Community-based propagation to scale up educational innovations in sustainability

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Many high-quality educational innovations are freely available, and some are known to motivate evidence-based climate and sustainability action. Typically, efforts to propagate educational innovations rely on outreach and word-of-mouth diffusion, but these approaches tend to achieve little. We develop and analyse a dynamic computational model to understand why and to test other propagation strategies. Our analysis reveals that outreach has limited impact and does little to accelerate word-of-mouth adoption under conditions typical in higher education. Instead, we find that community-based propagation can rapidly accelerate adoption, as is also shown by a small number of successful real-world scaling efforts. This approach supports a community of 'ambassadors', facilitating and rewarding their sharing the innovation with potential adopters. Community-based propagation can generate exponential growth in adopters, rapidly outpacing outreach and word-of-mouth propagation. Without it, we are unlikely to rapidly scale the educational innovations needed to build urgently needed capacity in sustainability.

The Earth system is already well outside the "safe operating space" for humanity as defined by the planetary boundaries[1]. For the key boundary of climate change, society is now well into a "critical decade" to accelerate climate action and cut emissions of heat-trapping gases by half[2]. Net-zero emissions pledges now cover most of the global economy[3], but policies and actions to achieve those pledges lag[2]. Widespread sustainability education to build capacity to understand and develop solutions is needed to close the gap between pledges and implementation[4].

After decades of investment in the development of educational innovations by government agencies and foundations, there are many freely available, effective educational innovations in sustainability[5,6]. Here we use 'effective educational innovations' broadly to refer to instructional techniques that are clearly described and known to deliver desirable educational outcomes[7]. Their developers are typically content experts[8], many of whom apply for grants to support innovation development and propagation[9]. Some innovations are known to deliver learning outcomes across students with diverse sociodemographic traits and sociopolitical values[10–14]. For example, the World Climate

and Climate Action Simulations combine interactive climate policy simulators and role-play to increase participants' knowledge about climate change and its potential solutions, their sense of urgency, and their desire to learn and do more to combat it[11,12,14]. Rapid scaling of educational innovations like these could help build the sustainability capacity needed.

But despite the intentions of their developers and funders, most educational innovations are not widely adopted[9]. Dissemination efforts generally assume that outreach and word-of-mouth diffusion are sufficient for widespread propagation[15,16]. Research shows they are not, as uptake rates from dissemination, active outreach or word-of-mouth diffusion among educators are rarely enough to support scaling[17]. A recent review identified only 43 "well-propagated" STEM educational innovations out of many thousands[9].

Here we develop a dynamic decision-support model to understand why most propagation efforts fall flat and to guide strategies to make such efforts more successful. We focus on higher education because of the critical role it plays in building capacity to address sustainability,

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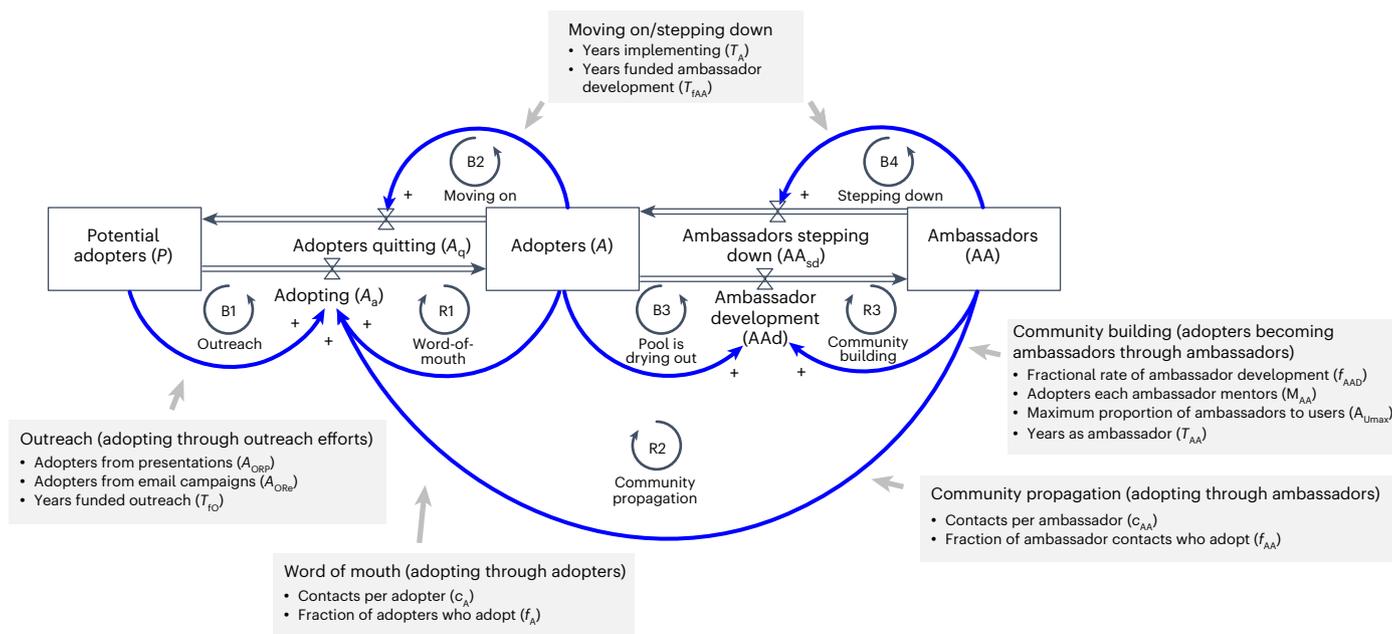
Fig. 1 | Overview of the processes driving the propagation of educational innovations. A diagram, equations and parameter values for the full model are available online[49] and are shown in Extended Data Fig. 1. Accumulations, or stocks, are shown as boxes. Flows are shown as pipes with valves, while information feedbacks are shown as blue arrows. Self-reinforcing feedback loops are marked 'R', while balancing feedback loops are marked 'B'.

preparing sustainability professionals and increasing sustainability literacy across professions[18]. Sustainability higher education also has strong potential for innovation and rapid growth[18]. It demands cross-disciplinary, active learning that enables students to understand complex systems, solve problems and be agents for change[18].

We build on prior research and the well-established Bass model of innovation diffusion[19], which shares key features with the propagation of innovations in higher education, including outreach and word-of-mouth diffusion. We use group model-building methods[20] to build confidence in the model structure and extend it to include community-based propagation. Through simulations, we identify high-leverage strategies for propagation. We find that word-of-mouth diffusion and outreach for propagation yield little impact. Instead, community-based propagation[21] can achieve rapid scaling and sustained impact.

Like the Bass model[19,22], our model includes potential adopters (instructors who could use the innovation) and adopters (instructors who use it). Initially, potential adopters become adopters because of outreach activities. But the proportion of educators convinced to adopt from these efforts is typically low: adopters are neither provided with sufficient information about how to use the innovation nor provided with support if they decide to try it[23,24].

As the number of adopters grows, some of those adopters share the innovation with people they encounter and convince some of them to adopt[19]. This creates a reinforcing word-of-mouth feedback that, in theory, has the potential to drive exponential growth in adoption. Strong word-of-mouth diffusion requires both a high rate of contact between adopters and potential adopters and a high probability of adoption from those contacts. The same underlying structure drives exponential growth dynamics in epidemics, as the COVID-19 pandemic made broadly familiar. Infection spreads rapidly when there is frequent contact between infected and susceptible individuals (adopters and potential adopters, respectively) and when the probability of infection (or adoption) from such contacts is high[22]. But these conditions are rarely met for the diffusion of educational innovations. In normal faculty work, educators tend not to share their educational practices with colleagues. They tend to interact with the same, small set of colleagues over a long time. Those interactions usually focus on sharing research or managing service obligations, not educational innovations[25,26]. And even if they do discuss educational innovations, adoption is unlikely[27,28]. Word-of-mouth diffusion is generally low for innovations in higher education[15,29–31] because contact rates and 'contagion' are low.

In contrast, community propagation of educational innovations can achieve rapid scaling[21,32]. In this approach, a community of 'ambassadors' uses the innovation successfully, believes in its value, shares it with and supports potential adopters, and encourages some adopters to become ambassadors. The ambassador community, in turn, is supported by a backbone organization that facilitates propagation, provides opportunities for collaboration and research, and rewards their work through professional recognition and opportunities. We capture the key dynamics of these community-based propagation approaches in an extended Bass model that builds on prior research and uses system dynamics methods[22] to develop a simulation model with the structure shown in Fig. 1 (see Extended Data Fig. 1 for the full model).

Several real-world examples show the potential of community-based propagation. The InTeGrate project funded by the National Science Foundation reached more than 100,000 students between 2012 and 2018[25] using a community-based approach[21,33]. It built a national community of sustainability educators by supporting the development of innovations by cross-disciplinary, multi-institutional teams; offering visible ways to share those innovations online and in workshops and conferences; and encouraging community members to use and share each other's innovations[21]. The POGIL project achieved widespread propagation through a community-based approach in which adopters are empowered to contribute new curricular materials and lead regional networks that support implementation and draw new members[34]. The community-based Learning Assistant Alliance has 2,953 members at 546 institutions representing 120 Learning Assistant programmes[32]. These efforts build communities of ambassadors who use and share the innovation successfully.

Our interactive, quantitative simulation model enables educational developers and funding agencies to explore what-if scenarios about propagation strategies without the cost and risk of doing so in the real world. It can be used to understand the systemic reasons that

Table 1 | Parameter values and simulation outcomes for each strategy

Parameter	Unit	Base (WoM[1])	Strategy 1a: WoM[1]+ outreach (4 yr funding)	Strategy 1b: WoM+outreach (15 yr funding)	Strategy 2a: WoM+outreach+ community-building (4 yr funding)	Strategy 2b: WoM+outreach+ community-building (15 yr funding)	Strategy 3a: WoM+community-building (4 yr funding)	Strategy 3b: WoM+community-building (15 yr funding)
Switch for outreach effort	Dml[2]	0	1	1	1	1	0	0
Switch for community development	Dml	0	0	0	1	1	1	1
Duration of funding for outreach	Years	0	4	15	4	15	0	0
Duration of funding for community-building	Years	0	0	0	4	15	4	15
Impact on…in year 4								
Adopters	Educators	59	84	84	170	170	132	132
Ambassadors	Educators	4	4	4	48	48	38	38
Users	Educators	63	88	88	218	218	170	170
Impact on…in year 15								
Adopters	Educators	25	28	69	202	4,606	162	3,409
Ambassadors	Educators	1	1	1	9	1,352	7	997
Users	Educators	26	29	70	211	5,958	169	4,407
Maximum number of educators over the 15-year simulation period								
Adopters	Educators	61 (year 3)	84 (year 4)	86 (year 6)	291 (year 8)	4,606 (year 15)	231 (year 8)	3,409 (year 15)
Ambassadors	Educators	8 (year 0)	8 (year 0)	8 (year 0)	48 (year 4)	1,352 (year 15)	38 (year 4)	997 (year 15)
Users	Educators	65 (year 3)	88 (year 4)	89 (year 5)	316 (year 8)	5,958 (year 15)	252 (year 8)	4,407 (year 15)
Cumulative educators after 15 years[3]								
Ambassadors	Educators	8	8	8	63	2,047	51	1,512
Users	Educators	187	229	337	950	9,654	759	7,137

For comparative purposes, the impact of each strategy on the number of adopters, ambassadors and users at 4 and 15 years is shown, as is the cumulative impact at the end of the 15-year simulation period. [1]WoM, word-of-mouth from adopters in a higher-education setting. [2]Dml, dimensionless. [3]Note that the cumulative number of adopters is not shown here because doing so would result in double-counting educators.

propagation of educational innovations succeeds or fails. And it can guide developers and funders to allocate limited resources to activities that drive success.

Results and discussion

We used the model to test the impact of different propagation strategies over a 15-year period and focused on outcomes for three stocks: adopters, ambassadors and total number of users (that is, the sum of adopters and ambassadors, or all educators who are actively using the innovation). We assumed that the developers serve as initial ambassadors who generate and mentor an initial cohort of adopters (Supplementary Tables 1–3). We tested several different propagation strategies:

- Word-of-mouth alone (the base case)
- Word-of-mouth with outreach (Strategy 1)
- Word-of-mouth with community-based propagation and outreach (Strategy 2)
- Word-of-mouth with community-based propagation alone (Strategy 3)

We used base-case parameter values and switched parameters to activate given model substructures (Table 1 and Supplementary Tables 1–9). Strategies 1a, 2a and 3a assume active propagation for four years (a typical length for US federally funded education projects), while Strategies 1b, 2b and 3b assume 15 years.

The base-case scenario reflects the commonly held belief that an educational innovation will become widely used through word-of-mouth diffusion. Its parameter values reflect the low levels of communication among educators about their instructional work[25] and the low probability of adoption from those interactions[27,28]. The number of adopters increases initially, peaks after three years and then declines[28] (Fig. 2 and Extended Data Fig. 2). The initial growth in adopters may lead developers to falsely believe that word-of-mouth propagation is effective. But word-of-mouth adoption is too weak to overcome the losses in adopters who quit using the innovation or retire. Instead, early growth is generated by the developers who serve as initial ambassadors, sharing their innovation compellingly until they step down. The base case generates only 187 cumulative users over 15 years (Table 1).

Active outreach, including presentations, workshops or digital campaigns, is considered 'best practice' for propagation[16,17,28]. Activating the outreach substructure of the model for four years increases the number of adopters when compared with word-of-mouth diffusion alone (Strategy 1a; Fig. 2 and Extended Data Fig. 3). But as the number of adopters grows, so does the rate at which adopters quit. There are only about one-third more cumulative users than in the baseline (Table 1). Note that the point change in the slope of adopters and users results from an abrupt end to outreach activity as funding to support outreach ends. Actual transitions may be smoother if prior contacts with potential adopters generate new adopters for a brief time after outreach ends.
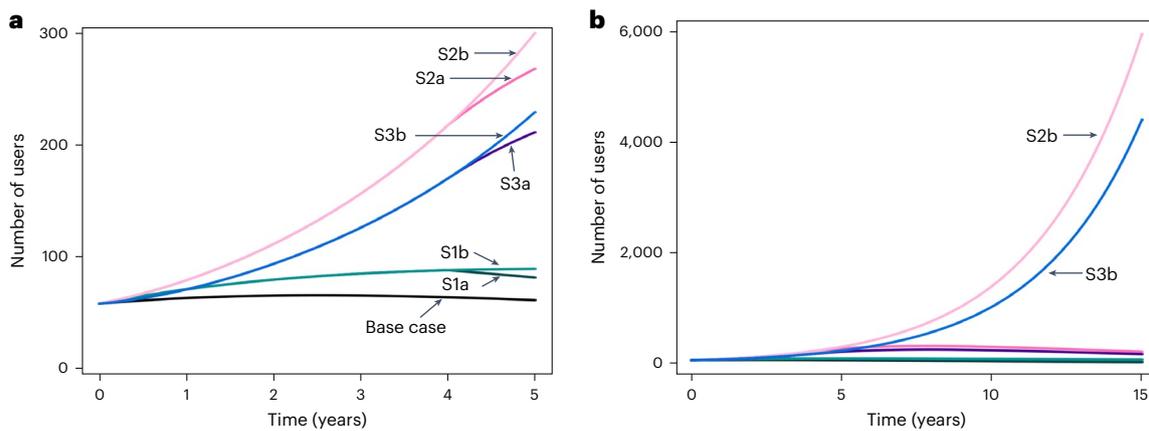
Fig. 2 | Number of users over time for each strategy. a,b, Behaviour over time for the number of adopters in the base case and in Strategies 1a, 1b, 2a, 2b, 3a and 3b over the first 5 years (a) and full 15 years of simulation (b).

Extending outreach for 15 years helps, with nearly 340 cumulative users after 15 years (Strategy 1b; Fig. 2, Table 1 and Extended Data Fig. 3). But the initial ambassadors eventually step down, causing the rate of adopting to decline. Without an active effort to develop more ambassadors, gains in new adopters cannot keep up with losses from adopters quitting. The long-term behaviour of the system is dominated by feedbacks that decrease the number of adopters (Fig. 1, B2—Moving on and B4—Stepping down).

Strategy 2 activates both outreach and community-based propagation. Ambassadors share the innovation with potential adopters and mentor adopters, some of whom become ambassadors. Ambassadors' activities strengthen two reinforcing feedbacks, R2—Community propagation and R3—Community-building (Fig. 1 and Extended Data Fig. 1), generating exponential growth in adopters and ambassadors (Fig. 2 and Extended Data Fig. 4).

Strategy 2a assumes that funding for both outreach and community-building stops after four years. With no funding, the mentoring efforts of ambassadors are no longer supported, feedbacks R2 and R3 are deactivated, and ambassador development stops. Ambassadors retire or step down to become adopters. Because of the latter, the stock of adopters continues to increase for a while, reaching its peak later than the stock of ambassadors (Fig. 2 and Extended Data Fig. 4). But the rate of adopters quitting reaches and then exceeds the combined rates of adoption and ambassadors stepping down, causing the number of adopters to peak and then decline. Cumulatively after 15 years, nearly 1,000 educators have used the innovation.

In Strategy 2b, community-building and outreach activities are funded for the full 15-year period, leading to continued exponential growth that is generated by the reinforcing feedbacks R2 and R3 (Fig. 2 and Extended Data Fig. 4). By year 15, there are more than 9,600 cumulative users. Over the long term, the impact of a community-building strategy enables scaling of the innovation at a level that far exceeds the potential of outreach alone. Note that community-based efforts are likely to be active for a longer time than a single development project. The community-based propagation efforts POGIL[35] and InTeGrate (https://serc.carleton.edu/integrate/about/project_products.html) were launched in 1994 and 2012, respectively, and continue gaining adopters in 2024.

Strategy 3 is similar to Strategy 2, but with no direct outreach effort (Table 1). It combines active community-building with passive word-of-mouth diffusion. This strategy would shift often-limited project resources away from outreach and towards building a community of ambassadors. Instead of focusing on project leaders presenting and sharing the innovation with their own networks and organizations, it works to form a backbone organization that supports ambassadors' work.

Community-building generates exponential growth in both adopters and ambassadors as long as it is active. Four years of community-building alone (Strategy 3a) yields about three times as many users as four years of outreach (Table 1, Fig. 2 and Extended Data Fig. 5). Once active community-building ends, the stock of ambassadors begins to deplete. But because ambassadors do not step down immediately, it takes time for their numbers to decline. Throughout the simulation, they continue to generate new adopters. Total users in this strategy peak in year eight. After 15 years, there are more than three times as many cumulative users than with Strategy 1a (Table 1). Extending funding for community-building to 15 years (Strategy 3b) results in continued exponential growth in adoption and more than 7,000 cumulative users, or more than 20 times more cumulative adopters than outreach funded over the same time horizon (Strategy 1b; Table 1 and Fig. 2).

The observed behaviour for the different strategies is especially interesting given how the number of adopters develops over the first five years of propagation (Fig. 2). During the first year, focusing on outreach efforts (Strategies 1a and 1b) performs better than community-building alone (Strategies 3a and 3b) because of the balancing feedback B1—Outreach, which, when activated, moves potential adopters quickly to adopters. Only community-building with outreach (Strategies 2a and 2b) is stronger. Beyond then, community-building with or without outreach (Strategies 2 and 3) rapidly outpaces the other strategies. The reinforcing feedbacks R2 and R3 (Fig. 1), active in Strategies 2 and 3, take time to generate momentum. Early evaluation of propagation outcomes may therefore lead decision-makers to focus on outreach instead of community-building, even though outreach is a far less effective strategy.

Sensitivity analyses

Sensitivity analysis allows us to test the full range of possible values for poorly constrained parameters, investigate how changing parameter values affects model outcomes and identify high-leverage parameters[36]. It enables decision-makers to test their own mental models about different propagation strategies and justify shifting scarce resources towards high-leverage activities. It also guides research efforts for improving propagation models by determining whether uncertainty about a parameter matters for outcomes. If varying a parameter over its full potential range has little impact, then its precise value does not need to be known.

For each propagation strategy, we assumed ranges for exogenous model parameters that can be influenced by propagation efforts,
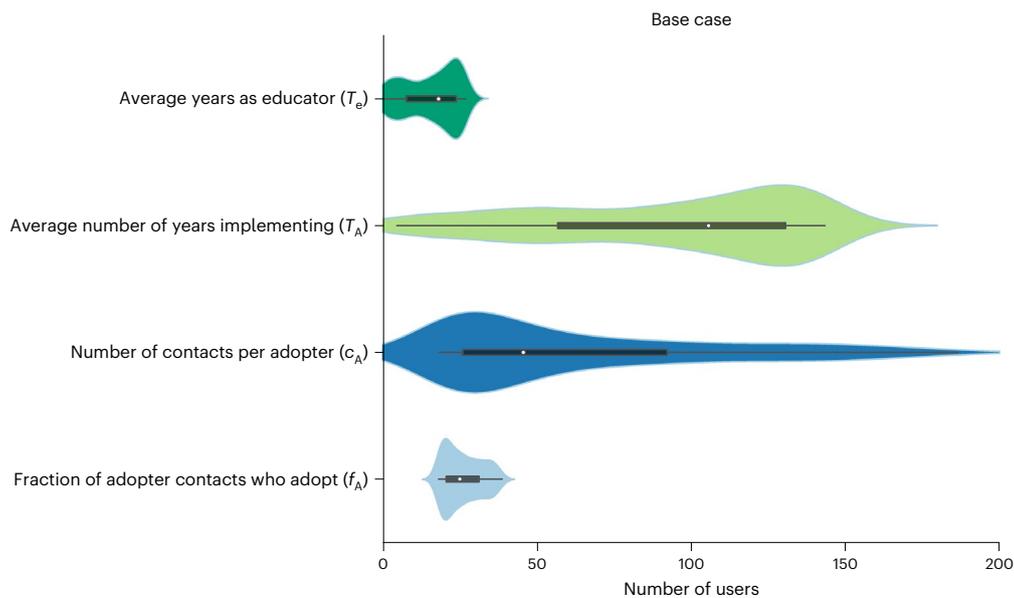
Fig. 3 | Sensitivity analyses of the impact of parameter values on the number of users in year 15 for the base-case scenario. The violin plots show nuances in the distribution of users at the end of 15 years when the input parameter values are varied over their full range. Each coloured region ranges from the minimum to the maximum number of users, with its width indicating the probability density of the distribution at any particular number of users. The violin plots also show the median values (white dots), interquartile ranges (thin black vertical lines) and 95% confidence intervals (thin black lines) of each distribution.

on the basis of prior research and our understanding of the system (Supplementary Tables 10 and 11). The outcome we focused on is the total number of users (that is, adopters plus ambassadors). We used univariate sensitivity analyses to test the full range of values for each parameter, thereby showing the probability density of the resulting outcomes (Figs. 3 and 4). Testing one parameter at a time, we simulated the model 200 times with independent randomly selected parameter values from uniform distributions within their specified ranges. Each propagation strategy was tested separately by using the 'switch' parameters to activate or deactivate model substructures (Table 1). We also conducted multivariate sensitivity analyses to assess the combined effects of varying different parameter values for the different strategy sets simultaneously, as described in the Supplementary Information.

When propagation relies on word-of-mouth alone (base case), the most influential parameters are the number of contacts that each adopter reaches, c_A, and the average number of years that adopters use the innovation, T_A (Fig. 3). Varying c_A across its full range of values leads to a more than sixfold increase in the number of users in year 15, from 18 to 188 educators. Varying T_A across its full range yields 1 to 144 users by year 15. Developers may influence this parameter by continually updating the innovation to ensure that it remains relevant and thereby increasing the likelihood that adopters continue to use it.

Without an intentional community-building effort, developers do not work to directly influence either the number of adopters' contacts, c_A, or the fraction of those contacts that adopt, f_A. Note that they may indirectly influence these parameters if their innovation is high quality and easy to adopt and meets educators' existing needs[37], potentially making it easier and more likely to be shared by adopters.

Strategy 1 adds outreach activities to word-of-mouth diffusion, which most developers assume would increase propagation substantively. But sensitivity analyses show that varying outreach parameters does little. Instead, the parameters with the highest leverage remain c_A and T_A (Fig. 4). Not surprisingly, a larger number of attendees per presentation over a longer time horizon enhances adoption. But at best, outreach impacts adoption linearly. In contrast, the reinforcing feedback R1—Word-of-mouth generates exponential growth behaviour.

Strategies 2b and 3b activate community-building for 15 years, generating as many as 75,700 educators (Fig. 4). The parameter T_{fAA} defines the time period that ambassador development is active and is therefore critical for initiating all community-building activities. Propagation outcomes are highly sensitive to T_{fAA}, illustrating the impact of shifting project resources towards ambassador development and community-building.

Sensitivity analyses show that when the reinforcing feedbacks R2 and R3 around community-building are activated, the number of contacts per ambassador, c_{AA}, and the fraction of ambassador contacts who adopt, f_{AA}, are high-leverage parameters (Fig. 4). The long, narrow tails of their probability distributions indicate that they continue to deliver gains in the number of users even as they approach their maximum expected values. These parameters directly affect the strength of reinforcing feedback R2, in which ambassadors drive new adoption (Fig. 1). They indirectly affect the strength of R3, in which ambassadors bring adopters into the ambassador community. When community-building is active for the full 15-year period, the influence of these parameters far outweighs that of any others. Not surprisingly, if community-building is active for only four years, the average number of years of implementation, T_A, also has a high impact on the number of users, similar to when only outreach is active in Strategy 1 (Fig. 4). Note that even four years of community-building yields far more users than 15 years of outreach alone (Figs. 2 and 4).

As before, including outreach in a propagation effort with community-building has little impact on the final number of users. With or without outreach (Strategies 2 and 3, respectively), parameters that affect community-building have the highest impact (c_{AA}, f_{AA}, T_{fAA} and T_A; Fig. 4). Increasing c_{AA} and f_{AA} strengthens reinforcing feedback R2. Increasing the number of years for community-building, T_{fAA}, strengthens reinforcing feedback R3. The number of years that educators use the innovation is also important: as it grows, the balancing feedback B2 is weakened, keeping educators in the stock of adopters for a longer time, enabling more of them to become ambassadors and to reach more potential adopters.

Including outreach with community-building yields slightly higher numbers of users, but the differences are negligible if ambassador
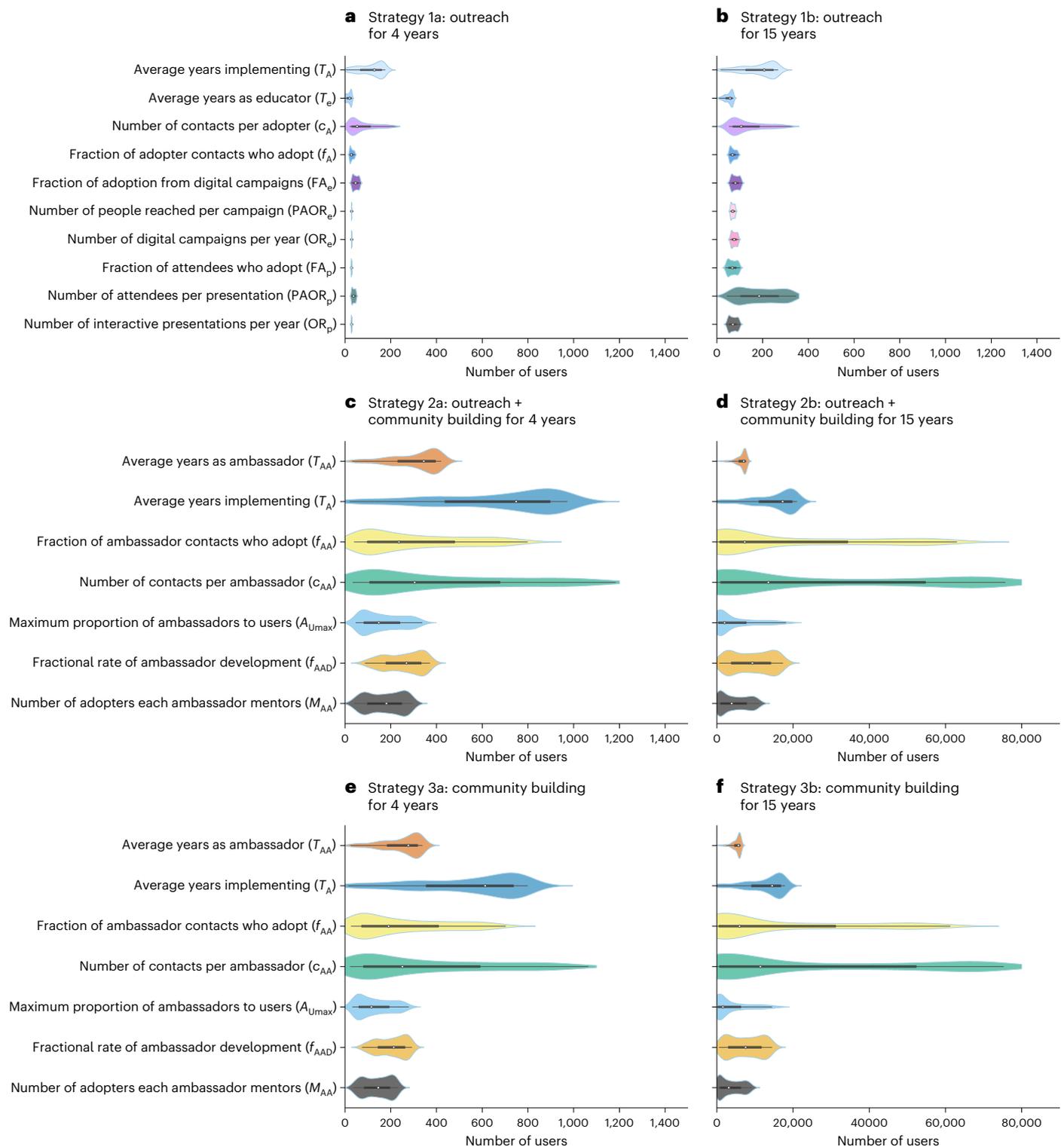
Fig. 4 | Sensitivity analyses of the impact of parameter values on the number of users in year 15 for different propagation strategies. a–f, Each violin plot shows the distribution of users at the end of 15 years when the input parameter values are varied over their full range for each strategy. Each coloured region ranges from the minimum to the maximum number of users, with its width indicating the probability density of the distribution at any particular number of users. The violin plots also show the median values (white dots), interquartile ranges (thin black vertical lines) and 95% confidence intervals (thin black lines) of each distribution. The results are shown for Strategies 1a (**a**), 1b (**b**), 2a (**c**), 2b (**d**), 3a (**e**) and 3b (**f**). Note that the results for Strategies 1a, 1b, 2a and 3a are shown on a scale from 0 to 1,400 users, while those for Strategies 2b and 3b are shown on a scale from 0 to 80,000 users.

development is active for 15 years (Fig. 4), and the overall patterns of sensitivity analyses are similar. This is because the balancing feedback B1 around outreach affects the dynamics only at the beginning of the propagation effort when it helps generate more rapid initial gains (Fig. 2). However, in the longer term, the reinforcing feedbacks R2 and R3 around the community dominate the system behaviour. Multivariate

sensitivity analyses (Supplementary Information and Supplementary Fig. 1) reinforce these findings: community-building approaches yield higher numbers of users than outreach alone, even as multiple parameters are varied simultaneously.

Implications for practice

Even though successful scaling of educational innovations is rare[9,15,16], most developers continue to use conventional dissemination and outreach approaches[17]. Our analysis reveals why these approaches do little to accelerate adoption under conditions typical in higher education. In contrast, both model-based analysis and prior research show that community-based propagation can achieve rapid scaling[21,32,35]. Shifting limited resources from outreach to activities that create, support and strengthen the impact of a community of ambassadors can generate exponential growth in adoption. By supporting adopters, ambassadors also make it more likely that adopters will continue to use the innovation (that is, increasing T_A; Fig. 1), helping overcome discontinuation, which is a known barrier to effective propagation[38]. Scaling efforts should enable educators to share their instructional strategies, support each other to sustain adoption, mentor new ambassadors and find ways for individuals to benefit from their shared successes. Ideally, these efforts should be long-term efforts and would therefore benefit from policy changes in funding programmes. Real-world examples[21,32] of successful scaling demonstrate the power of this community-based approach.

Limitations

Our stylized model of the diffusion of educational innovations enables users to explore strategies and create what-if scenarios to improve mental models and make better decisions. But it is clearly limited by modelling assumptions, data availability to inform its parameter values and the contexts in which it can be applied. For example, there is little quantitative information about propagation outcomes available to validate parameter values, especially over the time horizons needed to validate the parameters of our model (that is, more than ten years). Our focus is on the propagation of innovations in sustainability higher education. This context differs significantly from the propagation of educational innovations in other settings, such as US secondary education, where adoption is strongly influenced by educational policies and standards, teacher training and assessments, or widely used textbooks[39]. These factors do not apply to sustainability higher education, nor are they captured in our model, so they cannot be evaluated with it.

Implications for future research

One of the main outcomes of this work is to underscore the need for more research and innovation in community-based propagation—an approach that is rarely used in the real world but that we find has strong potential for rapid scaling. Our simulation model is designed to capture the core systemic structure that drives community-based propagation (Fig. 1 and Extended Data Fig. 1)—that is, a community that supports a growing number of ambassadors who, in turn, compellingly share the innovation with potential adopters and support them in their efforts to use the innovation. We allow for broad ranges in sensitivity testing of many variables because there is little information about their real-world values. There are undoubtedly additional variables that influence the ranges of those of parameters and that could be included in subsequent models. For example, community-based efforts must provide incentives for educators to join the community and support that facilitates their participation. Incentives depend on an educator's academic position or setting, which could be tested and captured in an improved model of propagation. For example, tenure-track faculty members at research universities may benefit from a community that offers opportunities to collaborate on grants and peer-reviewed papers related to the educational innovation. Teaching-focused faculty may benefit from evidence that their work as an ambassador improved instruction in their own and their colleagues' courses. Our work points to much-needed innovation and empirical testing of community-building approaches that could then inform further model development.

Future research could calibrate the model to real-world data. Such an effort could be a case study[40] of a particular propagation strategy, rather than a theoretical evaluation of different potential strategies, and would require data on potential adopter, adopter and ambassador numbers over time. However, univariate sensitivity testing shows that many of those parameters have little influence on model outcomes. Most parameters associated with word-of-mouth propagation and outreach efforts have little impact on propagation outcomes when they are varied over the assumed ranges of values. In contrast, several parameters associated with community-building have high impact, such as the number of adopters that each ambassador mentors. Future research should therefore focus on better defining factors that affect community-building and whether and how high-leverage factors can be enhanced.

Our model can be adapted to any other discipline and educational setting in which individual instructors drive adoption decisions. We focus on modelling the diffusion of sustainability innovations in higher education, which is central to preparing the next generation of decision-makers and leaders in society[41]. Its educators are generally free to teach new content in new ways, so that the propagation of educational innovations is possible without higher-level policy decisions. With a growing number of sustainability-focused programmes[42] and many disciplinary courses in which sustainability is relevant, it is fertile ground for rapid scaling of educational innovations.

Especially given the individualistic, competitive culture of academia[43], realizing the potential benefits of community-based propagation presents challenges. Most decisions to adopt curricula in higher education are made by individual educators who must be convinced that the additional time and effort needed to try something new is worthwhile. The benefits of belonging to a community of transformation must outweigh the time and effort it demands. The community's educational innovations must be high quality and relevant and must offer the instructor benefits over other resources. Research shows that social visibility and recognition motivate people to contribute to the greater good[44] and that having a sense of belonging to, identity with and satisfaction about a community of practice motivates its members to contribute to shared goals[45]. Community-building efforts may therefore be more successful if ambassadors' contributions are recognized and celebrated, preferably by professional societies they esteem. Communities can also encourage participation through annual meetings and online meetings that encourage interactions among the members, offering opportunities for learning and collaboration.

Methods

Model development

We began with interactive group model-building to adapt the Bass model to the diffusion of innovations in higher education. Group model-building is a facilitated process that elicits stakeholders' mental models of how a complex system works and builds a shared understanding of the structure that drives system behaviour[20,46,47]. It leverages human capacity for recognizing interactions between system elements and uses the visual 'language' of system dynamics to depict interacting stocks, flows and feedbacks[22]. Group model-building is often the initial step in the system dynamics modelling process. It was facilitated by the first author and included stakeholders with expertise relevant to the propagation of higher-educational innovations, including university-level educators in sustainability and related fields, developers of educational innovations, educational researchers, and researchers studying the propagation of higher-educational innovations and system dynamics (Extended Data Table 2). The resulting qualitative model depicts the participants' shared understanding of how the propagation of innovations works in higher education on the

basis of group members' prior research[9,28,38] and diverse experiences as university-level developers, educational researchers and educators.

We then developed a quantitative and interactive simulation model and formulated mathematical equations for the variables, using differential equation modelling and continuous time simulation to enable users to test expected outcomes from different propagation scenarios. We solicited further feedback on parameter estimation and the model structure and behaviour from stakeholders in educational innovation and propagation at professional meetings (for example, ref. 48) and reviewed the literature to iteratively improve the model structure, underlying equations and assumptions. The model is available for download[49] and can be run using the Vensim model reader (freely available at https://vensim.com/vensim-model-reader/). An interactive version of the model is freely accessible at https://exchange.iseesystems.com/public/florian-kapmeier/sustainability-education-propagation-simulator.

We focused on the diffusion of educational innovations in the US higher-education system, where most of the authors are based. In the United States, there is growing interest in sustainability[18], and decisions to adopt educational innovations are largely made by individual instructors. However, the model is easily adaptable to the diffusion of educational innovations in other countries, other disciplines and other educational levels, as long as adoption decisions are made primarily by individual educators.

Model structure

Figure 1 shows an overview of the propagation model. The simulation model[49] includes the formal specification of all model variables and the interactions among those variables. The full model is also shown in Extended Data Fig. 1. Supplementary Tables 1–3 show the model equations, parameter values and parameter value sources. The model captures three key groups, or stocks, of educators relevant to the propagation of educational innovations: potential adopters, adopters and ambassadors (Fig. 1; P, A and AA, respectively). Potential adopters are higher-education instructors who could use the innovation but currently do not. Potential adopters become adopters when they begin using the innovation. If adopters quit using the innovation, they re-enter the stock of potential adopters—and can potentially use it again in the future.

The purpose of the model is to help decision-makers better understand the dynamics of propagating educational innovations. We therefore focus on the high-level drivers of diffusion and aggregate variables that represent ease of adoption, quality of the innovation or relative attractiveness of the innovation in more general parameters, such as the fraction of potential adopters who adopt the innovation from different outreach or diffusion activities (for example, the fraction of adopter contacts who adopt, f_A, the fraction of adopters from different outreach activities, f_{Ap} and f_{Ae}, and the fraction of ambassador contacts who adopt, f_{AA}; Extended Data Fig. 1).

Ambassadors are members of a community who actively use and propagate the innovation—that is, educators who have a higher level of investment in the innovation, use it successfully and share their success with others. For example, ambassadors use the innovation more frequently and for a longer time than adopters (Supplementary Tables 4–9). Compared with adopters, ambassadors also share the innovation with more potential adopters and are more likely to convince those educators to adopt. Ambassadors are therefore central to community-based propagation. Adopters who become invested in the innovation become ambassadors, and ambassadors who step down revert to being adopters (Fig. 1; ambassador development and ambassadors stepping down, respectively). The model captures the four key processes that affect the propagation of educational innovations: word-of-mouth diffusion, outreach, community-building and community propagation (Fig. 1 and Extended Data Fig. 1). The full model accounts for additional flows such as potential adopters, adopters and

ambassadors retiring or otherwise moving on from their instructional positions; and hiring new educators who enter the pool of potential adopters (Extended Data Fig. 1 and ref. 49; these are not included in the model overview in Fig. 1 because they have little impact on model outcomes and do not change our findings).

The stock of potential adopters (P) increases when potential adopters are added (P_a) (Extended Data Fig. 1) and when adopters stop using the innovation, reentering the stock of potential adopters (at rate A_q), as shown in Extended Data Fig. 1. Supplementary Tables 1–9 provide details about the equations and parameters used to compute the rate at which potential adopters are added, which is dependent on the rate at which sustainability education is growing in American universities[50] and on the need to replace retiring faculty members.

The stock of potential adopters decreases as educators retire, P_r, which we assume by dividing the potential adopters, P, by the average number of years that a US tertiary educator teaches, T_e, acknowledging that this number may differ substantially for tenure-track versus adjunct or other temporary or part-time faculty members: $P_r = P/T_e$ (Extended Data Fig. 1 and Supplementary Tables 1–3). Furthermore, the stock of potential adopters is increased by new potential adopters, P_a, and adopters who quit using the innovation. It is decreased as educators adopt through three potential processes that we describe in more detail below: outreach efforts, a_{OE}, word-of-mouth via current adopters, a_A, or ambassadors, a_{AA}. Thus:

$$\frac{dP}{dt} = P_a + A_q - P_r - a_{OE} - a_A - a_{AA}. \tag{1}$$

We capture the dynamic nature of adopters, A, through the accumulation processes that increase or decrease this stock of educators. Adopters grow via the conversion of potential adopters to adopters, A_a (as described above and in equation (1)): that is, from outreach efforts, a_{OE}, and word-of-mouth adoption via adopters, a_A, and ambassadors, a_{AA}. The stock of adopters declines from adopters quitting, A_q, and as adopters retire, A_r. The stock of adopters also declines (through flow AA_d) when adopters become ambassadors, A_{AA}, and grows (through flow AA_{sd}) when ambassadors no longer actively share or promote the innovation, AA_{nc}, and return to the adopter group. Thus:

$$\frac{dA}{dt} = a_{OE} + a_A + a_{AA} - A_q - A_r - A_{AA} + AA_{nc}. \tag{2}$$

Adoption through outreach efforts, a_{OE}, includes two common outreach approaches: interactive presentations or workshops and digital campaigns. In both types of outreach, the fraction of educators who adopt, FA, is multiplied by the number of annual efforts, OR, and the potential adopters reached through the outreach effort, PAOR. So, adoption through presentation-based outreach is $A_{ORp} = F_{Ap} \times OR_p \times PAOR_p$, while adoption through digital campaigns is $A_{ORe} = F_{Ae} \times OR_e \times PAOR_e$. We added these to determine the total number of educators that adopt per year due to outreach, PAOR$_t$. Consistent with the Bass diffusion model, we assume a_{OE} by multiplying the number of educators reached by a probability that they adopt, P/E_a: $a_{OE} = PAOR_t \times P/E_a$. Outreach efforts are typically active only if funded, which we capture through the period of funding, T_{fO}.

The feedback that outreach efforts create is balancing (B1–Outreach, Fig. 1): when the number of potential adopters, P, is not a constraint, this feedback accelerates the number of potential adopters who adopt the innovation. Over time, however, and when potential adopters deplete, it gradually lowers the proportion of potential adopters to total educators and the rate at which adoption occurs. Similarly, we assume that adopters eventually stop using the innovation, creating a second balancing feedback, B2–Moving on (Fig. 1). Adopters who stop using the educational innovation, A_{nc}, are captured by dividing the number of adopters by the average time that they use the innovation,

T_A: $A_{nc} = A/T_A$. As the number of adopters grows, the rate at which they quit using the innovation also grows, depleting the number of adopters.

We assume the number of educators who learn about the innovation via adopters by multiplying the number of contacts per adopter, c_A, by the fraction of adopter contacts who adopt, f_A, the number of adopters, A, and the proportion of potential adopters, P, to total educators, E_a, or P/E_a; thus, $a_A = c_A \times f_A \times A \times P/E_a$. This process creates a reinforcing feedback, R1–Word-of-mouth (Fig. 1), which accelerates adoption as the number of adopters who contact potential adopters grows. A similar reinforcing feedback (R2–Community propagation, Fig. 1) results from ambassadors sharing the innovation with potential adopters, increasing the number of adopters and, eventually, ambassadors: $a_{AA} = c_{AA} \times f_{AA} \times AA \times P/E_a$. Note that adoption through contacts with both adopters and ambassadors also creates two balancing feedbacks, B0a and B0b–Depleting potentials (Extended Data Fig. 1). As the number of potential adopters depletes, the proportion of all educators, E_a, who are potential adopters, P, or P/E_a, declines; thus, the adoption rate decreases.

The model includes an explicit effort to build a community of ambassadors, AA, who use the innovation successfully and share the innovation with potential adopters. The number of ambassadors grows when ambassadors mentor adopters who then become ambassadors, AA_A. It declines when ambassadors step down from a leadership role but continue to use the innovation as adopters, AA_{nc}, or when they retire from teaching, AA_r:

$$\frac{dAA}{dt} = AA_A - AA_{nc} - AA_r. \tag{3}$$

The rate at which adopters become ambassadors, AA_A, depends on the fraction of ambassador mentees who become ambassadors, f_{AAD}, the number of adopters each ambassador mentors, M_{AA}, and the number of ambassadors, AA (Supplementary Tables 1–9). The number of adopters who have the time, resources, ability and desire to become ambassadors is limited, which is captured by the term A_{Umax}, or the maximum proportion of ambassadors, A, to users, U, of the innovation. As the actual proportion of ambassadors to users approaches A_{Umax}, the development of new ambassadors approaches zero, so: $AA_A = (1 - (A/U)/A_{Umax}) \times f_{AAD} \times M_{AA} \times AA$. This equation closes the third reinforcing feedback, R3–Community-building (Fig. 1), accelerating the development of new ambassadors as the number of ambassadors actively mentoring adopters grows. It also creates the balancing feedback B3–Pool is drying out (Fig. 1), which eventually limits ambassador development. Ambassadors revert back to being adopters, AA_{nc}, after an average number of years, T_{AA}, so that $AA_{nc} = AA/T_{AA}$, closing the balancing feedback B4–Stepping down (Fig. 1). We also capture the need for funding to support community-building efforts, which stop when the funding period, T_{fAA}, expires.

We use 'switches' that are set to a value of one to activate or zero to deactivate a given model substructure (Extended Data Fig. 1). This formulation provides a simple way to test the impact of distinct strategies, such as outreach or community-based propagation, or their combinations by changing a single parameter (Table 1). Each switch parameter is used to multiply relevant substructure outcomes by zero or one (with adopting through outreach efforts, a_{OE}, multiplied by the switch for outreach efforts and ambassador development, AA_d, multiplied by the switch for ambassador development).

Parameter values

When possible, we drew parameter values for numerical simulation from prior research on the propagation of educational innovations. However, little or no quantitative data are available for several relevant parameters, such as the average proportion of educators who adopt after attending a presentation or workshop about an innovation. Rather than excluding such parameters from the model—which would imply

that they have no impact—we included them and tested the sensitivity of model outcomes to a wide range of potential values for them. Base-case parameter values and references or descriptions of their sources are provided in Supplementary Tables 4–9. Supplementary Tables 10 and 11 and Extended Data Table 1 show the base case and the range of values used for sensitivity analyses. Sensitivity testing is used to determine whether parameters have high or low leverage on the simulation outcomes[36]. Such testing allows us to determine whether poorly constrained parameters are important in determining propagation success. It helps guide future potential research by indicating which parameters are important to determine accurately. And it helps guide propagation efforts by indicating which parameters—and types of effort—have the potential to accelerate propagation.

We include a scale indicating our level of confidence in the accuracy of each parameter value (Supplementary Tables 4–9). We have a high level of confidence in parameter values in published research or publicly available databases (category 4) and a much lower level in those parameter values for which our team is relying on our own expert opinions (category 1). For each parameter, we identified a most likely value (that is, the base case) and a full range of possible values to include in the sensitivity analyses.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data outputs from the main scenarios described here are available via Figshare at https://doi.org/10.6084/m9.figshare.23948922.v7 (ref. 49).

Code availability

The model is available via Figshare at https://doi.org/10.6084/m9.figshare.23948922.v7 (ref. 49) and can be interactively explored using the freely available VensimReader (https://vensim.com/vensim-model-reader/) with parameter settings that are specified by users or by the associated data files. An interactive version of the model is also online at https://exchange.iseesystems.com/public/florian-kapmeier/sustainability-education-propagation-simulator.

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Author contributions

J.N.R.-V. conceived and designed the model, performed the initial model runs, analysed the data and wrote the paper. F.K. improved the model, performed sensitivity analyses and contributed to documentation of the model, analysing the data and writing the paper. C.H. contributed to model conceptualization, grounding the model in real-world propagation examples, validating the model structure and parameters, comparing model outcomes to prior research on propagation and writing the paper. D.N.F. contributed to refining model structure, analysing the data and editing the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Extended Data Fig. 1 | Stock-flow diagram for the full model structure.
Accumulations, or stocks, are shown as boxes. Flows are shown as pipes with valves, while information feedbacks are shown as blue arrows. Self-reinforcing feedback loops are marked 'R,' while balancing feedback loops are marked 'B'. Signs ('+' or '-') at arrowheads indicate the polarity of the causality: a '+'represents an increase in the independent parameter or variable causes the dependent variable to increase, ceteris paribus (and a decrease causes a decrease).

Variables are shown in black. Parameters involved in word-of-mouth activities are shown in orange, those involved in outreach in dark blue, and those involved in community propagation in maroon. Switches to activate model structures are shown in pink and the time over how long the model subsections are active in dark green. Parameters involved in the growth in the field of sustainability are shown in light green and initial values of the stocks in light blue.
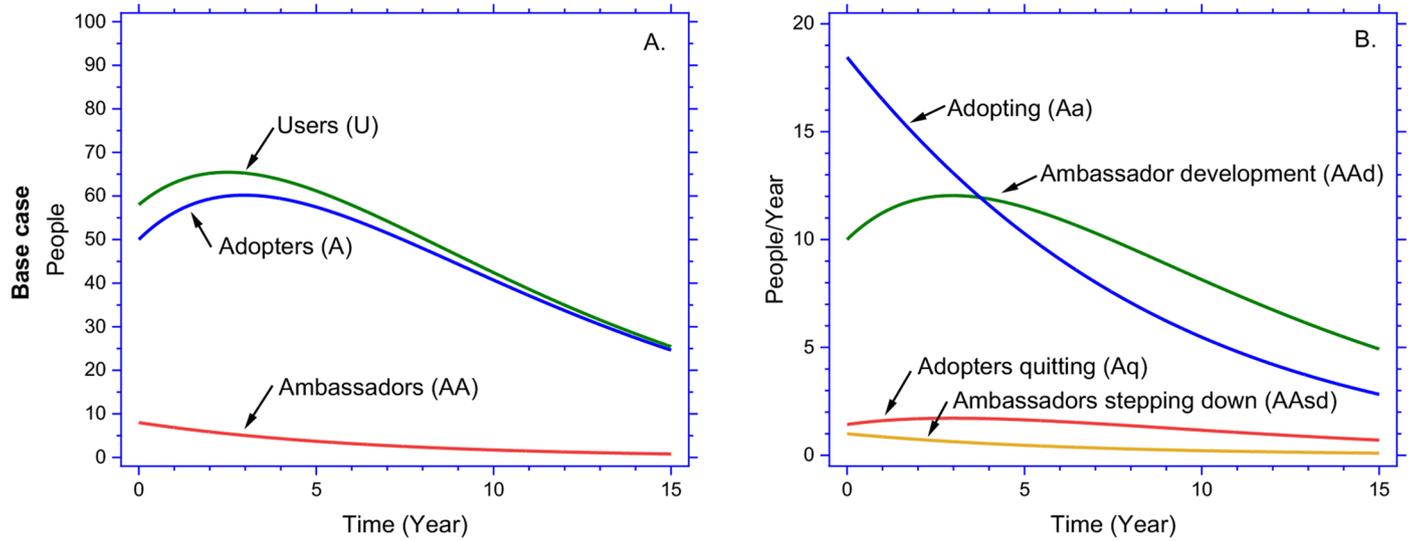
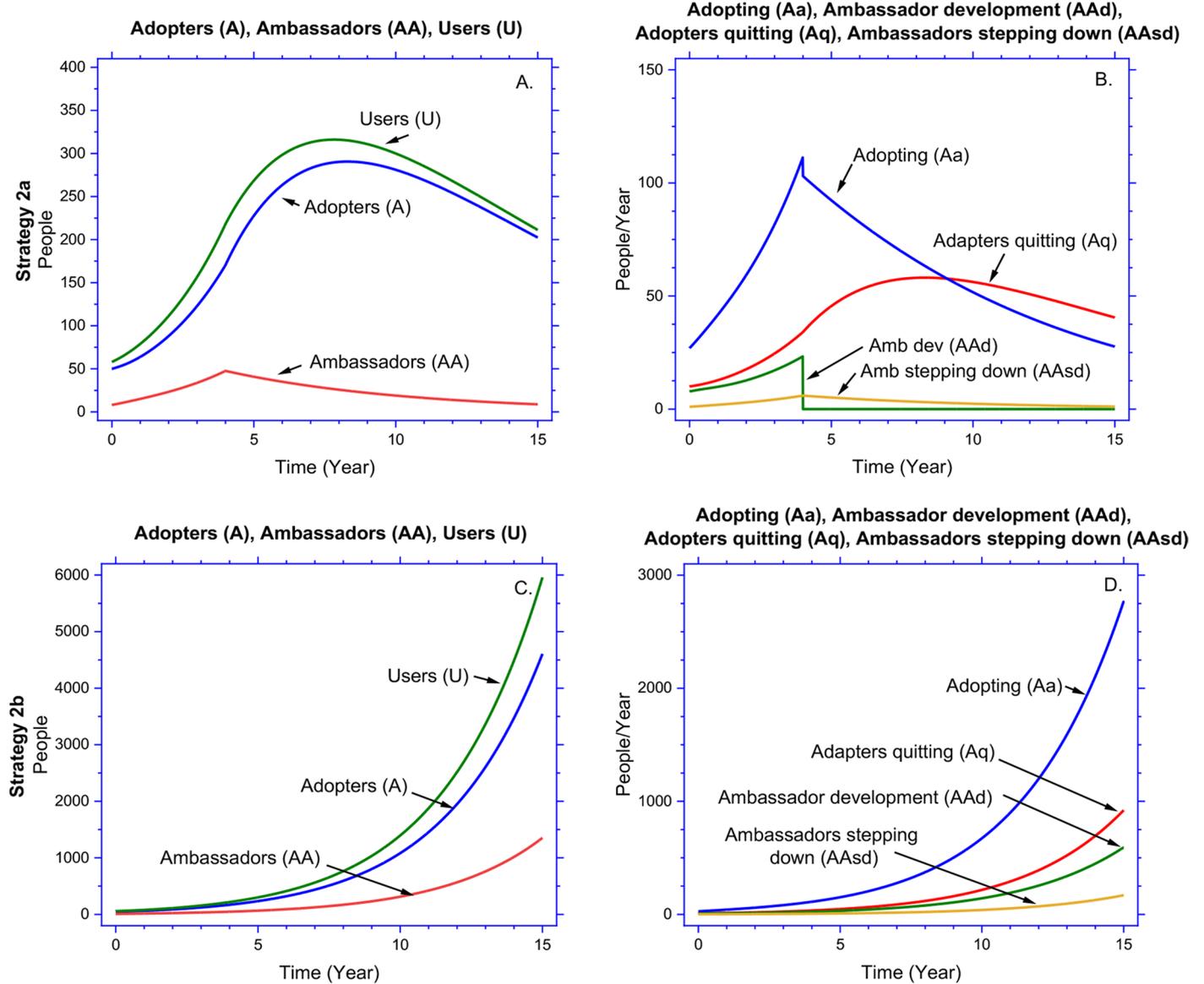**Extended Data Fig. 2 | Behavior over time for the base case scenario, with only word-of-mouth diffusion, over a time period of 15 years.** Panel A: Adopters (A), Ambassadors (AA), and Users (U). Panel **B**: Inflows and outflows to Adopters (A).
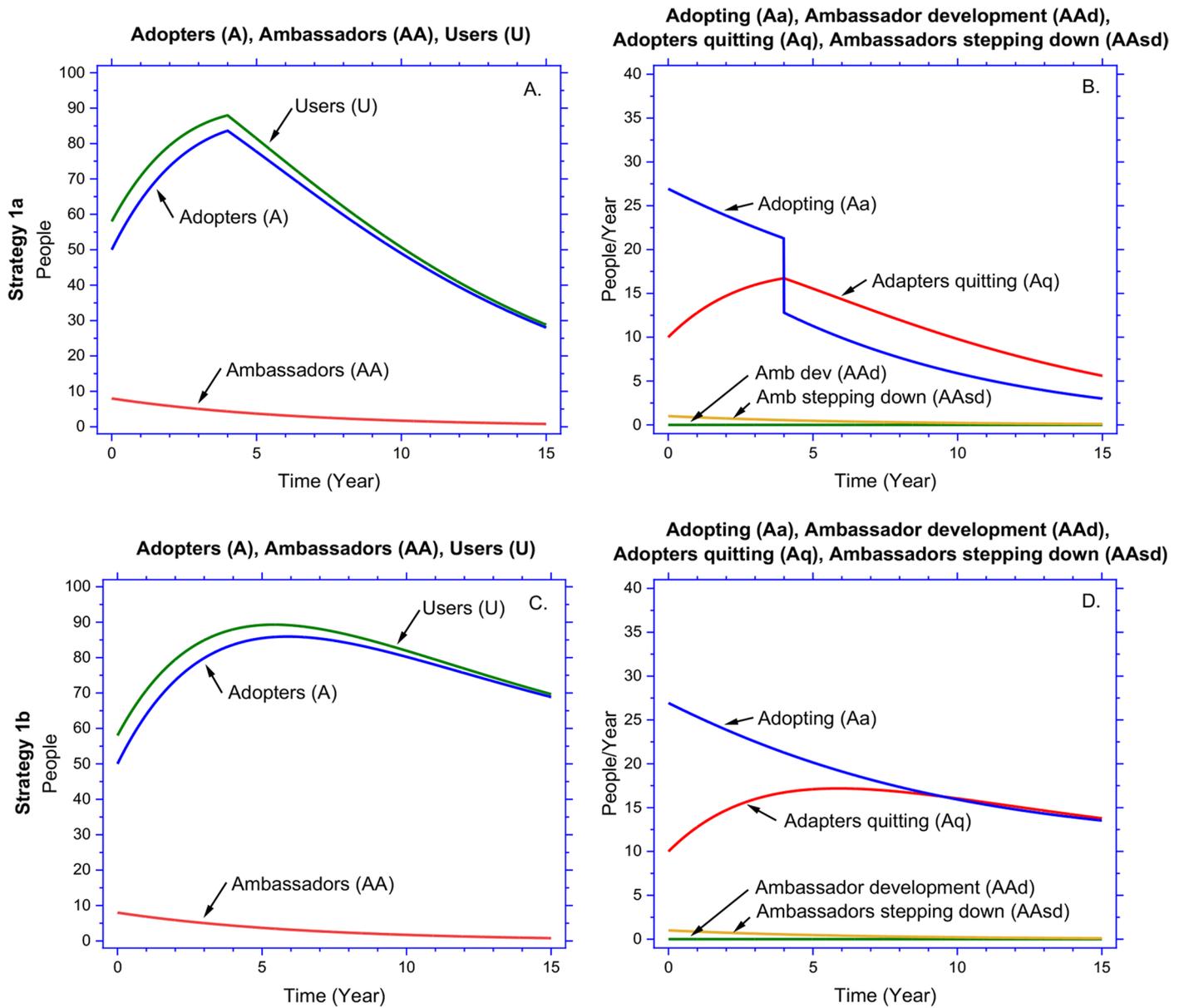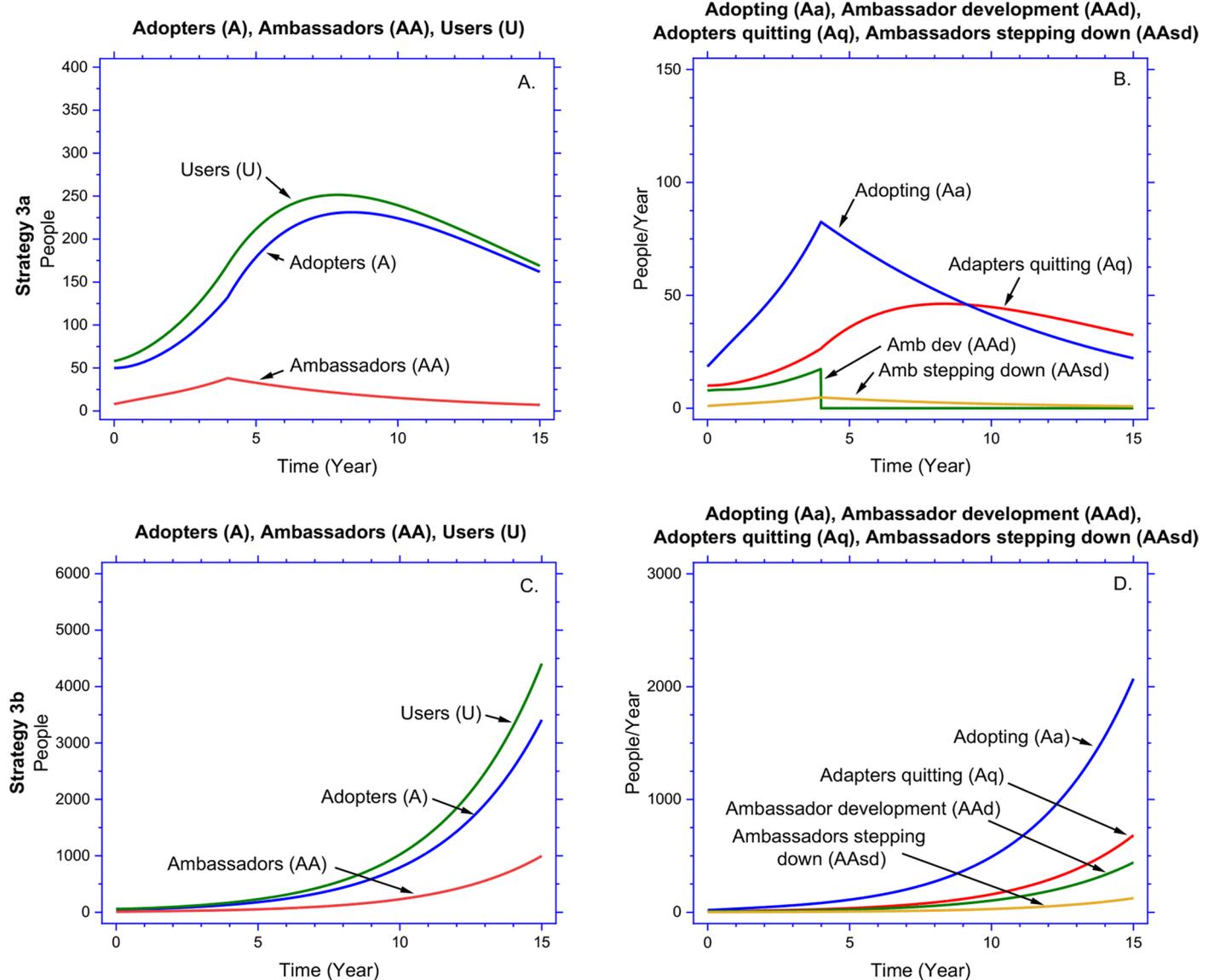
Extended Data Fig. 3 | Behavior over time for Strategies 1a and 1b with active outreach for 4 and 15 years, respectively. The impact of 4 years of active outreach is shown in panels A and B, while the impact of 15 years is shown in panels C and D. Stocks of adopters, ambassadors, and users are shown in panels A and C. Their corresponding inflows and outflows (adopting, adopters quitting, ambassador development, and ambassadors stepping down) are shown in panels B and D.

Extended Data Fig. 4 | Behavior over time for Strategies 2a and 2b with active community building with outreach that is funded for 4 and 15 years, respectively. The impact of 4 years of community building and outreach is shown in panels A and B, while the impact of 15 years is shown in panels C and D. Stocks of adopters, ambassadors, and users are shown in panels A and C.

Their corresponding inflows and outflows (adopting, adopters quitting, ambassador development, and ambassadors stepping down) are shown in panels B and D. Note the different scales for the stocks on the top and bottom left; and for the flows on the top and bottom right.

Extended Data Fig. 5 | Behavior over time for Strategies 3a and 3b with community building without outreach for 4 and 15 years, respectively.
The impact of 4 years of community building is shown in panels A and B, while the impact of 15 years is shown in panels C and D. Stocks of adopters, ambassadors, and users are shown in panels A and C. Their corresponding inflows and outflows (adopting, adopters quitting, ambassador development, and ambassadors stepping down) are shown in panels B and D. Note the different scales for the stocks on the top and bottom left; and for the flows on the top and bottom right.

Extended Data Table 1 | Sensitivity analysis: Switches and other parameter settings for the sensitivity runs

Model switches and parameter	W Word-of-Mouth (Base)	WO Word-of-Mouth + Outreach (S1a)	WOC Word-of-Mouth + Outreach + Community Building (S2a)	WC Word-of-Mouth + Community Building (S3a)	WOTfO$_{max}$ Word-of-Mouth + Outreach + TfOmax (S1b)	WOCTfAA$_{max}$ Word-of-Mouth + Outreach + Community Building + TfAAmax (S2b)	WCTfAA$_{max}$ Word-of-Mouth + Community Building + TfAAmax (S3b)
Switch for outreach effort	0	1	1	0	1	1	0
Switch for project ambassador development	0	0	1	1	0	1	1
Years funded outreach (T_{fO}); (years)	4	4	4	4	15	4	4
Years funded ambassador development (T_{fAA}); (years)	4	4	4	4	4	15	15

Note: We perform 200 runs in the multi-variate sensitivity analysis, drawing parameter values for the eight variables above within the Min and Max range using a uniform distribution and noise seed value 1234.

Extended Data Table 2 | Experts and stakeholders engaged in the group model-building effort

Name	Affiliation	Title	Relevant Expertise
M. Barlow	University of Massachusetts Lowell	Professor	Educator, climate change
D. Ford	Virginia Tech	Professor	System dynamics, higher education
T. Gao	University of Massachusetts Lowell	Assoc. Professor	Educator
C. Henderson	Western Michigan University	Professor	Propagation of educational innovations; STEM education researcher
F. Kapmeier	ESB Business School, Reutlingen University	Professor	System dynamics, corporate environmental sustainability, higher education
K. Kastens	Columbia University	Research Professor	Educational developer and researcher, climate change and sustainability
K. McNeal	Auburn University	Professor	Educational developer and researcher, climate change and sustainability
K. Rath	Rath Educational Evaluation and Research	Director	Educational researcher
J. N. Rooney-Varga	University of Massachusetts Lowell	Professor	Educator, climate change and sustainability, system dynamics
M. Sobkowicz-Kline	University of Massachusetts Lowell	Professor	Educator, sustainability
L. Stuntz	Creative Learning Exchange	Director	System dynamics, educational developer

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Reporting Summary

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For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐	A description of all covariates tested
☒	☐	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	We used Vensim simulation software (v. 10.2.1) to build and simulate our model. The model is available for anyone to download at: https://doi.org/10.6084/m9.figshare.23948922.v6 and can be interactively explored using the freely available VensimReader (https://vensim.com/vensim-model-reader/). An interactive version of the model is also online at: https://exchange.iseesystems.com/public/florian-kapmeier/sustainability-education-propagation-simulator.
Data analysis	Vensim simulation software (v. 10.2.1) and the model we built (available at https://doi.org/10.6084/m9.figshare.23948922.v6) were also used to analyze mode output.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about <u>availability of data</u>

All manuscripts must include a <u>data availability statement</u>. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our <u>policy</u>

The model and data outputs from main model runs are available for download at https://doi.org/10.6084/m9.figshare.23948922.v6 49 and can be interactively explored using the freely available VensimReader (https://vensim.com/vensim-model-reader/) with parameter settings that are specified by users or by the associated data files. An interactive version of the model is also online at: https://exchange.iseesystems.com/public/florian-kapmeier/sustainability-education-propagation-simulator.

Human research participants

Policy information about <u>studies involving human research participants and Sex and Gender in Research.</u>

Reporting on sex and gender	NA
Population characteristics	NA
Recruitment	NA
Ethics oversight	NA

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We develop and use a quantitative, dynamic model to test strategies for propagating innovations in sustainability education. We used group model-building to build a qualitative model that was then numerically formulated using a system dynamics modeling approach.
Research sample	No human subjects were used in this study. Our study analyzes outcomes from a deterministic numerical model, not a sample of human subjects.
Sampling strategy	We use a deterministic model, not a statistical sample or analysis. We handle uncertainty in parameter values by running sensitivity analyses that include the full range of potential parameter values..
Data collection	Data were collected from simulation model outputs. Researchers were not blinded to study hypotheses.
Timing	We do not collect data from the real world, but rather rely on outputs from a numerical model for our analyses. We began our analyses in June 2022 and completed them in January 2024, prior to submission of our revised manuscript.
Data exclusions	Data were not excluded.
Non-participation	Participants were not involved in the study.
Randomization	This was a deterministic study, not a statistical one. Therefore, there was no randomization of sampling.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems	Methods

Materials & experimental systems

n/a	Involved in the study
☒	Antibodies
☒	Eukaryotic cell lines
☒	Palaeontology and archaeology
☒	Animals and other organisms
☒	Clinical data
☒	Dual use research of concern

Methods

n/a	Involved in the study
☒	ChIP-seq
☒	Flow cytometry
☒	MRI-based neuroimaging