explain endogenous variables in college drinking and their connections; (c) incorporation of stakeholder views into models will be invaluable to designing and implementing interventions [36]; and (d) involvement in learning and strategic planning will increase model ownership and buy-in to the process [39]. These insights could then be used to develop a sequence of deliverables that push thinking and capture knowledge, together comprising dynamic hypotheses of the salient determinants of college drinking. Further, the process of unveiling latent assumptions will help the GMB team to think endogenously and holistically and turn inward their thoughts on causes and remedies to design the structure of college drinking [44].

Heuristic group model building

Facilitators guide the GMB team in a process of building a college drinking prevention model, which begins by understanding its purpose and clarifying the rationale behind using SDM. A particularly critical step is boundary-setting: during this model formulation process, the boundary will be set as the smallest number of factors that define the model's scope and where dynamic behavior is generated as it arises within its internal structure [45]. Thoughtful setting of model boundary is critical to proper delineation of the system's internal and external structure [28]. The core assumption that causal factors are endogenous [24] is critical to position the stakeholders to be 'systems thinkers' so they can contribute meaningfully to GMB. Boundary-setting requires closed boundaries around the system under investigation, whereby circular causality is imposed by closing off the system from exogenous influences, and causal influence is grounded solely within these boundaries [24]. Boundary-setting endeavors reflect an essential perspective, where causal influences are made endogenous and therefore within the stakeholders' sphere of control [24]. Boundary charts are developed which separate variables as endogenous (involved in feedback loops, whose behavior-over-time we seek to understand and explain) and exogenous (affecting endogenous variables, whose change-over-time we do not seek to explain) [28]. An initial boundary chart might include mechanisms, factors and policies that fall within government, business, college and student environments and student alcohol misuse.

The creation of behavior-over-time graphs (BOTG) follows boundary charts. Time-horizon selection is critical for helping stakeholders to estimate the depth and breadth of student alcohol misuse [46]. Time-horizon determination is linked with structural changes that have shaped college drinking over time and provides a reference for historical data for generating the BOTG. This provides an understanding the trajectories of key variables that characterize college drinking and how their underlying causes and patterns have changed over time [28]. BOTG will: (a) help define the time horizon that is necessary for model building and simulation; (b) provide hints about possible theoretical explanations of college drinking; (c) indicate if important endogenous causal factors are missing; and (d) guide SD model structure and plausibility [28,36].

Next, construction of the SD model begins. Figure 3 presents a simplified SD model, similar to what may emerge from a GMB process. The resulting sets of feedback loops, and how they influence the dynamic movement of student cohorts among stocks and flows, will be an initial explanation of the system's behavior. This heuristic model only includes 'alcohol availability', 'campus wetness', 'drinking social norms', 'law enforcement' and 'alternate transportation', among key drivers, to represent students' alcohol-use-related transition, and shows how SDM can enhance intervention efforts. It is a chain of stocks (boxes), flows (arrows with valves) and auxiliary variables forming feedback loops. This model features several numbered feedback loops. For example, Balancing loop B1a (Alcohol Availability and Promotion) illustrates how government regulations and business practices *vis-à-vis* alcohol availability, use and promotion can influence student alcohol misuse.

These feedback loops show how cascading consequences may affect student and community wellbeing and how collective efforts may curb such consequences. Examples include regulating 'Happy Hour' promotions, restricting alcohol sales during sporting events, or instituting 'Safe Rides' services. The lower-central section of this model represents the current state of college drinking, denoting that interacting market, government, community, school and social-network forces shape alcohol misuse in college environments. The upper-outer section represents a preventive scenario that explains how interacting policies, organizational responses and their aggregate capacity may prevent/reduce adverse consequences. The simulation and comparison of 'what-if' counterfactuals will aid in navigating policy configurations needed to trigger reductions in alcohol misuse.

Model calibration, simulation and validation

The mathematical representation of the SD model is a system of non-linear, first-order differential equations [i.e. $\frac{d}{dt}x(t) = f(x,p)$, where x = vector of stocks, p = set of parameters and f = non-linear vector-valued function] [29] to be converted into a testable and functioning form for conducting computer simulations [28,46]. The best

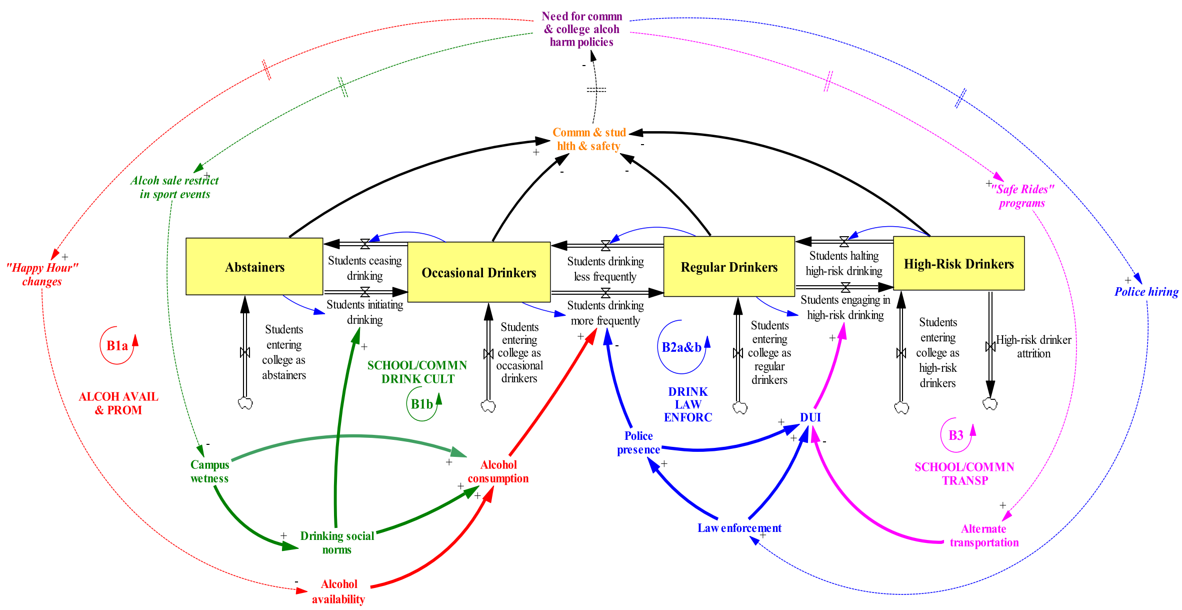

Figure 3 Simplified system dynamics model of alcohol misuse in college environments. [Colour figure can be viewed at wileyonlinelibrary.com]

available data are used to assign numerical values that indicate how causal forces might relate to each other. Because variables are not excluded due to lack of extant data, if any required data are unavailable or inadequate to inform some components of the model, expert-driven reasoned assumptions are typically made, and sensitivity tests [16,28,46] are conducted to examine significance of uncertain parameters. It is important to note that identification of uncertain parameters does not discredit a SD model. SD model building is typically an iterative endeavor aimed at strengthening confidence in SD models over time. Moreover, similar to confidence intervals in statistical modeling, uncertain parameters influence the confidence in conclusions drawn from subsequent model simulation. Additionally, the discovery of uncertain parameters can drive subsequent research endeavors, as gaps in knowledge identified through SD model building can be interpreted as critical avenues for future research [17] and can increase confidence in the SD model over time as these gaps are filled and uncertain parameters are specified with data.

SD models undergo testing regarding model parameters and assumptions, including sensitivity and robustness analyses, to build model confidence. This process may be more or less rigorous depending on the model's purpose. For example, more rigorous testing is common for models built to generate precise predictions. Using multiple data sources, qualitative diagrams are then calibrated, tested critically, analyzed and simulated [32] to identify optimal policy configurations. Replicating time–series data is an important way to test the model, as it is common to have several model versions (varying in their structural assumptions and input parameter values). Comparing simulation results across different versions to time–series data provides means to assess which models can be made consistent with historical trends through calibration.

Calibration data may come from a diverse range of historical [e.g. Centers for Disease Control and Prevention (CDC) surveys] and scientific literature (e.g. Core survey [47]) sources. Additionally, a variety of domains can inform calibration, such as: (1) governmental policies, including those related to business, distribution and consumption; (2) manufacturer policies, such as new product development, advertising and pricing; (3) environmental factors, including zoning, licensing, spatial distribution of alcohol outlets and transportation infrastructure; and (4) college policies, characteristics and cultural measures. Of particular value is the bulk of existing alcohol prevention research (e.g. National College Health Assessment [48]), as myriad studies and data sets can be combined synergistically in model formation, calibration and testing [49].

A fully developed SD model would probably have several hundred parameters, some of which might be of uncertain accuracy. As SDM is a behavior-oriented simulation method, sensitivity of behavior-pattern measures must be evaluated to explore the effects of parameter uncertainty on behavior patterns [34]. Models are tested to determine the impacts of changing any given parameter, which allows insight into the robustness of the model to its parameters and assumptions and indicates the importance of missing/estimated data in overall model functioning [34]. One such technique involves Monte Carlo-style analyses, where a model's parameters are varied across a wide range, and simulation results are then compared across these different model configurations [50]. These approaches are intended to safeguard against faulty model outputs due to uncertainties during model calibration [16].

The simulation of calibrated and tested SD models can improve the ability of stakeholders to anticipate probable effects of interventions, where pathways from interventions to outcomes may be indirect, delayed or affected by nonlinearities. These benefits are demonstrated partially by the second heuristic concept model (Fig. 2; Supporting information, Concept model S2), which illustrates a scenario where social norms of drinking or non-drinking might affect changes in level of drinking over time. Here, the percentage of the population in the two heavier drinking stocks is used to influence transitions toward and away from these drinking states. The mathematical equation underlying this scenario is:

$$\begin{aligned} O_t = {} & O_{t-1} + pAI * (0.5 + percRH_{t-1}) * A_{t-1} \\ & - pOD * (1.5 - percRH_{t-1}) * O_{t-1} - pOI * O_{t-1} \\ & + pRD * R_{t-1} - pLCO * O_{t-1}, \end{aligned}$$

- $percRH_{t-1}$ = the percentage of students who drink regularly or heavily in time t–1 (other terms are defined previously).

To illustrate the impact of these changes in the equation for O_t, in the extreme case where the entire population is a regular or heavy drinker, pAI is multiplied by 1.5. If, instead, no one drinks regularly or heavily, then pAI is multiplied by 0.5. As the simulation results (Table 1) reveal, in both scenarios a 50% decrease in the escalation of occasional drinkers generates the most effective outcomes compared to similar reductions among regular drinkers or abstainers, as it results in the lowest percentage of students leaving school and the lowest percentage of students overall who are regular or high-risk drinkers. This suggests that policies aimed at occasional drinkers represent superior interventions, as they are comparatively more effective than policies targeting the other two groups. While these results are based on expert estimates and would require an actual study for validation, these findings demonstrate the value of SDM in capturing just a few of the complex relationships which define college drinking into a functioning SD model and using simulation to determine optimal intervention configurations to shape college drinking.

Table 1 Concept model simulation results for two scenarios addressing alcohol misuse in college environments.

			50% Decrease in the escalation of		
	Beginning of year	*No intervention*	*Regular drinkers*	*Occasional drinkers*	*Abstainers*
Scenario: no social norms influencing drinking					
Number of students					
Abstainers	100	76	76	83	106
Occasional drinkers	550	414	425	541	394
Regular drinkers	300	357	382	242	394
High-risk drinkers	50	105	71	88	104
Number of students left school		53.7	49.8	49.8	53.3
Percentage of students regular or high-risk drinkers	35.0%	48.5%	47.5%	34.6%	49.9%
Percentage of students' high-risk drinkers	5.0%	11.0%	7.4%	9.2%	10.4%
Scenario: norms of non-drinking de-escalate drinking					
Number of students					
Abstainers	100	87	88	107	118
Occasional drinkers	550	439	452	582	420
Regular drinkers	300	328	348	186	317
High-risk drinkers	50	99	68	81	98
Number of students left school		52.2	48.6	48.0	51.8
Percentage of students regular or high-risk drinkers	35.0%	44.8%	43.5%	28.0%	43.6%
Percentage of students' high-risk drinkers	5.0%	10.4%	7.1%	8.5%	10.3%

At the conclusion of the GMB process, and in the context of a learning-laboratory environment, the stakeholders, guided by modelers and facilitators, offer their insights and engage in model testing and refinement and model-informed policy planning to allow the team to refine the final model. This leads to a second phase, where the relative effects of policy alternatives can be explored. These scenarios can be simulated under various configurations, thereby anticipating different rates of alcohol misuse in college settings. The purpose of studying these scenarios is to predict future trajectories and determine how the direction of these problems may plausibly change in varied intervention configurations [46]. Without such tools, policy decisions result from processes in which the analyses of the consequences of policy alternatives are fragmented, static and unsystematic, potentially reaching conclusions that overlook important features of all complex systems [46].

CONCLUSIONS

There are many resources available for those interested in integrating SDM into their work. First, Vensim software includes excellent support documentation, including a user guide, tutorials and message boards. Secondly, because SDM has been used in fields outside alcohol prevention research, there are several strong books available. Thirdly, several institutions offer work-shops on a regular basis, including comprehensive work-shop offerings during the annual conference hosted by the System Dynamics Society. Finally, the scientific literature includes a growing base of knowledge from which to draw.

While underutilized in alcohol prevention, computational modeling and simulation can be of tremendous value in prevention research. Because of its amenability to participatory methodologies, community-based SDM can provide avenues for creating sustainable changes in college student alcohol misuse. Computational simulation methodologies, such as SDM, can be integrated into the current armamentarium of alcohol prevention research. This integration can synergistically move alcohol prevention research forward, providing avenues for breakthroughs in research and action that can curtail or reverse alcohol misuse in college environments.

Declaration of interests

None.

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Supporting Information

Additional Supporting Information may be found online in the supporting information tab for this article.

Appendix S1 Walkthrough and simulation results for supporting concept models.
Table S1 Model parameters for supporting concept models.
Model S1 Basic stock and flow structure determining level of alcohol consumption for cohort of first year college students.
Model S2 Basic stock and flow structure determining level of alcohol consumption for cohort of first year college students, with system feedback structure.