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The Use of System Dynamics for Modeling Innovation Diffusion

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Abstract
The aim of this publication is to synthesize dynamic models for selected innovation diffusion models. For this purpose, modeling in the system dynamics (SD) convention was applied to represent the flow between the stock of potential and current users of innovations in three selected diffusion models: the Bass model, the source model, and the contact model. The AnyLogic software was used as the simulation environment. As a result of the study, simulation models were developed that enable forecasting the behavior of participants in a given population depending on predefined coefficients. This solution is particularly useful for the cost optimization of promotional activities in enterprise departments responsible for marketing innovative products, as well as for diffusion understood as the dissemination of modern organizational and process methods among employees of an organization.

Keywords
innovation diffusion, system dynamics, simulation modeling, innovation diffusion models, mathematical models of innovation diffusion.

Introduction

Innovations are activities that not only revolutionize the market and introduce entirely new products that satisfy new customer needs or address existing needs in a novel way. A common classification divides innovations into technological and non-technological. Within technological innovations, products and processes are distinguished, while among non-technological innovations there are, for example, marketing and organizational methods, ways of communicating with customers, or the implementation of new digital technologies (Domnich, 2022; Janasz & Kozioł-Nadolna, 2011; Kamutando & Tregenna, 2024; Kochetkov, 2023). Additionally, any product or process that is new to the enterprise may be considered an innovation, even if it is not new to the customer or employee (Gwarda-Gruszczyńska, 2013).

The literature distinguishes various types of innovations, including disruptive, forced, coupled, and uncoupled innovations, which stand out from the rest and illustrate the dynamic development of enterprises in response to the current market (Cywiński, 2020; Edwards-Schachter, 2018; Garcia, 2002). This reality also shapes the way the innovation process is carried out today. It is a “demand-driven” process, in which information about the need for novelty originates directly from customers who express their requirements. The enterprise then undertakes actions aimed at developing the technology, implementing it, and delivering it to end users (Karpińska & Protasiewicz, 2019).

Innovation diffusion is understood as “the process of spreading ideas underlying product innovations and business process innovations, as well as the adoption of such products or business processes by other enterprises” (OECD, 2020). This means that innovations of all types can undergo diffusion, which consists of reaching the largest possible group of individuals in the considered population (customers, employees, etc.).

The process of spreading new solutions can be divided into several stages. First, individuals acquire knowledge about the possibility of using an innovation. Then, as interest grows, comes the stage of persuasion, during which recipients actively seek information about the given technology. After persuasion comes the most important stage: the decision to adopt or reject. This is crucial for every enterprise, because it is at this moment that customers decide whether to purchase the product, which directly translates into financial profits. After a positive decision, the stages of implementation and confirmation follow, during which the individual begins to use the solution, tests it, and decides whether to continue its use (Rogers, 1983).

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The most critical moment of the innovation diffusion process – the acceptance and start of use of a novelty – is influenced by many factors. To stand out, an innovation must meet such conditions as (Bharadwaj & Deka, 2021; Firlej & Żmija, 2014): superiority over earlier solutions, compatibility with values and prior experiences, low complexity, trialability (the ability to test), and observability (the opportunity to see how the technology performs for other users). Additionally, absorption – the adoption of innovations – is also influenced by the personal characteristics of individuals in the population, such as education, attitude toward learning, or curiosity about the world, all of which facilitate the acceptance of novelty (Klincewicz, 2011).

In economic practice, every diffusion proceeds differently and it is never possible to reproduce it exactly in the same way again. However, thanks to the use of mathematical descriptions of diffusion, it becomes possible to shape it by means of characteristic parameters. The selected models will be analyzed in order to represent them as system dynamics (SD) models.

In the literature, the most frequently presented diffusion model is the Bass model (Brdulak et al., 2021; Guidolin & Manfredi, 2023; Mahajan et al., 1990a; Mahajan et al., 1990b; Mitra et al., 2020; Ramírez-Solis & Rodriguez-Marin, 2022). It assumes a two-channel diffusion process. In the first channel, diffusion occurs through the marketing activities of the innovation emitter, e.g., through demonstrations, promotions, or advertisements. The second channel is related to mutual interactions within the population, i.e., word-of-mouth marketing – both recommendations and discouragements to purchase (Fant et al., 2023).

The Bass model is described by the following differential equation (1), whose solution leads to the curve shown in equation (2):

$$\frac{\mathrm{d}N(t)}{\mathrm{d}t} = p\left[m - N(t)\right] + \frac{q}{m}N(t)\left[m - N(t)\right] \quad (1)$$

where:
- $N(t)$ – number of users adopting the technology at time t,
- t – time,
- m – maximum number of potential users of the technology,
- p – innovation coefficient, representing the impact of organizational marketing activities on the population,
- q – imitation coefficient, representing the influence of social interactions and the effectiveness of word-of-mouth marketing,

$$n(t) = p \cdot P(t) + \frac{q \cdot P(t) \cdot U(t)}{m} \quad (2)$$

where:
- $n(t)$ – number of users at time t,
- $P(t)$ – number of potential adopters at time t,
- $U(t)$ – number of current users up to time t.

Apart from the Bass model, there are two separate diffusion models which assume that diffusion occurs either only due to marketing activities or only due to interpersonal interactions within the population.

The first is the source model of innovation diffusion (Kot et al., 1993). It assumes that the increase in the number of supporters over time is proportional to the current number of non-adopters. This can be expressed by the following differential equation (3), whose solution is given in equation (4):

$$\frac{\mathrm{d}y}{\mathrm{d}t} = k\left(n - y\right) \quad (3)$$

$$N(t) = n\left(1 - e^{-kt}\right) \quad (4)$$

where:
- y – number of users adopting the technology at time t,
- t – time,
- n – size of the population under consideration,
- k – proportionality coefficient reflecting the susceptibility of individuals to the source.

The model representing diffusion driven solely by interpersonal interactions within the population is the contact model of innovation diffusion. It assumes that contacts are made randomly and that not every contact results in persuasion, but only with a certain probability. Under these assumptions, the number of individuals convinced to adopt the innovation per unit of time can be expressed by equation (5). With an additional assumption that variables f and l are constant throughout the diffusion process, the increase in the number of adopters can be described by the differential equation (6), whose solution yields curve (7):

$$P = fl\frac{n - y}{y} \quad (5)$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = ay\left(n - y\right) \quad (6)$$

$$y(t) = \frac{ne^{nat}}{n - 1 + e^{nat}} \quad (7)$$

where:
- y – number of users adopting the technology at time t,
- t – time,
- P – number of individuals persuaded to adopt the innovation per unit of time,
- f – effectiveness of persuading innovation supporters,
- l – number of contacts per individual per unit of time,
- $a = \dfrac{fl}{n} = \text{const.}$

The above mathematical models of innovation diffusion represent only examples of possible models. In the literature, one can find many other, proprietary models (Guidolin & Manfredi, 2023; Mahajan & Peterson, 1985; Sharif & Ramanathan, 1982; Singhal et al., 2019; Skiadas, 1985), and it is also possible to develop new models based on specific assumptions and conditions in which diffusion occurs. For the purposes of this paper, in the section devoted to the construction of system dynamics models, the above mathematical descriptions will be used. The choice of these models is the result of a literature review (Brdulak et al., 2021; Guidolin & Manfredi, 2023; Mahajan et al., 1990a; Mahajan et al., 1990b; Mitra et al., 2020; Ramírez-Solis & Rodriguez-Marin, 2022).

Due to the fact that these models are expressed as differential equations, they are difficult to analyze, especially for management practitioners. Therefore, it is reasonable to transform them into forms that can be visualized as time functions in an interpretable way and allow for experimentation based on selected innovation implementation scenarios.

The aim of this study is to synthesize innovation diffusion models and to compare their structures and embedded parameters. This is necessary to develop a version that enables the analysis of innovation diffusion scenarios, i.e., the analysis of time trajectories based on predefined initial parameters of innovations. Due to the structure of the presented models (differential equations), as well as the long periods of analysis, the high level of generalization, the strategic framing of issues, and the knowledge of relationships between objects in the environment – while simultaneously lacking knowledge of interactions and dependencies between individual objects subject to diffusion (customers, consumers, producers, objects under diffusion) – the use of the system dynamics method appears justified.

The conceptual and methodological contribution of this paper lies in the systematic translation of classical diffusion of innovation models, traditionally expressed as differential equations, into the system dynamics formalism. The study demonstrates how adoption mechanisms driven by innovation and imitation can be consistently represented using causal loop diagrams and stock-and-flow structures, enabling interpretation in terms of feedback dynamics. This approach preserves the original theoretical assumptions of the diffusion models while improving their transparency and comparability. By bridging mathematical and system-based perspectives, the paper provides a unified framework for analyzing diffusion processes beyond purely analytical formulations. The proposed framework also establishes a foundation for future model extensions, including scenario-based simulation, sensitivity analysis, and empirical calibration within the AnyLogic environment.

The structure of this paper is as follows. First, the methodological approach based on System Dynamics is introduced. Next, the Results section presents the outcomes of the conducted analyses and simulations, following the logical sequence of dynamic model development: initially, qualitative causal loop diagrams are constructed, followed by quantitative stock-and-flow diagrams, and finally the resulting innovation diffusion curves are presented. The Discussion section examines the advantages of modeling innovation diffusion using system dynamics and outlines potential practical implications. The Conclusions section summarizes the study's limitations and identifies directions for future research.

Method

System dynamics modeling is applied to phenomena characterized by long time horizons and focused on strategic rather than detailed operational aspects of individual objects. Furthermore, because such phenomena are described by mathematical equations in a continuous rather than discrete manner, the system dynamics method is the appropriate approach (Cosenz & Noto, 2016; Morecroft, 2020; Naugle et al., 2024).

The environment subject to innovation implementation can be considered a system in which dependencies exist between its individual elements. These dependencies directly affect specific objects, determine their states over time, and, through feedback loops, influence other elements of the system.

If we treat the innovation implementation environment as a system, are able to identify the relationships between its components, and additionally can determine the quantitative nature of these dependencies, then system dynamics modeling becomes the natural methodological choice.

Currently, the scope of system dynamics applications is very broad and covers elements such as supply chain management – including production, procurement, distribution, and transport (Angerhofer & Angelides, 2000; Shepherd, 2014); economics (Gładysz & Santarek, 2017; Grobel-Kijanka, 2016); as well as engineering, construction, and occupational health and safety (Kedir et al., 2023; Zhou et al., 2023). System dynamics is also applied in medical, social, ecological, and energy-related areas (Azar, 2012; Cosenz & Noto, 2016; Ford, 1997).

In summary, system dynamics appears to be the most appropriate method for representing innovation diffusion for the reasons outlined above.

The reproduction of three differential equations known from the literature, which describe innovation diffusion, will be carried out in the AnyLogic system dynamics modeling environment. The models will be developed in accordance with the qualitative–quantitative approach to dynamic model building (Walters et al., 2016), after which the possibilities for further experimentation on these models will be presented.

Results

The aim of each developed model is to reflect reality as accurately as possible based on appropriate initial parameters. The most universal model is, of course, the Bass model, which takes into account both the marketing activities of the innovator and word-of-mouth recommendations among market participants. It should be remembered, however, that not every innovation diffusion process occurs in this way. For some products and services, due to user sensitivity, no interactions may take place between individuals, and the only means of communication is through the producer's advertising activities. Examples of such products may include items of a private or sensitive nature, such as certain medicines or hygiene products. Conversely, there are also products that cannot be advertised for legal reasons (e.g., cigarettes or alcohol), where the primary carriers of information about novelties are users themselves, who exchange knowledge about the products.

Figures 1–3 below present qualitative causal loop diagrams illustrating the relationships between system elements in the Bass, source, and contact diffusion models.

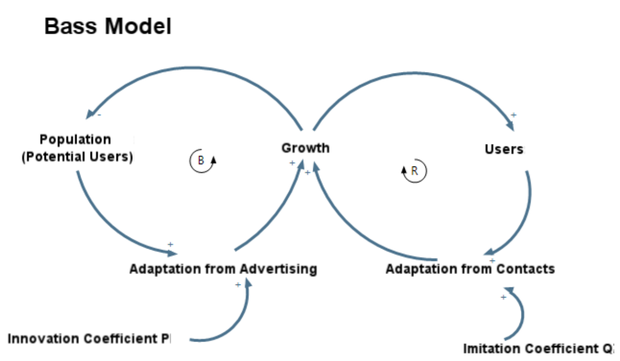

Fig. 1. Causal loop diagram of the Bass model. Source: authors' own elaboration.

In the Bass model, two variables influence the rate of growth: adoptions from advertising and adoptions from contacts. They differ in terms of parameter dependence. Adoptions from advertising are affected by

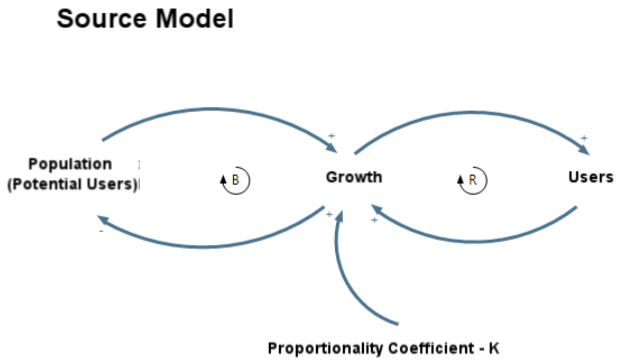

Fig. 2. Causal loop diagram of the Source model. Source: authors' own elaboration.

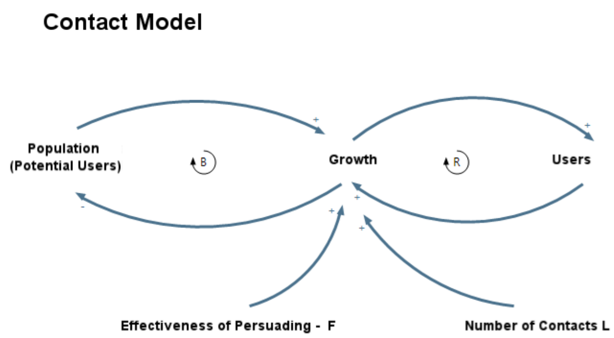

Fig. 3. Causal loop diagram of the Contact model. Source: authors' own elaboration.

the innovation coefficient and the current number of population members who are not yet users. Adoptions from contacts, in turn, are influenced by the imitation coefficient and the current number of users who can promote the product. This model contains two loops: the first loop, "population – adoption from advertising – growth," is a balancing loop, whereas the second loop, "users – adoption from contacts – growth," is a reinforcing loop.

In both the source model and the contact model, one can observe only the influence of the coefficients resulting from the differential equations (3 and 6) on the flow between potential users and current users. Feedback loops are also visible here: the first, in the relationship "population – growth," is a balancing loop in both cases, while the second, in the relationship "growth – users," is a reinforcing loop.

Based on the above CLD diagrams, stock-and-flow diagrams (SFDs) were constructed (Figs. 4–6). For this purpose, the AnyLogic simulation environment was used. This tool enables modeling not only within the system dynamics framework but also with other modeling methods such as Discrete Event Simulation (DES) and Agent-Based Modeling (ABM) (Ivanov, 2017).

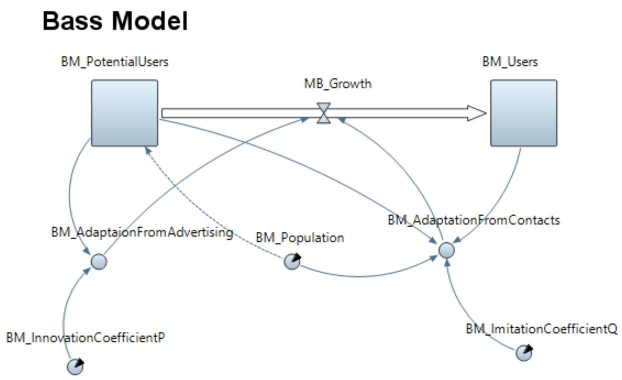

Fig. 4. Stock-and-flow diagram of the Bass model. Source: authors' own elaboration.

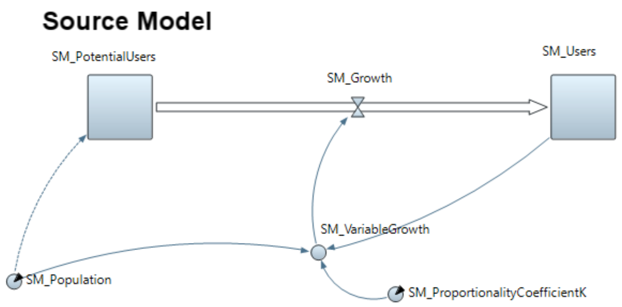

Fig. 5. Stock-and-flow diagram of the Source model. Source: authors' own elaboration.

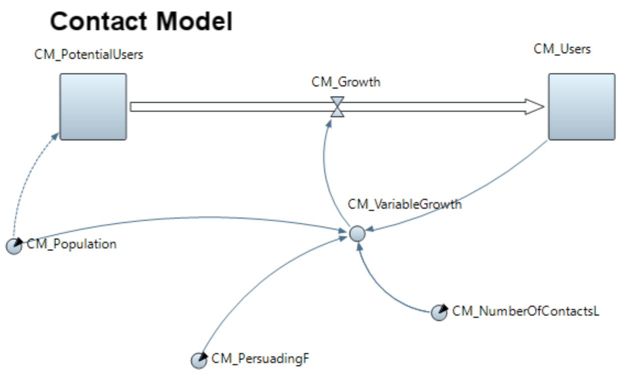

Fig. 6. Stock-and-flow diagram of the Contact model. Source: authors' own elaboration.

In all models, it can be observed that the essence of diffusion is the flow from the population of potential users to the population of actual users. This is realized through the flow "growth," which is defined by the appropriate differential equations for the given model. Other variables and parameters define the relationships between these elements.

Subsequently, simulations were carried out to verify whether the generated curves correspond to those described in the literature (Fant et al., 2023; Kot et al., 1993), i.e., to the previously mentioned equations (2, 4, and 7). Figures 7–9 present the generated curves of the growth in the number of users over time (the first chart) and the curves representing the flow magnitude per unit of time (the second chart), which is the derivative of the first curve. Table 1 presents a set of initial parameters for which the following graphs of innovation diffusion curves were obtained.

Table 1
Initial model parameter values

Type of Diffusion Model	**Parameter**	**Initial Value**
Bass Model	Population	1000
	Starting Users	1
	Innovation Coefficient P	0.01
	Imitation Coefficient Q	0.3
Source Model	Population	1000
	Starting Users	1
	Proportionality Coefficient K	0.1
Contact Model	Population	1000
	Starting Users	1
	Persuading F	0.1
All	Simulation Time	Until 98% of population of users

Source: author's own elaboration.

The parameters and coefficients for these models were selected in accordance with the most frequently cited values in the literature in order to illustrate the shape of the curves and to demonstrate that they reflect the theoretical models. At this point, it can be concluded that the objective of building a simulation model representing the process of innovation diffusion based on established mathematical descriptions has been achieved. The models created in this way are suitable for further testing, simulation, and decision-making based on the obtained results.

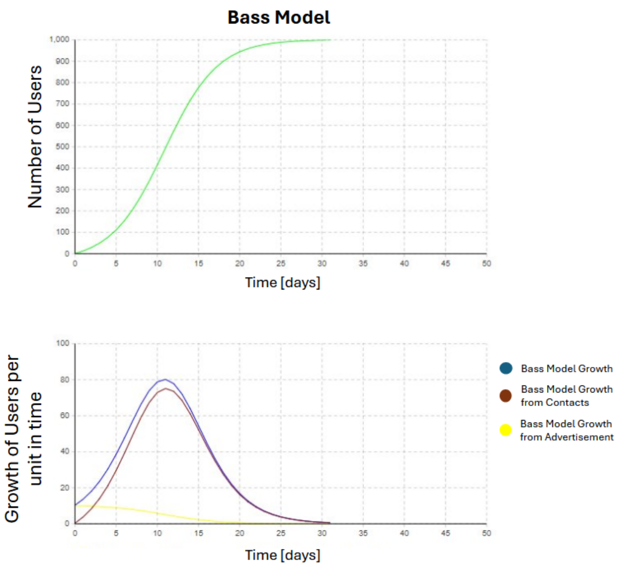

Fig. 7. Increase in the number of users and change in growth coefficients in the Bass model for parameters: $m = 1000$; $p = 0.01$; $q = 0.3$.
Source: authors' own elaboration.

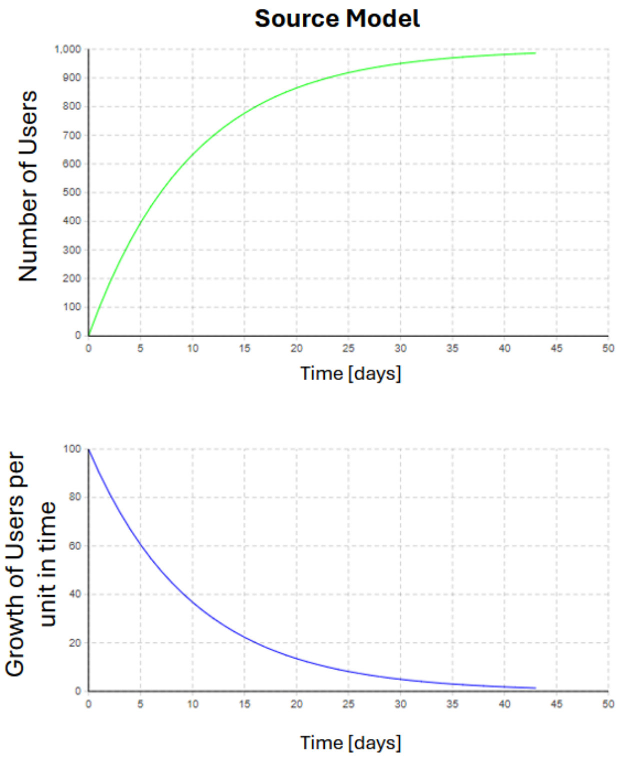

Fig. 8. Increase in the number of users and change in the growth coefficient in the Source model for parameters: $n = 1000$; $k = 0.1$.
Source: authors' own elaboration.

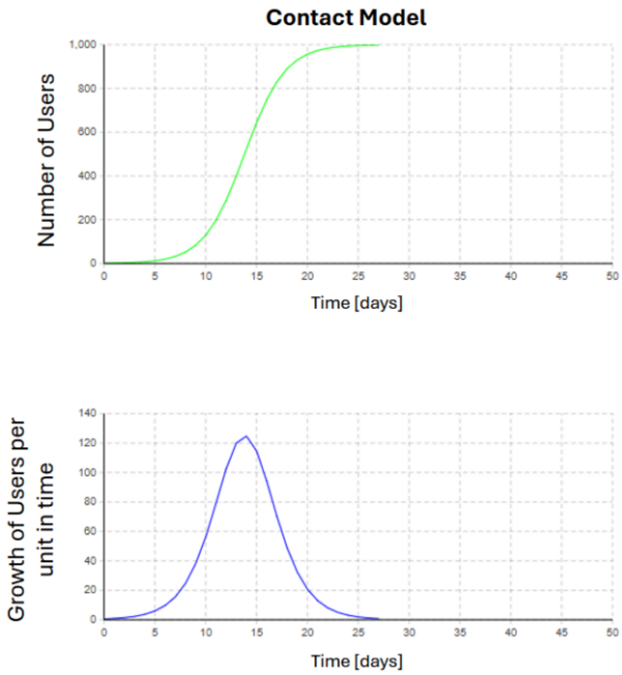

Fig. 9. Increase in the number of users and change in the growth coefficient in the Contact model for parameters: $n = 1000$; $f = 0.1$; $l = 0.5$.
Source: authors' own elaboration.

Discussion

This publication has presented the potential of modeling innovation diffusion processes within the system dynamics (SD) framework. This method is well-suited for representing systems in which flows occur continuously or within clearly defined time intervals, but where it is not possible to unambiguously distinguish discrete iterative steps of such flows. An example of such a process is innovation diffusion, which was illustrated here through feedback mechanisms linking innovation adoption, imitation effects, and marketing influence. In addition, selected mathematical models (the Bass model, the source model, and the contact model) were presented, as formal representations of different adoption mechanisms driving diffusion dynamics over time. These models were reconstructed through the use of simulation modeling in the system dynamics convention using the AnyLogic tool which enabled their direct comparison within a unified modeling framework.

The curves obtained in the previous section dynamic adoption trajectories characteristic of innovation diffusion processes, showing the relationship between the number of users and time. The fact that the generated curves differ in shape results both from their mathematical formulation and from the parameters adopted which represent different dominance structures of innovation-driven and imitation-driven adoption. The source model assumes the influence of marketing activities on society capturing exogenous adoption impulses characteristic of mass communication in early diffusion stages. Such actions are sudden and reach a large number of individuals, which is why a significant initial increase in users is observed. The contact model is based on interpersonal interactions within the population and depends on the effectiveness of recommendations reflecting endogenous diffusion driven by social contagion mechanisms. Therefore, growth in this model is initially minimal, but then increases dynamically as the number of users rises. The Bass model combines both concepts into a single framework allowing simultaneous representation of innovation and imitation effects within one diffusion structure. Depending on the chosen parameters, the curve in this model may differ from the others.

Depending on the product subject to diffusion, it is necessary to choose the most appropriate model, as different innovations are characterized by distinct dominant adoption mechanisms. Specific products, such as medicines or hygiene items, are better represented by the source model, due to the possibility of advertising but the limited interpersonal exchange of information. In contrast, for products such as cigarettes or alcohol, the contact model better reflects diffusion, since legal restrictions prohibit advertising, while individuals exchange experiences through social interactions. In most other cases, the Bass model appears to be the most suitable, as it captures the mixed nature of diffusion processes observed in many consumer markets.

The presented models do not have to refer solely to the diffusion of innovative products on the market but may also concern the spread of novel organizational, process, or marketing ideas within an enterprise where adoption occurs among employees rather than consumers. In such cases, instead of customers who need to be convinced of a product, it is the employees of the organization who adapt to the new situation and may either accept it or attempt to reject it and return to earlier ways of working which can also be conceptualized as a diffusion process governed by feedback dynamics.

The models developed in this publication should not be considered as final versions ready for direct use by enterprises as innovation diffusion models require context-specific calibration to reflect real adoption conditions. A distinctive feature of modeling is the ability to adapt each element of a model to represent concrete adoption drivers, barriers, and feedback structures. Therefore, it is possible to enrich the model with additional parameters and variables, such as marketing intensity, adoption delays, or resistance to change, to modify the differential equations characterizing flows, or to add new stocks – all with the aim of achieving a more realistic representation of innovation adoption dynamics. The outcome should be a model suitable for conducting various "what-if" scenario analyses focused on diffusion strategies and for generating answers to decision-making questions related to accelerating or stabilizing adoption processes.

For this reason, even a properly constructed and validated model representing innovation diffusion should be treated as a starting point for the work of marketing or development departments. The next step should be to compare the obtained results with the costs incurred to achieve them linking adoption dynamics with resource allocation decisions. In this way, it becomes possible to test many different marketing scenarios, in which both the workload and financial expenditures influence the size of the indicators that increase or decrease the flow between potential and current users thus directly affecting the speed and saturation level of diffusion. This enables these departments to apply optimization strategies aimed at maximizing outcomes by minimizing expenditures, or at least to rationalize marketing and promotional processes in such a way as to deliver the desired results.

It should also be recognized that not every diffusion process unfolds in the same way. Everything depends on the specificity of the innovation, the environment in which it is introduced, and the population it concerns, all of which influence key diffusion parameters and feedback structures. Therefore, in each case, the variables and parameters describing the system must be defined individually with explicit reference to the underlying adoption mechanisms. Likewise, changes in policies promoting products may have varying impacts on these coefficients depending on the prevailing conditions, both in the immediate and broader environment of the organization, leading to structurally different diffusion trajectories.

Conclusions

As demonstrated in the present study, system dynamics enables the representation of innovation adoption processes within the broader framework of innovation diffusion. This approach allows different mathematical formulations of diffusion phenomena to be modeled in a flexible manner and presented in a form that is accessible and intuitive for individuals who do not have experience with describing processes using differential equations.

This study has several limitations that should be considered when interpreting the results. First, the proposed models are primarily conceptual and simulation-based and have not been subjected to extensive empirical validation using real-world adoption data, which limits the assessment of their predictive performance. Second, the models rely on simplified assumptions typical of classical diffusion theories, such as population homogeneity and time-invariant diffusion parameters, which do not fully capture the complexity of real market dynamics. Moreover, the system dynamics approach adopted in this study is based on continuous modeling and does not explicitly account for adopter heterogeneity or underlying social network structures that may significantly influence diffusion processes. An additional limitation is the focus on selected classical diffusion models and their implementation within a specific simulation environment (AnyLogic), which may constrain the generalizability of the findings and their direct replicability in other modeling platforms.

Future research should primarily focus on the empirical validation of the proposed models, particularly through their calibration using real-world adoption data and the evaluation of forecast accuracy in both ex post and ex ante settings. This would allow for an assessment of the predictive validity of the models and enable comparisons with alternative approaches to modeling innovation diffusion. Another important direction for further work is the gradual extension of model structures by incorporating additional parameters and mechanisms, such as marketing activities, price effects, supply constraints, decision delays, or regulatory influences, in order to better reflect real-world market processes. Such extensions would enhance both the realism of the models and their usefulness for scenario analysis and strategic planning related to innovation diffusion.

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