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A generative decision analytics framework for modelling disruptive innovation diffusion

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ABSTRACT

The framework of disruptive innovation has changed how we analyse and interpret many successful businesses, especially those that start from a disadvantageous position. A wealth of real-world cases has been studied to offer valuable insights into what disruptive innovation is and how it evolves. However, case studies only focus on a small set of numerous possible outcomes, unable to answer "what-if" questions — essential for revealing the core factors/mechanisms that define disruptive innovation. Following the philosophy of generative social science, this research builds an analytics framework that incorporates an agent-based model, aiming to "grow" typical diffusion patterns of disruptive innovation from microscopic consumer decisions while investigating underexplored mechanisms and alternative outcomes via numerical experiments. The duality of value dimensions is assumed to be the most essential characteristic of disruptive innovation in the framework. Other factors, including heterogeneous consumer preferences, complementary technologies, technological progress, and pricing, are experimented with as key factors that may shape the diffusion processes. The results demonstrate that the model can reproduce multiple diffusion patterns and stylised facts regarding disruptive innovation, such as market encroachment on low-end markets, opening new markets, capturing market shares from mainstream markets, being impacted by new disruptors, and its coexistence with sustaining innovation. The analysis indicates that the dual value dimensions endow an innovation with the potential of being disruptive, while other factors can adjust its actual disruptive effect. Based on the findings, theoretical and practical managerial suggestions are provided for disruptive innovation researchers and practitioners.

1. Introduction

Innovation is a key driver of the development of human societies. Disruptive innovation, in particular, has garnered significant interest from both academic and industrial sectors. In Christensen's seminal work, "The Innovator's Dilemma", the framework of disruptive innovation is introduced and applied extensively to diverse industries to explain why small startups can grow and even overtake incumbent companies [1]. A widely known case study detailed in Christensen's work is the hard drive industry in the U.S. It was observed that large, established hard drive companies often failed in the face of disruptive innovation, despite being innovative and operationally efficient. In contrast, smaller, emerging companies were seen as the disruptors capable of overthrowing these giants.

Over two decades have passed since Christensen introduced the disruptive innovation framework, and it continues to captivate and inspire many researchers and practitioners to explore a simple yet profound question: why do companies succeed or fail [2]? However, a critical and frequently asked question is what the definition of disruptive innovation is. Christensen has noted that many technologies are misunderstood as disruptive [3,4], highlighting a persistent challenge in this area: the lack of a broadly accepted definition or identification criteria for disruptive innovation. Other researchers have also recognised this ambiguity [5–7]. Disruptive innovation is often identified retrospectively — determining whether an innovation is disruptive only after it has demonstrated so [8,9]. This hindsight approach can lead to problematic attributions and survivorship biases, undermining its usefulness as an analytical framework. Unsuccessful disruptive innovations, those that fail to achieve significant market impact, may not even leave enough records in history to become researchable.

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Although empirical studies have provided valuable materials and insights that help to understand disruptive innovation, empirical data is case-specific and relies on historical events. The cases involved in the analyses only consist of a small portion of numerous possible outcomes. That is, relying on incomplete inductive methods is insufficient for developing a robust, generalisable theoretical or analytical framework for disruptive innovation. To address this issue, deductive methods, such as counterfactual "what-if" scenarios, should be employed to carefully examine what driving factors are essential and what are "optional" in disruptive innovation [10]. Ideally, controlled experiments should be conducted to assess the influence of various factors identified in previous studies. Nonetheless, due to financial costs, time constraints, operability challenges, and ethical considerations, real experiments are infeasible. An expedient approach is to resort to computational modelling and numerical experiments.

Empirical studies have shown that disruptive innovation can have different diffusion patterns [1,11]. From the perspective of complex adaptive systems, innovation diffusion is a macroscopic phenomenon that emerges from the interactions and decisions of numerous consumers [12]. Agent-based modelling is a widely used "bottom-up" approach that employs computational entities to represent real-world decision-makers, allowing macroscopic system behaviours to "grow" spontaneously [13,14]. Agent-based modelling resonates with the idea of generative social science, which advocates that "*If you don't grow it, you don't explain it* " [15]. In this sense, if one can "grow" disruptive innovation in a virtual world, the mechanisms that underpin such growth should contain a plausible explanation of the target phenomenon, and therefore may be able to serve as a testbed for analysing causal links and exploring alternative outcomes.

The idea of generative social science is often introduced in combination with the KISS (Keep It Simple, Stupid) principle [12]. The KISS principle suggests maintaining the simplicity of a model, and complicatedness should be added incrementally only when the current level of simplicity does not generate meaningful results, e.g., replicating patterns and stylised facts observed in the real world. As Hopp et al. [16] suggested, applying Occam's razor to trim superfluous components from the theory of disruptive innovation could lead to greater theoretical parsimony and help integrate conflicting elements more effectively. In line with this philosophy, we introduce the concept of duality (detailed in Section 2.1) as the conceptual core of disruptive innovation, guiding the development of the analytics framework and model building. Numerical experiments and analysis will focus on factors considered crucial for disruptive innovation in previous studies [11,17–19], including heterogeneous consumer preferences, complementary technologies, technological progress, and pricing. It is noteworthy that, while real-world disruptive innovation involves an enormously large number of interconnected factors, this paper is not intended to build a big, all-embracing framework. Quite the opposite, we intentionally restrict the conceptual basis tightly and explore whether a parsimonious set of assumptions is able to "grow" repeatedly observed patterns of disruptive innovation. Fig. 1 illustrates how to map generative social science onto the analytics framework of disruptive innovation.

2. Methodology

2.1. Duality as the core attribute of disruptive innovation

Following the KISS modelling principle [12], we started model building by hypothesising that duality is the core attribute that underpins disruptive innovation, i.e., disruptive innovation cannot exist without duality. Here, duality refers to the characteristic of disruptive innovation wherein it encompasses not just an existing value dimension that is familiar to and valued by existing markets but also introduces a new value dimension that is novel and probably under-recognised, distinguishing it from sustaining innovation, which only focuses on the existing value dimension. Here, we term the two dimensions the first value dimension and the second value dimension, respectively.

The concept of duality has been implicitly present in the literature on disruptive innovation from its inception. Christensen's [1] analyses of the hard drive industry, for instance, highlight storage capacity as a key value dimension. However, the introduction of portability as a second value dimension marked the emergence of disruptive innovation in this sector. Utterback and Acee [20] illustrated this idea by classifying novel products or technologies into core and auxiliary attributes, where core attributes define the product's category, and auxiliary attributes represent newly added value dimensions. Similarly, Adner [21] created a computational model dividing a product's attributes into two orthogonal dimensions, showing how varying combinations of these dimensions can result in different disruptive innovation diffusion patterns. Duality has also been explicitly employed as a theoretical component for both conceptualisation and mathematical modelling in several studies [18,19].

At the microscopic level, we introduce a two-dimensional value system to depict the duality of disruptive innovation. In this model, consumers are interlinked through a social network and function as adaptive decision-makers [22]. They choose between disruptive and sustaining innovation based on their perceived utility. To maintain a manageable scope for the model, we concentrate on the original theory of Christensen and investigate critical factors through numerical experiments: price, consumer preferences, complementary technology, and technological advancement.

It should be emphasised that this paper is not intended to "reinvent" duality. Instead, the aim is to formalise and operationalise this very simple conceptual core within a parsimonious analytics framework, which is expected to "grow" multiple patterns of disruptive innovation observed in the real world. Should the parsimonious modelling framework manage to reproduce key emergent patterns, it possesses the power to explain how the simulated system works and to explore counterfactual questions, which methodologically complements case studies extensively used to research disruptive innovation.

2.2. Model design

Consumer decision-making plays a central role in new technology adoption [23,24]. In the context of disruptive innovation, the basic microscopic entities are consumers who go through a sequence of decision-making processes and select their preferred technology. The original innovation decision process proposed by Rogers consists of five stages: knowledge, persuasion, decision, implementation, and confirmation [25]. For simplicity, this model focuses on the first three stages. In the knowledge stage, the model building starts with the analysis of the Bass diffusion model. As an acknowledged model, the Bass diffusion model not only provides a reliable starting point for building agent-based diffusion models but also serves as a reference for model validation. Bass used ordinary differential equations to build an innovation diffusion model [26]:

$$dy/dt = (p + q \times Y(t)/N) \times (N - Y(t)) \tag{1}$$

where dy/dt denotes the number of innovation adopters in year t; N represents the total number of potential innovation adopters in the market; $Y(t)$ represents the total number of cumulative adopters. p and q are two very crucial parameters in the Bass diffusion model. p represents the impact of the mass media on consumers, while q represents the impact of word-of-mouth communication on consumers [27]. Under different combinations of p and q, the Bass diffusion curves have different shapes, whereas still follow an "S-shaped" growth on the whole [26]. Similar to the Bass model, we use p_k to represent the probability that potential adopters recognise an innovation through mass media and q_k to represent the probability that potential adopters recognise an innovation through interactions with others in the social network. A random network is implemented to mimic the social

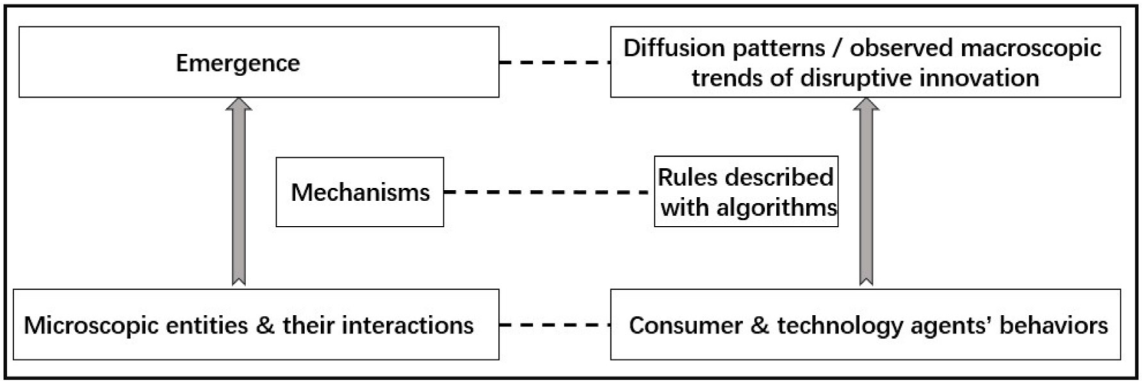

Fig. 1. Mapping generative social science onto the analytics framework of disruptive innovation. A key objective is to leverage agent-based modelling to simulate consumer decision-making while letting disruptive innovation patterns and stylised facts "grow" organically. The mechanism and hypotheses used in the model may contain a plausible explanation of real-world disruptive innovation dynamics. Meanwhile, the model can be used to systematically examine the roles of multiple driving factors and alternative outcomes that empirical studies fail to capture.

connections between consumers. Consumers in the random network become aware of an innovation via mass media or word-of-mouth with the probability:

$$P_{ik}(t) = p_k + [1 - (1 - q_k)^{b^i_k(t)}] \tag{2}$$

where $P_{ik}(t)$ denotes the probability that the ith consumer in the network realises the existence of technology k at time t; p_k represents the probability of a consumer being influenced by the mass media; q_k represents the probability of being influenced by the word-of-mouth effect; $b^i_k(t)$ represents the number of consumers linked to consumer i that have known technology k at time t. Consumers incorporate the technology into an alternative purchase set $O_i(t)$ after realising its existence.

$$O_i(t) \in \{\varnothing, \{tech_1\}, \{tech_2\}, \{tech_1, tech_2\}\} \tag{3}$$

If $O_i(t) \neq \varnothing$, consumers choose a technology based on their purchasing power af_i and the product price pr_k ($af_i > pr_k$), and further evaluate the utility of each technology in the alternative set as their preference, thus selecting the technology with the maximum utility:

$$u_i(t) = max\{\vec{\lambda}_i \cdot \vec{q_{ik}}(t)\} \tag{4}$$

where $u_i(t)$ represents the maximum perceived utility of consumers; $\vec{\lambda}_i$ is a two-dimensional vector representing the consumers' dual preference for the technologies; $\vec{q_{ik}}(t) = [h_{k1}(t), h_{k2}(t)]$ is also a two-dimensional vector denoting the value dimensions of the corresponding technology in the set $O_i(t)$. The use of two-dimensional vectors to represent both consumer preference and technology attributes is the core idea for simulating duality in the context of disruptive innovation. h_k is updated as follows:

$$h_k(\tau) = \frac{h_{0k}\overline{C}_k}{h_{0k} + (\overline{C}_k - h_{0k})e^{-r_k \sum_t^{\tau} \psi_k(t)}} \tag{5}$$

where h_{0k} is the initial value of technological progress of technology k; $\overline{C}_k$ denotes the upper limit of technological progress of technology k; $\psi_k(t)$ represents new purchases of $tech_k$ at time t; r_k denotes the nonlinear correction coefficient adjusting the rate of technological progress of technology k; the rate of technological progress of technology k. Eq. (5) is a variant of Zeng et al. [28], reflecting the fact that enterprises need to use revenues to conduct R&D to improve their technologies [29–31]. The difference is that Eq. (5) mirrors the marginal decrease of technological progress under a given technological paradigm. r_k is a parameter used to adjust the decreasing speed of technology progress.

Fig. 2 illustrates the structural diagram of the model. The model can be divided into two parts, including the supply side and the demand side. The supply side provides two types of technologies, entering the market at the time T_1 and time T_2 respectively. These two technologies compete for consumers on the demand side. The consumers in complex networks are affected by mass media and word-of-mouth, and make decisions according to Rogers' innovation decision model. They select the technologies that can provide maximum utility [32], and purchase their preferred technologies periodically. The purchase times of consumers are fed back to the supply side to update the technology performance. The consumers reassess the updated technology (first-time purchase or repeat purchase) in the next year and make the purchase decision.

2.3. Model process

Algorithm 1 shows the pseudocode of the model process. Initially, the model initialises the network, generates a random network composed of N nodes (each node represents a consumer agent), and puts N nodes into the set C. Variables in each node are initialised, including the preference vector $\vec{\lambda}_i$ and Boolean variables indicating if the consumers have recognised or adopted $tech_1$ or $tech_2$, the purchase interval $purchase\_interval$, and the payment capacity af_i, etc. In this study, consumers' $\vec{\lambda}_i$ and af_i are evenly or triangularly distributed to explore the system behaviour under different consumer preferences and purchasing power distributions. A pair of nodes is randomly selected and connected according to the probability p_{nd} till all node pairs are traversed to generate a complex network with density p_{nd}.

Subsequently, all consumers in the network are randomly selected, traversed, and enquired about their awareness of $tech_1$. If a consumer does not yet recognise $tech_1$ in the current iteration of the simulation, the consumer's state of adoption remains unchanged. If a consumer has already recognised this technology, the technology is included in the consumer's private variable set $options$. Consumers continue to be asked whether they need to purchase the new technology. All the consumers are set to have purchase needs in the initial state, which is represented by a private variable $toBuy = True$. Consumers have new purchasing needs only after the product life cycle ends. Consumers with purchasing needs initially determine the alternative set $Q_i(t)$ according to their purchasing power, use Eq. (4) to select the technology giving the maximum utility, and set $toBuy$ to $False$, indicating that the technology is still in the life cycle and there is no need to purchase the new technology.

After all the consumer agents have made their decisions, the number of new purchases in this iteration is counted, and the technology is updated according to Eq. (5) to provide a reference for the next decision of consumers. Then, some tag variables that need to be refreshed are updated conditionally. For example, some consumers who have reached the purchase interval reset $toBuy$ to $True$. The above process proceeds until $stopTime$ is met. During this period, the RUN routine monitors whether it is time for $tech_2$ to enter the market. If so, $tech_2$

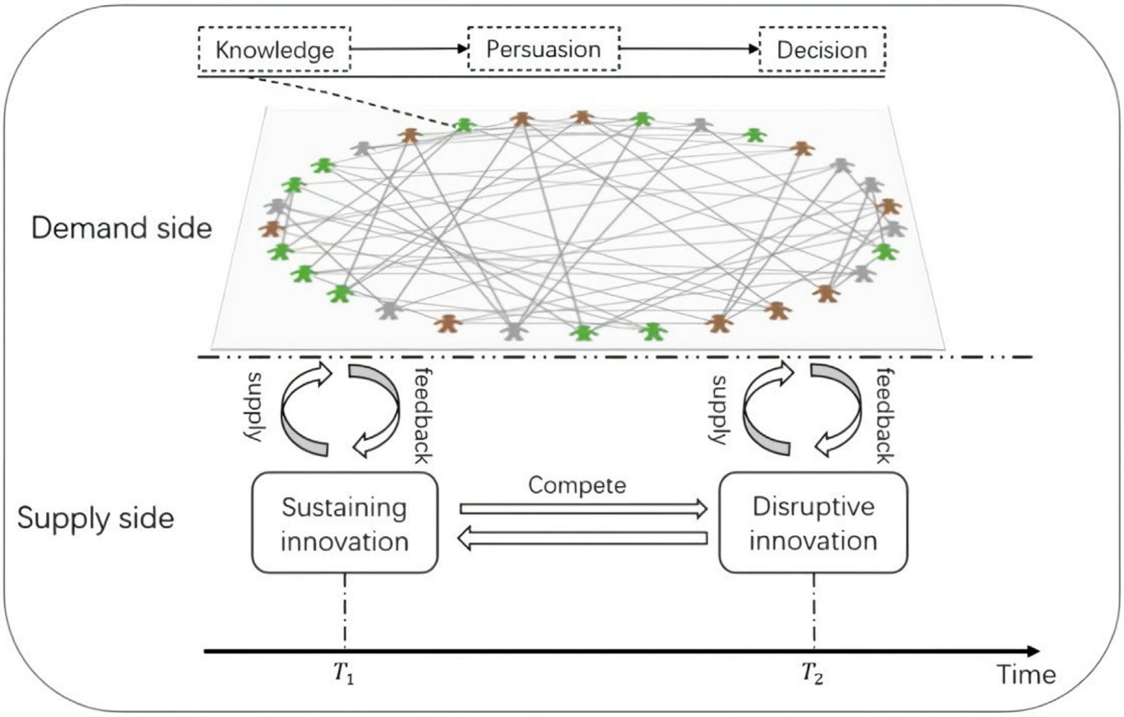

Fig. 2. The architecture of the agent-based model. The demand side is represented by a social network of consumer agents. The agents can interact and make innovation adoption decisions. The supply side incorporates two competing innovations – sustaining and disruptive – for consumers to choose from.

is initialised. Subsequently, consumers will face a trade-off between the two technologies in the remaining simulation iterations. The model calibration and validation are given in Appendices A and B.

3. Results and analysis

3.1. Baseline scenario analysis

In the baseline scenario, the natural diffusion processes of both sustaining innovation and disruptive innovation are investigated. The impacts of external factors, e.g., affordability and minimum value demand, are temporarily not considered; instead, the focus is on the impact of combinations of different value dimensions of disruptive innovation on diffusion processes. Since the advantages and disadvantages of disruptive innovation are relative, the two value dimensions of sustaining innovation are fixed when conducting numerical experiments, and the combinations of different value dimensions of disruptive innovation are altered to examine the diffusion processes.

To make the corresponding value dimensions of sustaining innovation and disruptive innovation comparable, according to Shi et al. [33], the upper and lower limits of the two value dimensions are set to 1 and 0, respectively. The value dimensions of sustaining technology $tech_1$ are set as a vector $[0.6, 0.3]$. The entry time $Enter$ of the disruptive technology is set to 10, and the purchase interval $Period$ of consumers for two technologies is set as 5. Consumers are given enough purchasing power to ensure that af_i is greater than pr_k to exclude the constraint of prices. Furthermore, it is assumed that the preferences of consumers for the value dimensions follow the uniform distribution between 0 *and* 1. The value dimensions of disruptive technology $tech_2$ change from $[0.3, 0.3]$, $[0.3, 0.5]$ to $[0.3, 0.7]$. That is, the first value dimension of $tech_2$ is only 50% of $tech_1$, while the second value dimension corresponds to 100%, 167% and 233% of $tech_1$ respectively, which reflects the relative disadvantage of disruptive innovation in the existing value dimension and the relative advantage in the new value dimension. Each parameter combination is simulated 300 times, and the average market shares (denoted by Ms) of the two technologies in each iteration are collected. The results are shown in Fig. 3.

The subgraph (a) in Fig. 3 is the basic scenario of $tech_2 = [0.3, 0.3]$. Because $tech_2$ has no advantage over $tech_1$ in both dimensions, $tech_2$ only diffuses to a small market share after it enters the market, and then drops back to 0. The initial diffusion indicates $tech_1$ has not yet been adopted by the whole market when $tech_2$ enters the market. Meanwhile, some consumers are still unaware of the existence of $tech_1$. Subgraph (b) shows the scenario of $tech_2 = [0.3, 0.5]$. $tech_2$ is not dominant in the first dimension but is superior to $tech_1$ in the second dimension. Thus, it captures nearly two-fifths of the market eventually. It can be speculated that the market share of $tech_2$ partly comes from its encroachment on the market of $tech_1$ (as can be seen from the market share of $tech_1$ reaching the peak and then falling back), and partly comes from its occupation of the market that $tech_1$ has not yet been touched. These two effects are more noticeable in subgraph (c), where $tech_2 = [0.3, 0.7]$. $tech_1$ and $tech_2$ initially experience concurrent growth until the diffusion ratio of $tech_1$ reaches the peak in the 33rd iteration, and then gradually falls back.

In the process of falling back, $tech_2$ gradually approaches the market share of $tech_1$, then surpasses it, and finally stabilises. In this scenario, the decline of the market share of $tech_1$ can only be caused by the encroachment of $tech_2$. The red area in subgraph (c) is the result of two technologies competing for the same group of consumers, reflecting the red ocean effect; Besides the market share captured from $tech_1$, the rest of the market share is contributed by consumers who have not been reached by $tech_1$. This portion of the market share is represented by the blue area, reflecting the blue ocean effect. It is notable that $tech_1$ and $tech_2$ are eventually stabilised at market shares of around 0.45 and 0.55 respectively, instead of substituting one another, mirroring many real-world cases that disruptive innovation does not mean that incumbent enterprises must be completely replaced [7,17,34]. In addition,

Model Algorithm 1

procedure Initialize-Network (p_{nd}) ▷ *initialize network*
  $time \leftarrow 0$
  generate a set C containing N consumer nodes
  for all $c \in C$ **do**
    randomly select two consumers $c_i, c_j \in C,\ i \neq j$
    randomly generate a number $\gamma \in (0, 1)$
      if $\gamma < p_{nd}$ & $E_i \cap E_j = \varnothing$ **then** ▷ *E is the edge set of* $\boldsymbol{c}$
        generate a new edge between i and j
procedure Initialize-Consumers ($mode$) ▷ *initialize consumer agents*
  for all $c \in C$ **do**
    if triangularOn = True **then**
      $\lambda^1 \leftarrow \beta,\ \beta \sim P_{tri}(0, mode, 1)$
    else
      $\lambda^1 \leftarrow \beta,\ \beta \sim U(0,1)$
    $\lambda^2 \leftarrow 1 - \lambda^1$
    $\lambda \leftarrow [\lambda^1, \lambda^2]$
    toBuy ← *True*
procedure Initialize-Technology ($h1_{init1}, h1_{init2}, price_1$) ▷*initialize* $tech_1$
  price ← $price_1$
  initPerformance ← $[h1_{init1}, h1_{init2}]$
procedure RUN ($t_2, stopTime, h2_{init1}, h2_{init2}$)
  while $time \leq stopTime$ **do**
    if $time = t_2$ **then**
      $tech_2$ emerges and initializes
    procedure Knowledge (p_1, p_2, q_1, q_2) ▷ *"knowledge" stage*
      for all $c \in C$ **do**
        if do not know about $tech_1$ **then**
          know about $tech_1$ as $p_1 + (1 - (1 - q_1)^{nb_1})$
          $options \leftarrow options \cup \{tech_1\}$
        if $tech_2$ exists and is not known **then**
          know about $tech_2$ as $p_2 + (1 - (1 - q_2)^{nb_2})$
          $options \leftarrow options \cup \{tech_2\}$
    procedure Persuasion ▷ *"persuasion" stage*
      for all $c \in C$ **do**
        if $toBuy = True$ & $options \neq \varnothing$ **then**
          for all $tech \in Options$ **do**
            calculate and rank the utility $techU$
    procedure Decision ▷ *"decision" stage*
      for all $c \in C$ **do**
        adopt technology with maximum $techU$ in $options$
        $toBuy \leftarrow False$
    procedure Technology Development
      update technology using Equation (5)
    procedure Fresh Labels
      update Boolean variables
    $time \leftarrow time + 1$

when observing the number of new purchases per year (considering consumers' repeat purchases), despite the fluctuations resulting from periodic repeat purchases by consumers, the general trend is consistent with this pattern (see the embedded graph in subgraph (c)). Subgraph (c) shows a successful path of disruptive innovation, which has experienced four processes with incumbent enterprises, including simultaneous diffusion, alternative diffusion, surpassing, and stabilisation. The process is in accordance with the sales trend of the hard drive industry in the United States [35]. The model reproduces the stylised fact that disruptive innovation opens up new markets and competes in old markets simultaneously in the process of market encroachment, which further supports the validity of the model.

The substitution of $tech_2$ for $tech_1$ does not start at the diffusion peak of $tech_1$ (i.e., the 33rd year in subgraph (c)). According to the number of new adopters and converters between $tech_1$ and $tech_2$ per year, $tech_1$ adopters start to switch to adopt $tech_2$ shortly after $tech_2$ entering the market, as indicated by the green curve in subgraph (d). Similarly, some $tech_2$ adopters become $tech_1$ adopters during the diffusion of $tech_2$, represented by the red curve in subgraph (d). The blue curve in the figure shows the number of new adopters of $tech_1$ each year, and the orange curve shows the number of new adopters of $tech_2$ each year. In the early stage of $tech_2$ emerging, the number of new adopters of a technology is larger than the number of converters of the corresponding technology. Besides encroaching on the existing markets through

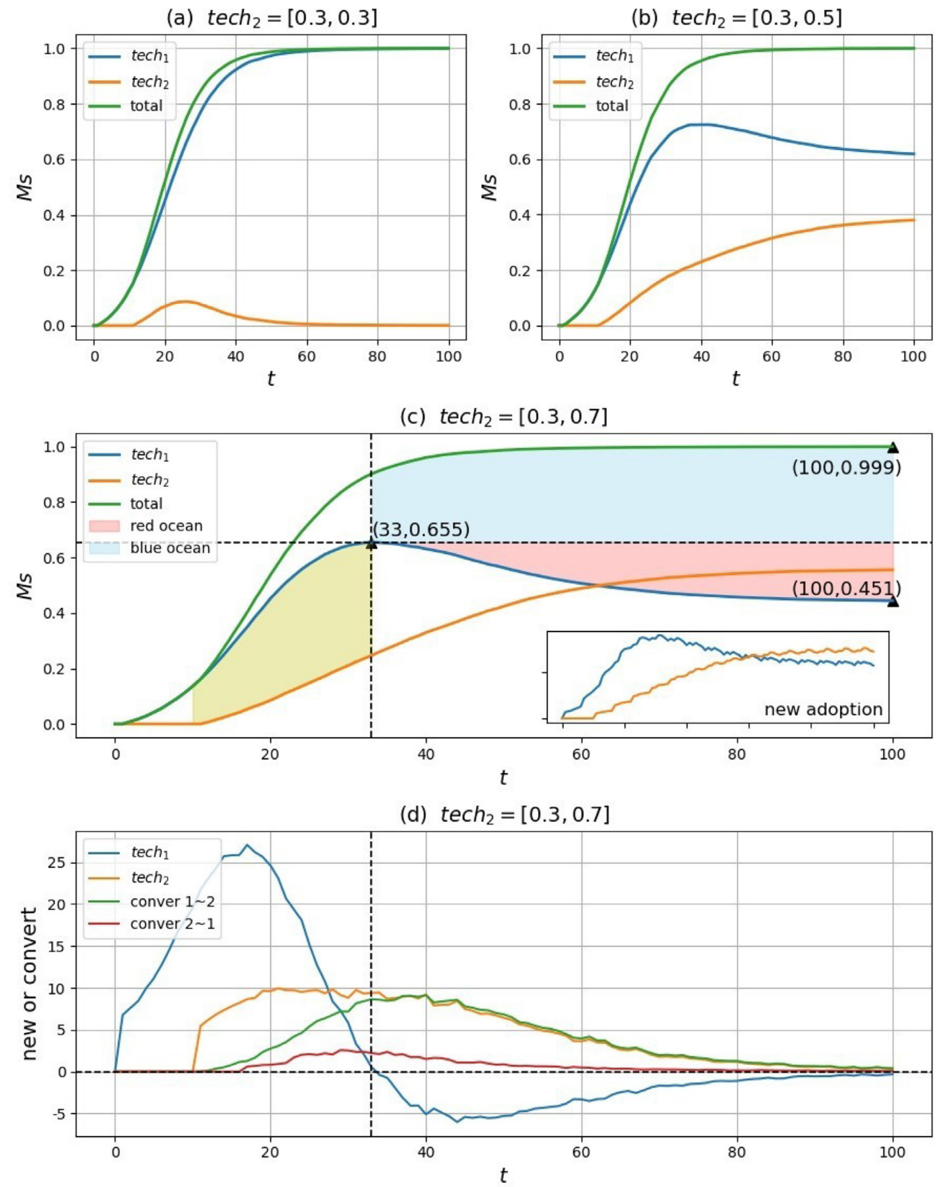

Fig. 3. The diffusion processes of disruptive innovation with various technologies' initial values.

substitution, the two technologies also attract consumers from new markets. It can be speculated that incumbent enterprises can identify the disruption of new technologies by examining the substitution effect in the early stage. The red curve demonstrates the co-existence of incumbent enterprises and disruptive enterprises rather than substituting for each other.

3.2. Impact of preference distribution and prices

The heterogeneity of microscopic individuals is an important feature driving complex system dynamics. It is necessary to explore the effect of consumers' heterogeneous preferences on disruptive innovation diffusion. The above analysis considers the scenario where consumers' preferences are evenly distributed, but the reality is more complex. To add another layer of realism, the consumers' initial preference in the model can be set as a triangular distribution $p_{tri}(lower, mode, upper)$ with different modes. We use three different preference distributions, i.e., $p_{tri}(0, 0.2, 1)$, $p_{tri}(0, 0.5, 1)$ and $p_{tri}(0, 0.8, 1)$, based on the parameter settings of subgraph (c) in Fig. 3, which exhibits an example of successful disruptive innovation. The results are shown in Fig. 4.

The experimental results demonstrate that the preference distributions have a significant impact on the diffusion of the two technologies. When the consumer $mode = 0.2$, the final market share of $tech_2$ approximately reaches 0.7, as shown in subgraph (a). With the increase of $mode$, an increasing number of consumers switch from $tech_2$ to $tech_1$, resulting in the decline of the market share of $tech_2$, as shown in subgraph (c) and subgraph (e). This means disruptive enterprises should consider how consumers' preferences will be distributed after the introduction of new value dimensions. If a new value dimension fails to attract many consumers, it may lead to a low market share or even failure.

In the real world, the income of consumers approximately follows the power-law distribution. This means there is a higher proportion of consumers with lower incomes. In macroeconomics, it is common to assume that consumer expenditure is proportional to income. Therefore, it can be assumed that the highest price that consumers are willing to pay for a product (i.e. reservation price) also follows the power-law distribution. However, both ends of the power-law distribution are open, which is inconvenient to use in computational models. This model uses the triangular distribution $p_{tri}(0, 0, 1)$ to simulate the purchasing power of consumers, which retains the key property of the

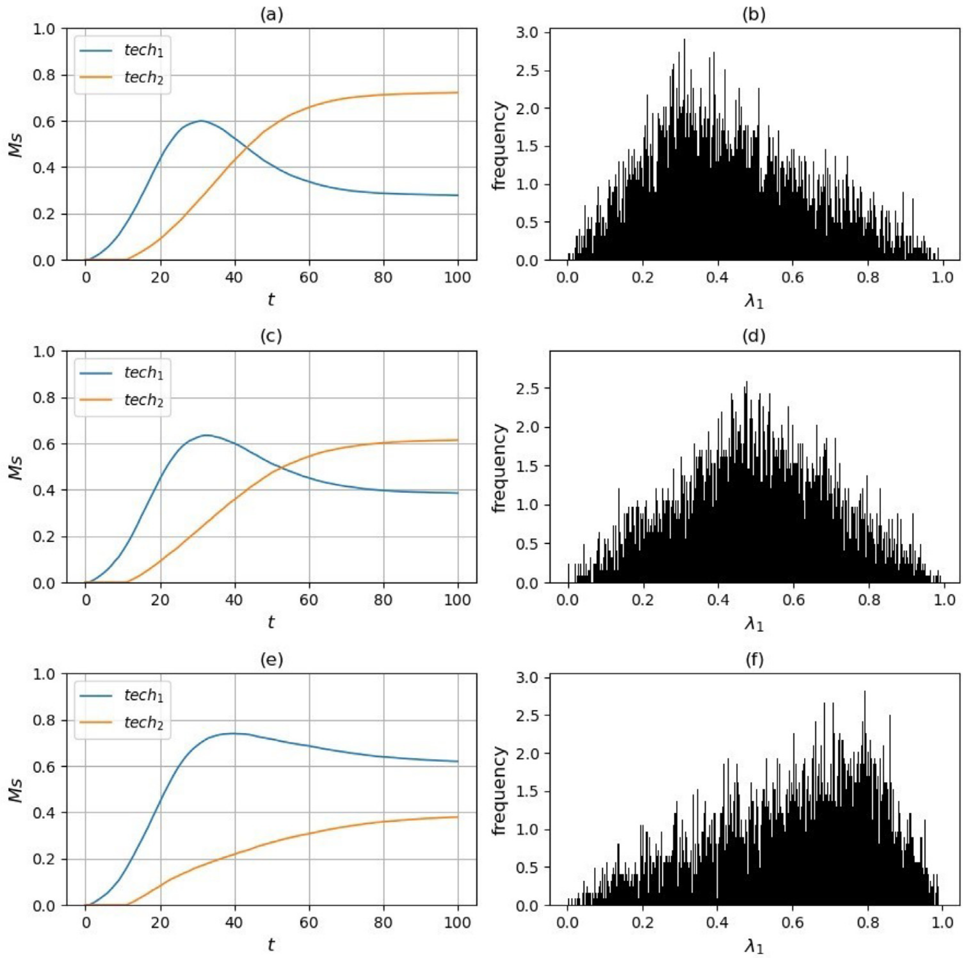

Fig. 4. The diffusion patterns of disruptive innovation with different preference distributions.

power-law distribution purchasing power, but offers more simplicity for implementation. The analysis starts from a single technology. There is only one technology in the market, and the price varies from 0 to 0.8 in increments of 0.2. Each parameter is simulated 300 times, and the average value of market share is collected, as shown in Fig. 5.

The impact of prices on technology diffusion is mainly reflected in two aspects. First, higher prices lead to a lower diffusion ratio; Second, the increase in prices reduces the speed of technology diffusion in the network. Taking the market share $Ms = 0.2$ as an example, when technology prices are 0.0 (equivalent to no price constraints), 0.2, and 0.4, the corresponding timing to reach the market share of 0.2 is delayed more. The decreasing speed of diffusion implies a decrease in network connectivity. Due to the constraint of purchasing power, some consumers cannot afford new technologies. These consumers can be regarded as missing nodes in the network. The missing nodes mean the absence of edges linked to them. Similarly, taking $price_1 = 0.2$ as an example, 288 consumers in the network cannot adopt new technologies, which can lead to a maximum of 36% fewer edges (expectations) in the network. The lack of edges reduces the efficiency of information spreading between nodes and results in the slow speed of technology diffusion.

Whether consumers have sufficient purchasing power depends on the relative value of the consumers' affordability and technology prices [36]. To keep consumers' purchasing power following the distribution of $p_{tri}(0, 0, 1)$, one can change the technology prices to reflect the constraints of consumers' purchasing power. Taking $price_1 = 0.2$ as the benchmark, $price_2$ is altered to 0.25, 0.20, and 0.15, respectively. 300 simulation runs are conducted for each value. The average market shares of the two technologies are shown in Fig. 6. In subgraph (a), the disruptive technology can still obtain a market share of 0.3, which is slightly lower than that of the sustaining technology, when its technology price is 0.25 (25% higher than the sustaining technology). This is because disruptive technology has a relative dominance in the second value dimension, which caters to consumers who have sufficient purchasing power and prefer the second value dimension.

Compared with Fig. 5, disruptive technology enters the market at a relatively high price but does not change the proportion of total adopters, which means that the market share of disruptive technology is obtained by encroaching on the potential market of incumbent enterprises. The former begins to attract potential consumers before the latter's diffusion rate peaks. Similar to the situation of $price_2 = 0.25$, when $price_2 = 0.20$ (as shown in subgraph (b)), although disruptive innovation occupies a larger market share, the proportion of total adopters has not changed. This is because the prices of the two technologies are identical, and the proportion of consumers with sufficient purchasing power is given, but the consumers can only choose the technologies with the maximum utility in the feasible sets. Therefore, there is a trade-off between the market share of disruptive technologies and sustaining technologies.

To comprehensively explore the effect of consumers' preference distribution and technology prices on the market encroachment of disruptive innovation, the joint impact of these two factors is analysed. $mode$ and $price_2$ are changed from 0.1 to 0.9 in increments of 0.1, and 300 numerical experiments are conducted for each parameter combination. The market shares Ms_1 and Ms_2 are gleaned when $t = 100$. The results are shown in Fig. 7. It can be seen that the price

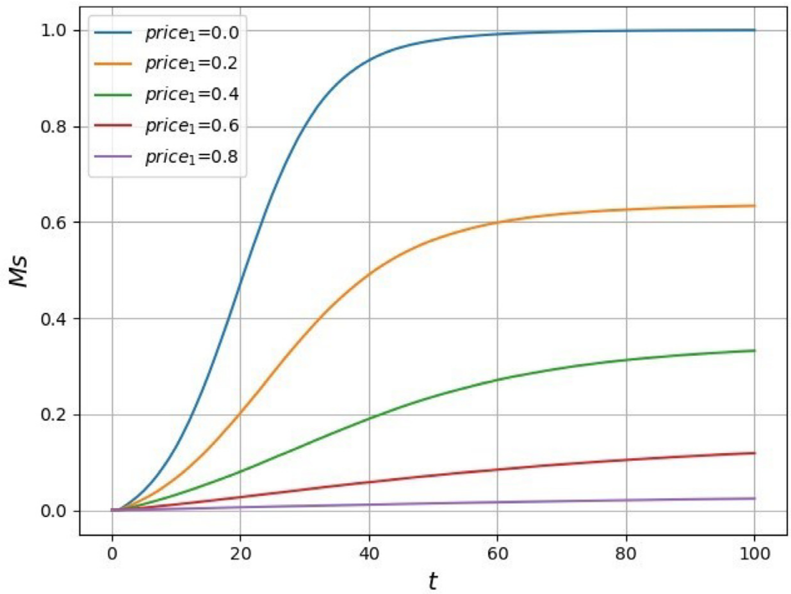

Fig. 5. The impact of prices on innovation diffusion.

reduction of $tech_2$ has a significant effect on the increase of its market share. This effect is subject to a marginal increase, indicating that it is an effective strategy for emerging technologies to enter the market with a low price. The increase in consumers' preferences for $tech_2$ (decrease in $mode$) is positive for expanding its market share.

However, since the model assumes that the utility generated by the two value dimensions of the technologies is replaceable, the effect of consumers' preferences is much smaller than that of technology prices; moreover, the effect of consumers' preferences on market share is weak when $price_2$ is high, but more notable when $price_2$ is low. This indicates that low prices can serve as an effective approach for $tech_2$ to encroach on the market, but it is still moderated by the distribution of consumers' preferences. For example, when $price_2 = 0.1$, reducing $mode$ from 0.9 to 0.1 can increase the market share of $tech_2$ by about 30%. In addition, Fig. 7 displays that the increase of $price_2$ has a marginally decreasing effect on expanding the market share of $tech_1$, while the decline of $price_2$ has a limited effect in lessening the market share of $tech_1$. When $price_2$ is reduced to 0.1, $tech_1$ still maintains a portion of the market share, which is consistent with cases of disruptive innovation in reality. It is common that successful disruptive innovation reaps the market share from incumbent enterprises rather than completely replacing them.

3.3. Impact of complementary technology constraints

Complementary technology constraints mean that the usefulness of one technology is constrained by other technologies. A useful product is an integration of many complementary technologies. Putting incompatible technologies together is meaningless. Modelling complementary technologies is an intimidating challenge due to their complexity and diversity. Here, we only consider the case of hard drives, which should have different sizes to satisfy various needs ranging from microcomputers to mainframes. Hard drives with a large size can be integrated into mainframes, but cannot be used in laptops. For simplicity, it is assumed that each consumer has a threshold requirement for a value dimension (e.g., size or portability). Under this threshold, a technology does not function and produces zero utility. Specifically, the utility of consumer i under the constraint of complementary technologies is calculated as follows:

$$U_i = \begin{cases} [\lambda_i^1, \lambda_i^2] \cdot [tech_k^1, tech_k^2]^T, & tech_k^2 \geq th_i \\ 0, & tech_k^2 < th_i \end{cases} \tag{6}$$

where th_i is a threshold following the triangular distribution $tri\left(0, mode_{th}, 1\right)$ to mirror the diverse demand. Eq. (6) means that the second value dimension of a technology should be greater than a threshold; otherwise, its utility for consumer i is zero. 100 experiments are conducted for each value of $mode_{th}$ from 0.01 to 0.9 in increments of 0.03, and the average market share at $t = 100$ (denoted by $Ms(100)$) is obtained. Fig. 8 presents four points of interest. First, as $mode_{th}$ increases, consumers have increasingly high requirements for the lower bound of $tech_k^2$; as a result, the market share of $tech_1$, $tech_2$ and their total market share displays a downward trend. Second, the market share of $tech_2$ manifests an upward trend in the range of $mode_{th} \in [0.01, 0.4]$, but begins to decline when $mode_{th} > 0.4$. Third, the sensitivity of $tech_1$ to the change of $mode_{th}$ gradually decays. Fourth, compared with Fig. 3, complementary technology constraints have a significantly negative effect on $tech_1$ diffusion; however, the negative effect gradually decreases with increasing intensity of complementary technological constraints. The existence of complementary technology constraints makes $tech_1$ unable to meet some consumers' rigid technological demands. When $tech_2$ enters the market, it mainly occupies the blue ocean market left by $tech_1$, avoiding competing with $tech_1$ directly. In the range of $mode_{th} \in [0.01, 0.4]$, the increase in the market share of $tech_2$ does not outpace the decrease in the market share of $tech_1$, causing their total market share to decrease (see "total" in Fig. 8).

The decrease in the total market share indicates that tightening complementary technology constraints exerts a negative effect on both sustaining technologies and disruptive technologies. However, disruptive technologies can mitigate this negative effect by encroaching on markets that $tech_1$ cannot reach. When $mode_{th} > 0.4$, as $mode_{th}$ continues to increase, the market share of $tech_2$ undergoes a more notable decline, while the market share of $tech_1$ diminishes mildly, suggesting $tech_1$, as a first-mover technology, meets the demand of some consumers in the existing value dimension. Even if disruptive technology occupies most of the market, $tech_1$ adopters do not vanish. This is consistent with many cases in that disruptive innovations do not replace sustaining innovations entirely. In the case of the hard drives, under the impact of disruptive innovation, incumbent enterprises increasingly concentrated on existing customers and moved towards a more narrow high-end market [35,37].

The results also reveal a double-edged sword effect of complementary technology constraints on disruptive innovation. On the one hand, complementary technology constraints act as a barrier protecting

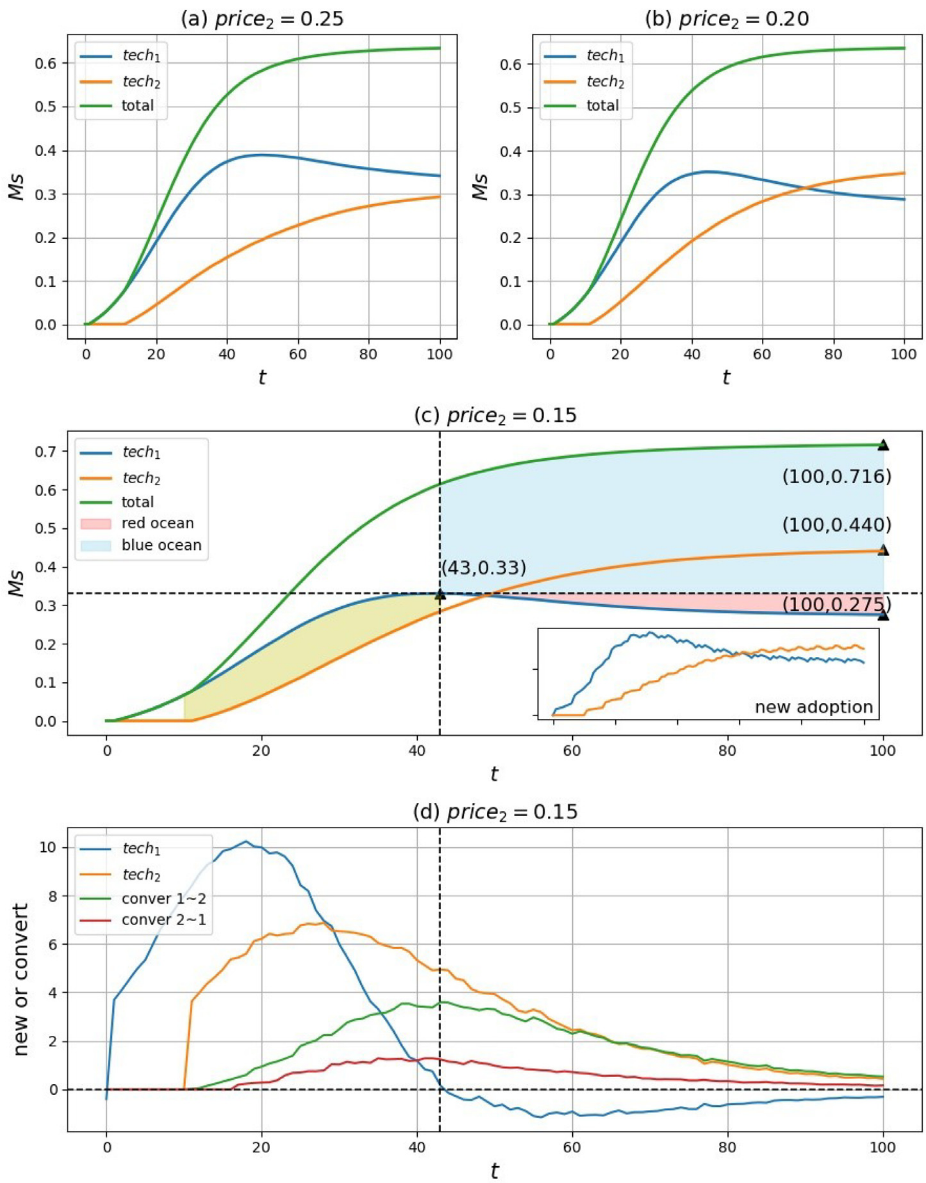

Fig. 6. The diffusion processes of disruptive innovation with various prices.

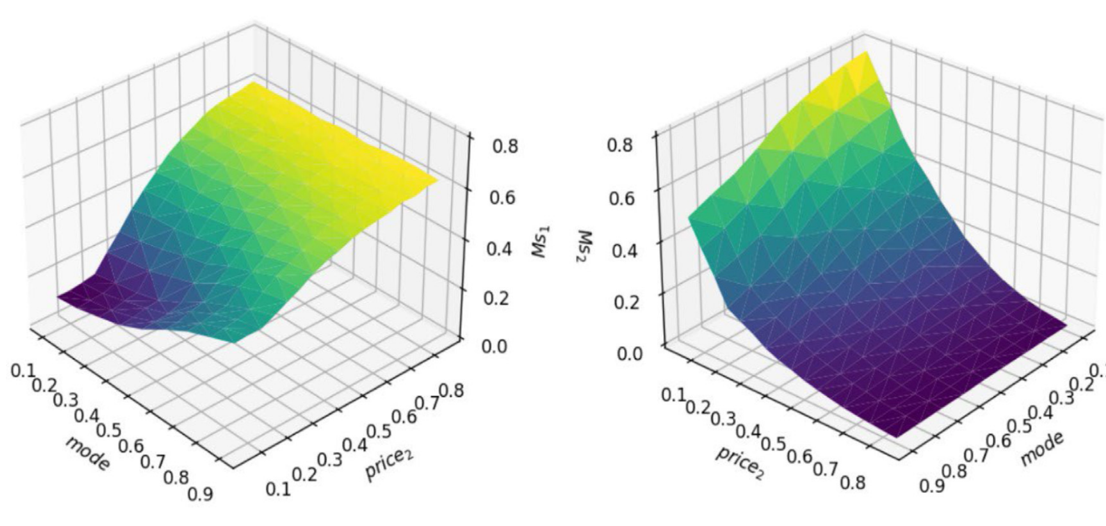

Fig. 7. The joint effect of prices and consumers' preferences on market share.

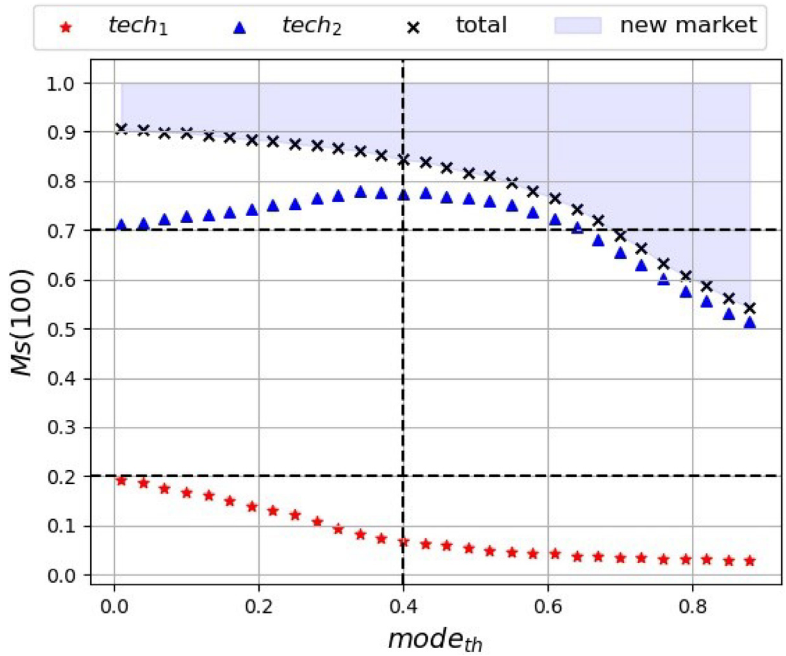

Fig. 8. The market share variations under complementary technology constraints.

disruptive innovation diffusion in emerging markets; on the other hand, they unintentionally open doors for new disruptors. To illustrate this, we experiment with $tech_2^2 = 0.4$, 0.5, 0.6, and 0.7, respectively. The average $marketshares$ at the end of $t = 100$ across 100 times simulations are shown in Fig. 9. Despite $tech_2^2$ set to different values, the market shares of $tech_1$ and $tech_2$ display a downward trend as $mode_{th}$ increases; however, the reduced market share of $tech_2^2$ leaves larger gaps in the market, which creates opportunities for new disruptors. This explains why 8-inch, 5.25-inch, and 3.5-inch hard drives successively entered the market and caused disruptive effects on the predecessors, leading Christensen to consider disruptive innovation as a repeatedly occurring phenomenon [1].

3.4. Impact of technological progress

Disruptive innovation normally does not stop evolving after it enters the market but strives to improve the existing value dimension to mitigate its relative inferiority. In the hard drive case, disruptive enterprises endeavoured to improve memory density, aiming to narrow the gap between their products and the mainstream products in terms of storage capacity. To maintain competitiveness, incumbent enterprises, though they might not be interested in shrinking their hard drive sizes, also seek to further improve storage capacity. That is, there exists competition between disruptive enterprises and incumbent enterprises on the existing value dimension. Incorporating technological progress into the model adds an extra layer of complexity to the analysis. For simplicity, this model solely considers the technological progress in the existing dimension. According to Eq. (5), if r_k is large, technology progress may meet the upper bound too early before the technology diffuses sufficiently, which compromises its dynamics and simply becomes a technology with fixed value dimensions; contrarily, if r_k is small, disruptive technologies can easily dominate the market for their advantage in the second value dimension, leading to $tech_2$ replacing $tech_1$ as soon as $tech_2$ enters the market. Although these outcomes are practically reasonable, they are unable to offer new theoretical insights. It makes more sense to find a suitable value of r_k to stimulate the model to present rich dynamics.

According to Eq. (5), if $\sum_t^{\tau} \psi_k(t) \to \infty$, then $h_k(\tau) \to \overline{C}_k$, that is, $\overline{C}_k$ determines the upper bound of technology k. For $tech_1 = [\overline{C}_{11}, C_{12}]$, $tech_2 = \left[\overline{C}_{21}, C_{22}\right]$, consumer preference $\vec{\lambda}_i = [\lambda_{i1}, \lambda_{i2}]$, if the utility of different dimensions is additive (for instance, without considering complementary technology constraints) and the utility provided by both technologies for consumer i is equal, then $\lambda_{i1} = \frac{C_{22}-C_{12}}{\overline{C}_{11}-C_{12}-\overline{C}_{21}+C_{22}}$ is the point that divides the consumers into $tech_1$ adopters and $tech_1$ adopters. To illustrate this, assume consumer preferences follow a uniform distribution and run this model 300 times with $tech_1 = [0.01, 0.3]$, $tech_2 = [0.01, 0.6]$, $r_1 = 0.002$, $r_2 = 0.001$, $\overline{C}_{11} = 1$ and $\overline{C}_{21} = 0.5$, which indicates that disruptive technology is superior to sustaining technology in the second value dimension but markedly inferior in terms of both the speed and the upper bound of technological progress. It can be calculated that $\lambda_{i1} = 0.375$, which is consistent with the simulation results in Fig. 10 showing a sample of the final market shares of $tech_2$ (denoted by Ms_2). It can be seen that the market share of $tech_2$ fluctuates around 0.375, which is in line with the calculation and confirms that the market share is closely related to the upper bounds of technological progress.

However, if r_1 is assigned some specific values, "abnormal" results appear. Let $r_1 = 0.0013$ and other parameters remain unchanged (the progress rate of $tech_1$ is still larger than $tech_2$), 300 simulation runs are conducted. Some typical results are shown in Fig. 11. Although subgraphs (a), (b), and (c) have different diffusion processes, the final market shares possessed by these two technologies are approximately the same. These outcomes are still consistent with the above analysis. Nevertheless, subgraph (d) shows that $tech_1$ is completely replaced by $tech_2$ before stabilising. The parameter settings indicate the upper bound of $tech_1$ is twice that of $tech_2$. Despite that, $tech_1$ might not have a chance to reach the ceiling. In contrast, there are chances that disruptive technologies leverage the advantages in the second value dimension to outgrow and suppress the diffusion of sustaining technologies, which could be termed the "suppression effect".

The suppression effect is an outcome of the stochastic process underlying the model. To derive a more comprehensive view of the suppression effect, we run the simulation 120100 times in total using the parameter settings: $r_1 = 0.0013$, $tech_2 = [0.3, tech_2^2]$, $tech_2^2 \in (0.3, 0.8)$ in increments of 0.05 and the technological progress rate $r_2 \in (0.001, 0.0015)$ in increments of 0.00005. The probability that the suppression effect emerges under each parameter combination is collected.

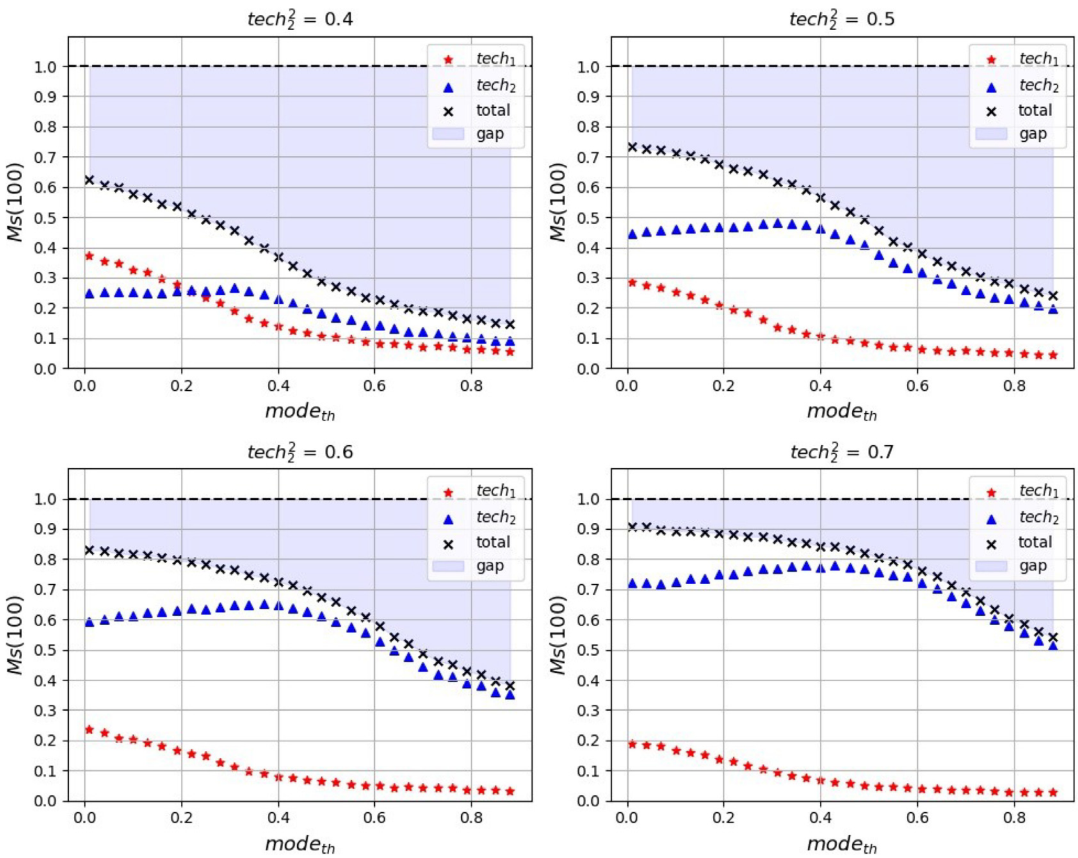

Fig. 9. The effect of new value dimension on the disruptive innovation diffusion under complementary constraints.

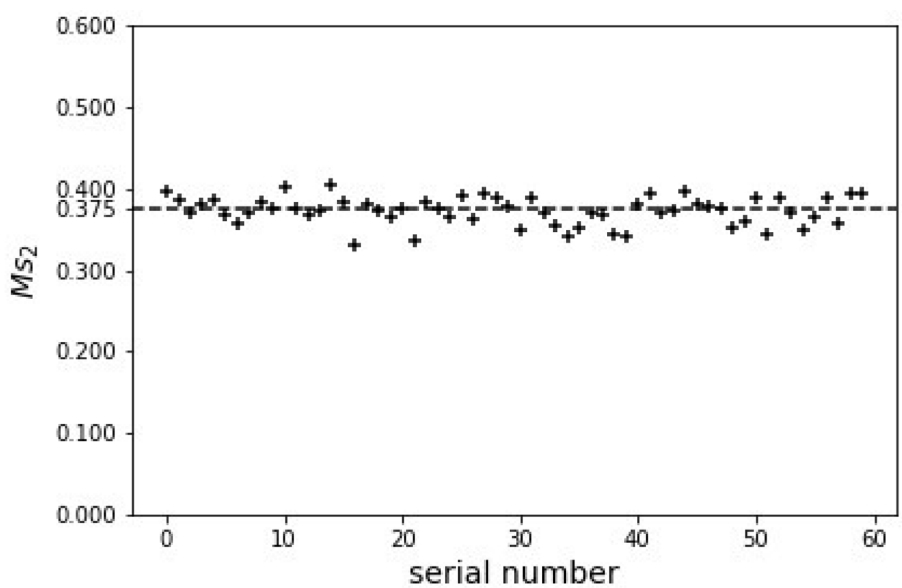

Fig. 10. The relation between technological initial values and final market shares.

The suppression effect is defined as $Ms_1(200) = 0$, that is, when $t = 200$ (the market shares of both technologies stabilise), the probability that the market is completely occupied by $tech_2$. Fig. 12 is a heat map illustrating the probability of the suppression effect under different combinations of $tech_2^2$ and r_2. By averaging all the values in the heat map, the overall probability of the suppression effect is about 17.1%. In other words, there is more than 80% probability that $tech_2$ cannot replace $tech_1$. The outcomes largely mirror previous observations about disruptive innovations as documented in the literature, showing that they do not completely replace sustaining innovations. However, this study offers a new insight: there are chances that disruptive innovations can supplant sustaining innovations if the former has a significant advantage in the second value dimension (large $tech_2^2$) and are bolstered by rapid technological progress (large r_2).

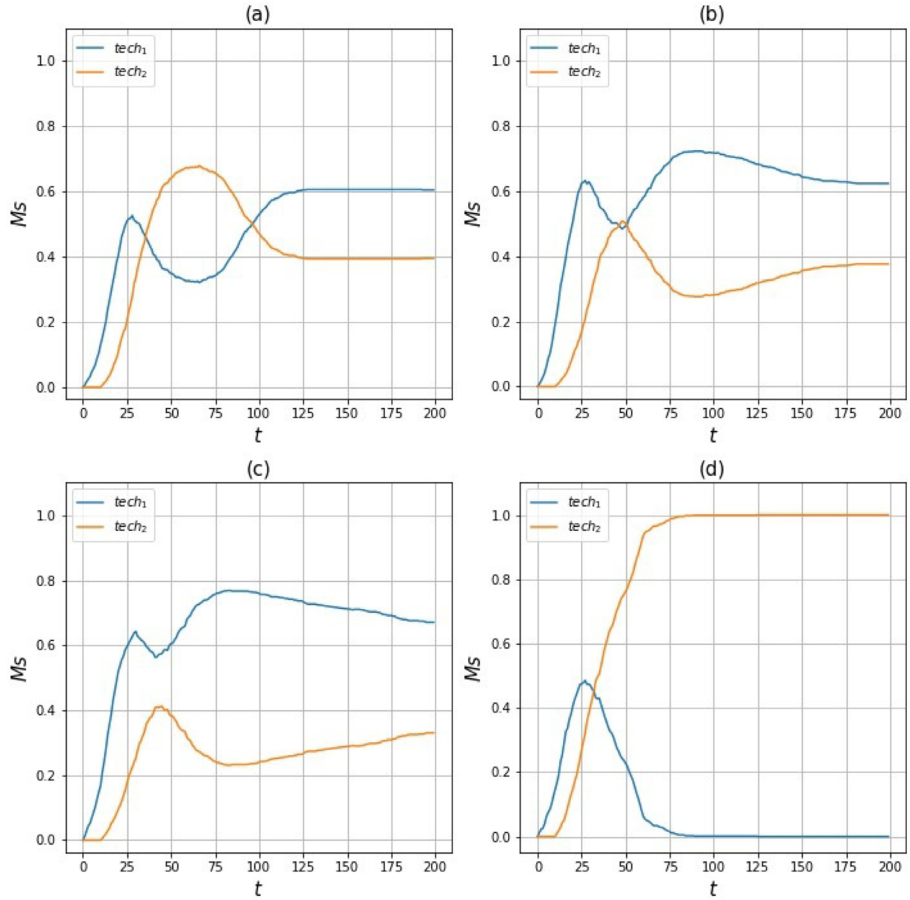

Fig. 11. Samples of the diffusion curves when considering technological progress.

4. Discussions

To provide intuition on the sensitivity of the model, we summarised how key parameters influence the diffusion outcomes. Overall, price and consumer preference distribution have the strongest effects on market shares, while complementary technology constraints and technological progress mainly affect the speed and pattern of diffusion. Importantly, across a wide range of parameter settings, the model is consistently able to reproduce key stylised facts such as market encroachment, coexistence, and potential dominance of disruptive innovation, indicating the robustness of the results. We also noted that while quantitative outcomes (e.g., exact market shares) vary with parameters, the qualitative patterns remain stable. Based on the results, the discussion is unfolded by reflecting on emergent patterns, conceptual role of duality, managerial implications, and modelling choices.

4.1. Emergence

Following the methodology of generative social science, this paper builds an agent-based model upon a simple concept, duality, to "grow" the emergence of the diffusion patterns of disruptive innovation. The results demonstrate that the model not only replicates the crucial stylised facts but also reveals a set of new insights into disruptive innovation.

Disruptive innovation with inferior performance can encroach on the market of incumbent companies. Christensen highlighted that disruptive innovation introduces new value to markets and changes customers' metrics for evaluating relevant technologies, and consequently, transforms the foundation of market competition. In the baseline scenario, we investigated how the new value dimension endows disruptive innovation with the ability to challenge incumbent companies. The results show that despite being inferior in the existing value dimension, disruptive innovation's new value dimension can offer advantages, enabling it to encroach on the existing market, which is consistent with real-world observations [1,3,38].

Sustaining innovation and disruptive innovation can diffuse simultaneously. Empirical studies indicate that sustaining innovation and disruptive innovation do not compete throughout their entire diffusion lifecycle. Fig. 13 shows the simultaneous growth in sales of hard drives with varying capacities and sizes. Simulation analyses reveal that adopters of disruptive innovation fall into two groups. The first group comprises new adopters, individuals who are introduced to either of the two technologies for the first time. The second group consists of converters, those who are aware of both technologies but choose to switch from one to the other. This simultaneous expansion can be attributed to the incomplete diffusion of both technologies. Consequently, the net increase in new adoptions is a cumulative outcome of these new adopters and converters, rather than a result of direct competition between the two types of innovation.

Low-priced disruptive innovation attracts extra adopters from low-end markets and enlarges the entire market. It is a well-established principle that lower prices typically stimulate increased demand. The efficacy of low-priced disruptive innovation in attracting adopters has been documented in numerous prior studies [8,39,40]. This paper builds on these earlier findings but offers new insights: a relatively low price not only captures customers in the low-end market, which incumbents often overlook, but also appeals to consumers in the existing market due to their diverse preferences. As a result, the impact of low-priced

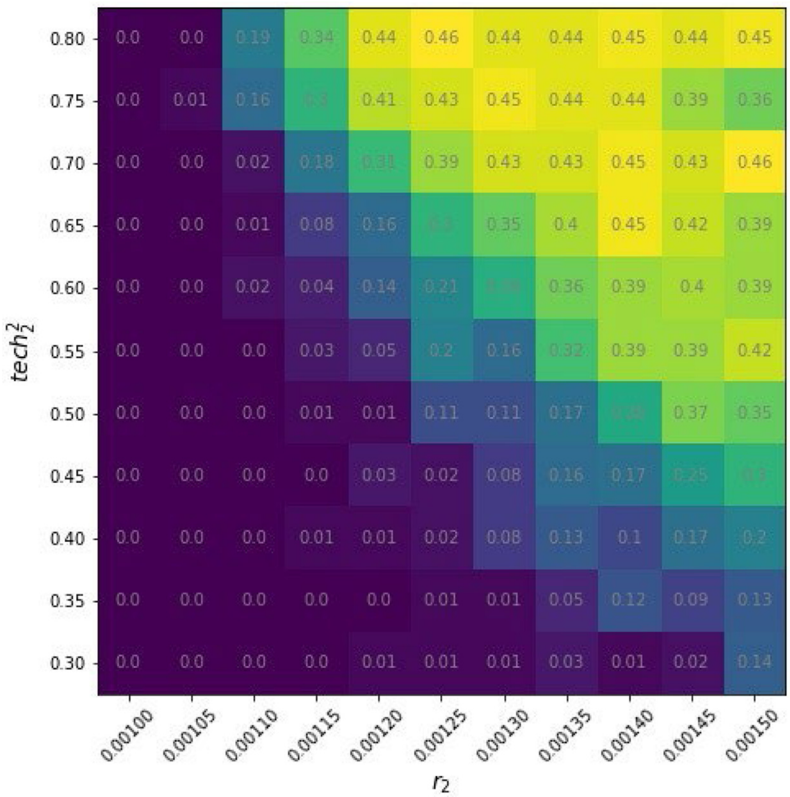

Fig. 12. Probability of the "suppression effect".

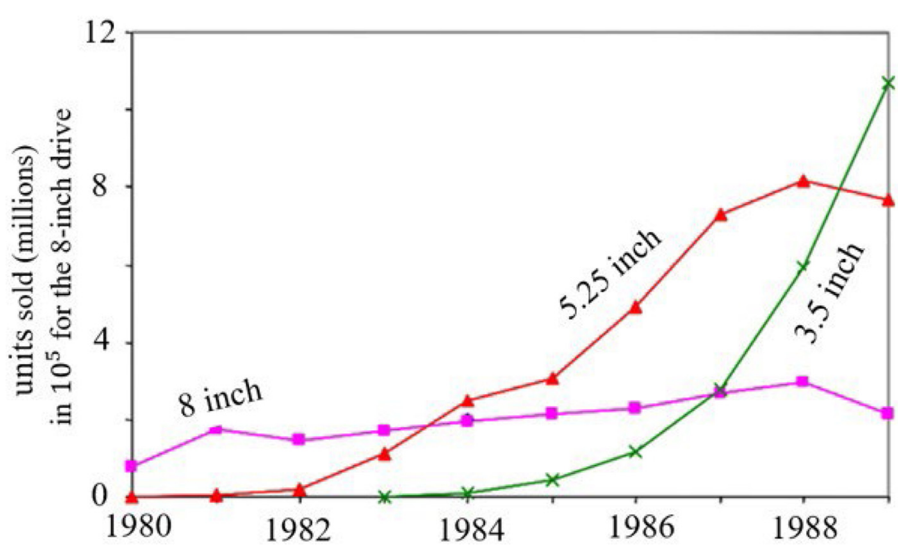

Fig. 13. The sales volume of hard drives [11].

disruptive innovation is twofold: it reduces the market shares of incumbent firms while simultaneously expanding into and broadening the scope of the low-end markets.

Disruptive innovation and sustaining innovation can coexist. The coexistence of disruptors and disruptees has been emphasised in many previous studies [1,4,7]. This phenomenon can be better understood by considering both supply and demand factors. From the supply perspective, disruptive innovations offer advantages in terms of pricing and introducing new value dimensions. However, these advantages are relative and asymmetric, meaning they vary in impact across different market segments and conditions. On the demand side, consumer affordability and preferences are diverse, indicating that no single technology can meet all consumer demands universally. Hence, the impact of these advantages is inherently limited, placing a ceiling on the ability of disruptive innovations to capture market shares from established incumbents.

Complementary technologies provide opportunities for disruptive innovation to encroach on new markets. Building on previous research in innovation networks and ecosystems, it is evident that disruptive innovation necessitates collaboration with a range of external factors for success [41–43]. The evolution of complementary technologies

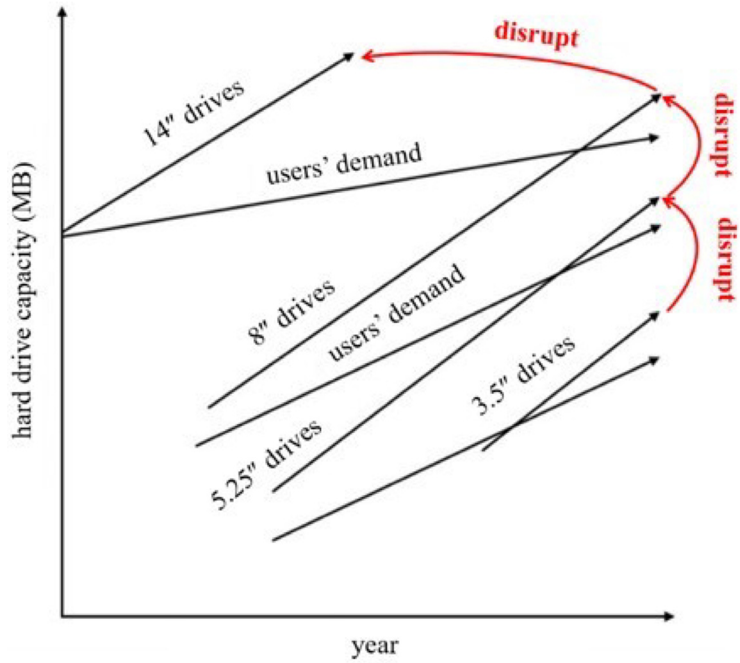

Fig. 14. Reoccurrence of disruptive innovation in the hard drive industry.
Source: Modified according to Christensen [1].

often signifies the rise of new market demands. Disruptive innovations, embodying new value dimensions, can align with these technologies, thus encroaching on new market niches. For instance, initial hard drives were specially designed for mainframe computers due to the nascent state of semiconductor technologies. However, following Moore's Law, a shift occurred in the consumer electronics market, prioritising portability as a key value dimension in electronic products. Consequently, hard drives were miniaturised, penetrating a market previously unexplored by established players. This scenario illustrates how disruptive innovators, despite being late entrants, can secure a first-mover advantage in new markets over existing incumbents.

The development of complementary technologies brings opportunities for new disruptors to "disrupt" the ex-disruptor. The numerical experiments reveal a noteworthy pattern: constraints from complementary technologies adversely affect the market shares of both sustaining and disruptive technologies, with sustaining technologies bearing a greater impact. This finding offers a compelling explanation for the recurrent emergence of disruptive innovation in the hard drive industry. During the industry's pivotal period, companies that excelled were those offering high-capacity hard drives; the potential of hard drives with lower capacity but smaller sizes was overlooked, not just by the market but also by the disruptive companies themselves; these companies initially focused on reducing size, attempting to compete with incumbents on existing value dimensions [1]. Interestingly, these once-successful disruptive companies eventually became targets for newer disruptors. An analysis of the technological evolution in the industry, as depicted in Fig. 14, shows that hard drive sizes correspond to discrete market segments, each with its own demand for higher technological performance. However, many disruptors repeated the error of their predecessors, prioritising investment in existing value dimensions and overlooking nascent market segments. This oversight created openings for new disruptors to enter and capitalise on these emerging markets.

The simultaneous presence of sustaining and disruptive innovation does not guarantee their coexistence; there are chances that incumbent companies may be ousted from the market. Our final numerical experiment delves into the impact of technological progress on the existing value dimension. With the inclusion of technological progress, the model's outcomes become more erratic. We observed the suppression effect, indicating that incumbents, despite having advantages and the potential for higher technological progress in the existing value dimension, can still risk market expulsion before fully capitalising on these advantages. A prime example is the displacement of Nokia mobile phones, known for their durability, by Android smartphones, which prioritised large, though fragile, touch screens. Currently, rugged mobile phones meeting military standards occupy only a small niche, while mainstream products are evolving differently. This mirrors real-world scenarios and adds nuance to Christensen's observation that incumbents often retreat to niche markets rather than being entirely supplanted by disruptors. The numerical experiments reveal that the probability of the suppression effect occurring is about 17.1%. This suggests that while the coexistence of sustaining and disruptive innovation is more common, it is not an inevitable outcome.

4.2. The role of duality in theorisation

The experimental results affirm that a model grounded in duality can replicate key stylised facts of disruptive innovation. This suggests that duality can be used to identify disruptive innovation without the need for hindsight or the involvement of survivorship bias. Operationally, duality enhances theoretical clarity through a dichotomous conceptual core. Compared to numerous controversies about disruptive innovation, its counterpart, sustaining innovation, is much less ambiguous. Sustaining innovation refers to advancements solely along the existing value dimension.

Innovations are dichotomised as sustaining, which progresses in just one dimension, and disruptive, which encompasses two dimensions. While innovations may involve more than two "dimensions", it should be noted that value dimensions are conceptually distinct from "dimensions" we use loosely. For example, dimensions may refer to performance attributes, such as speed, acceleration, manoeuvrability, and safety in vehicles. These attributes, though critical for design and market-specific product optimisation, are components of the existing value dimension. In contrast, electric vehicles (EVs), integrated with attributes, e.g., greenness and artificial intelligence, can be categorised

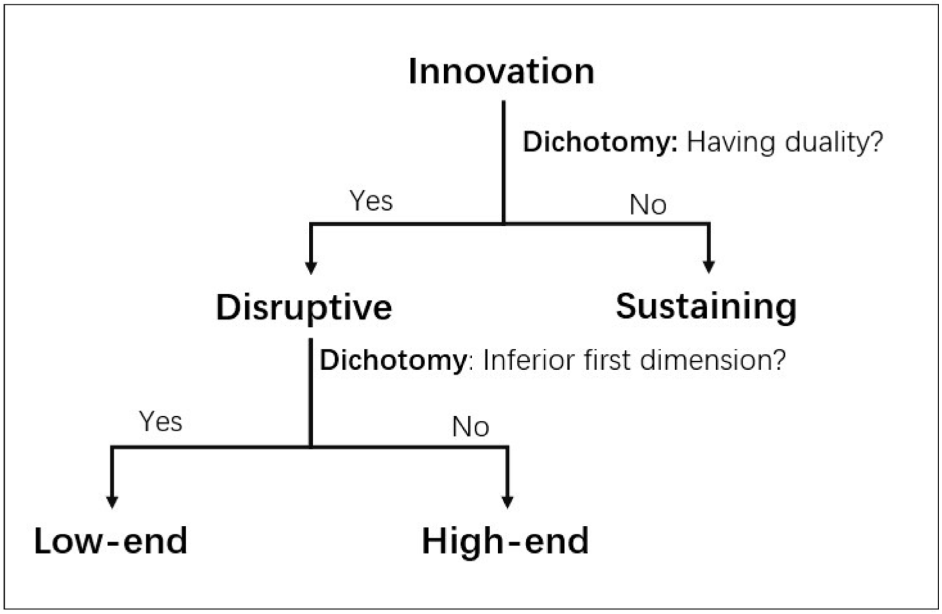

Fig. 15. The dichotomy of disruptive innovation.

as disruptive innovation because they bring new value and the awareness of the new value initially unrecognised in the market. When EVs enter the market, they compel a reconstruction of vehicle assessment criteria. This view in effect expands the scope of disruptive innovation, which is typically considered cheaper and low-end in its early phase.

While duality determines whether an innovation is disruptive, low-end market encroachment should not be treated as an identifier that determines whether an innovation is disruptive for two reasons. Firstly, the simulation results show that, although lower prices facilitate the spread of disruptive innovations, price differences do not fundamentally alter their diffusion patterns — it is duality that defines their disruptive nature. Secondly, low-end market encroachment still relies on hindsight because it often implies that an innovation will eventually outgrow its low-end niche, as demonstrated in the hard drive industry.

Fig. 15 shows how an innovation can be identified as disruptive innovation. The first step is to determine whether the innovation has duality, i.e., bringing a new value dimension. Then, low-end or high-end are only used to determine the subtypes within the disruptive innovation category. It is noteworthy that the dichotomy results from the parsimony we pursued throughout the modelling process. To achieve parsimony, rich elements associated with disruptive innovation are omitted. This omission strictly filters a minimal set of elements that are key to "growing" widely observed patterns of disruptive innovation. The dichotomy approach is, therefore, a deliberate abstraction for traceability, interpretability, falsifiability, and structural simplicity.

4.3. Managerial implications

Based on the analysis in this paper, several practical managerial implications can be drawn. These implications should not be taken as rigid action rules but rather as overall principles, which, combined with specific domain knowledge, should be able to help decision-makers identify and deal with disruptive innovation.

Firstly, enterprises implementing disruptive innovation strategies or identifying the disruptive potential of new technologies need to first determine whether the technology has dual value dimensions; the expected market impact of disruptive innovations needs to be further estimated by considering a range of moderating factors.

Disruptive innovation, in contrast to sustaining innovation, introduces novel value dimensions, transforming the foundation of competition and the criteria consumers use to evaluate technology, products, or services. In its developmental phase, particularly when entering the market with comparatively lower performance and reduced prices, disruptive innovation can avoid direct confrontations with well-established, dominant enterprises. All the simulation results demonstrated in this paper indicate that the new value dimension of disruptive innovation endows it with the capacity to forge new markets, while its existing value dimension enables it to infiltrate the markets currently dominated by incumbent enterprises. Nevertheless, the duality nature of disruptive innovation is a necessary but not sufficient condition for successful market encroachment. Its actual market impact is subject to a range of factors, including the distribution of consumer preferences, purchasing power, the presence of complementary technologies, the initial level of technology, the pace of technological advancement, and shifts in consumer perceptions. Therefore, enterprises should first ascertain whether an innovation possesses a dual value dimension to determine its potential for causing a disruptive impact. Subsequently, they should undertake a thorough analysis of factors such as consumer preference distribution and initial technology level to accurately forecast their mode and potential for market penetration.

Secondly, disruptive enterprises should leverage new value dimensions and consider competitive pricing strategies to penetrate niche markets; managers should track consumer preferences dynamically to estimate the potential impact of disruptive innovations.

Disruptive enterprises, despite resource limitations in technology R&D and product promotion, can gain asymmetric competitive advantages by introducing new value dimensions through disruptive innovation, particularly in markets overlooked by incumbent companies. Entering these markets with lower prices can facilitate smoother market entry. However, the simulation results in Section 3.2 show that the distribution of consumer preferences plays a crucial role in moderating the efficacy of this strategy, especially with lower-priced disruptive innovations. It is beneficial for both disruptive companies and incumbent companies to pay close attention to how consumers react to emerging value dimensions. Periodically utilising tools like conjoint analysis might be an effective approach to tracking consumer preferences. By understanding consumer preferences, managers can gauge the potential impact of disruptive innovations on their market share. In scenarios where consumer preference for the new value dimension is low, disruptive innovation is more favoured in the low-end market that might not interest incumbent companies. However, a strong preference for the new value dimension means disruptive innovations could open new markets, probably signifying a necessity for changes in incumbent companies' value networks or establishing an autonomous corporation.

Thirdly, both disruptive and incumbent enterprises should focus on continuous improvement in the primary value dimension and closely monitor complementary technology constraints; addressing unmet needs in the new value dimension can expand market reach and protect against new disruptors.

Complementary technology constraints significantly influence the entry of disruptive innovations into new markets, offering comparative advantages over existing technologies while also creating opportunities for new disruptors. However, strong constraints may hinder the diffusion of these technologies. The experiments in Section 3.3 indicate that complementary technology constraints alone are insufficient for disruptive innovations to completely replace existing technologies, instead compressing their market share. Disruptive innovations reliant on these constraints for market penetration are unlikely to significantly impact incumbent enterprises' market share in the short term. Over time, as disruptive innovations continuously improve in their primary value dimension, they may begin to erode the market share of incumbents. Therefore, both incumbents and disruptors need to focus on continuous improvement in the primary value dimension and monitor the market for unmet needs due to strong complementary technology constraints. Enhancing the second value dimension can not only expand the current market boundaries and increase profits but also guard against new disruptors.

Lastly, to avoid suppression effects, incumbent enterprises should proactively embrace new value dimensions and boost technological advancements in the existing dimensions.

The suppression effect, presented in Section 3.3, demonstrates that fast technological progress and great utility brought by the new value dimension boost suppression effects. Nokia's failure well exemplified this. From 1990 to 2008, the shift in consumer preferences towards new features like larger touchscreens diminished the importance of durability, once a key value dimension. As mobile phone technology evolved, consumer preferences shifted away from durability to more advanced features, leading to Nokia's reduced market share. The conditions for the emergence of the suppression effect are stringent and occur when both r_2 and $tech_2^2$ reach high levels. For incumbent enterprises, technological progress is essential for maintaining or improving market share. However, if disruptive innovations significantly outperform in new value dimensions, incumbents must be cautious of suppression effects. To counter this, increasing investment in technology R&D to enhance the rate of technological progress is advisable, albeit with diminishing returns. The most effective approach to circumvent suppression effects is to actively improve in the new value dimension, viewing disruptive innovation not as a threat but as an opportunity to explore new possibilities and facilitate transformation.

4.4. Reflection on modelling decisions

Modelling disruptive innovation is challenging because real-world cases are complex. Here, we reflect on some key assumptions and rationale behind modelling decisions to gain more transparency, which also can be helpful for further development of this analytics framework.

Utility additivity and consumer rationality are key assumptions, which may bring the risk of oversimplification of real-world decision-making. These assumptions result from a careful trade-off between realism and interpretability. In reality, non-linear preferences, satisfying behaviour, social influence beyond imitation, and learning processes are important factors. However, it should be noted that (1) research on formal models of disruptive innovation is still limited, (2) the modelling purpose is to expose a clear-cut conceptual core, and (3) the definition of disruptive innovation is not yet crystal clear and has been interpreted very differently. In this context, high realism should not be the top concern. Instead, proper simplification and abstraction are the real challenges.

Complementary technology is narrowly defined without considering rich, diverse real-world possibilities. Although it is definitely meaningful to explore diversity, our modelling practically adopts an Occam's razor principle, and the scope is deliberately restricted to well-documented and widely known disruptions with the purpose of exposing core mechanisms without introducing additional complications. Furthermore, in the framework, the constraints of complementary technology and the technological progress on the new value dimension are relatively qualitative and static compared with the conventional value dimension. This treatment is a simplification, but it reflects the commonality shared across many disruptive innovations: they start with an inferior conventional value dimension but gradually attracted more mainstream customers by improving their conventional dimension to reach a good-enough threshold, for example, such as small, portable hard drives versus high-performance large hard drives in storage capacity, mini steel mills versus large-scale mills in quality, hydraulic excavators versus cable ones in reliability, among others. Thus, despite the simplification, this framework still respects observed facts.

The modelling relies on stylised facts rather than tangible empirical cases. This reads more like an "accusation" rather than a modelling choice. However, it should be emphasised that stylised facts are condensed empirical evidence, representing stable, case-independent patterns abstracted from a wide range of real-world phenomena. Many of these stylised facts were derived from the hard drive industry. In Christensen (1997), the hard drive industry is viewed as a "model system" rather than "another individual case". The repeatable patterns observed in the hard drive industry make the stylised facts particularly robust in contrast to specific individual cases. In addition, our stylised-fact-focused modelling approach actually follows the principle of pattern-oriented modelling (POM) [44], where the objective is to reproduce shared patterns instead of a specific empirical case. POM has been widely adopted in complex system modelling, where uncertainty in data and mechanisms is often challenging to handle.

5. Conclusions and limitations

The model presented in this paper was designed to simulate the macro-level diffusion patterns of disruptive innovation from micro-level consumer decisions. A notable aspect of these diffusion patterns is their dual capability: they can both encroach upon existing markets and create new markets. The replication of the diffusion patterns in the model implies that the theory of disruptive innovation could be conceptually grounded in duality. This notion of duality could potentially simplify the categorisation of innovations, enhancing theoretical consistency and reducing the reliance on retrospective identification. Practitioners might find the concept of duality useful as a guideline for recognising disruptive innovation or developing strategic responses. This approach may leads to a more coherent and consistent analytical framework, providing a basis for further exploration and understanding in both academic and practical realms.

While it is important to understand the organisational behaviours underlying disruptive innovation phenomena, this paper intentionally does not examine these factors. Future research could expand on this model to incorporate firms' internal dynamics, such as R&D investments, organisational learning, and competitive reactions. In addition, different network typologies should be tested to check whether and how disruptive innovation is affected.

Establishing a widely accepted definition of disruptive innovation is challenging; this paper does not aspire to do so. Instead, it aims to propose a core concept and a structured model that could foster more focused and fruitful future discussions. Subsequent studies could provide further evidence supporting or contesting the effectiveness of the concepts of duality in theorisation and analytical processes.

Table A.1
The estimated values of parameters in the Bass model from some existing studies.

Innovation	p value	q value	Time (year)	Sources
fuel vehicle	0.0912	0.4692	5	[45]
Prius hybrid vehicle	0.0016	1.45	7	[46]
electric vehicle	0.025	0.4	10	[47]
steam iron	0.028632	0.32791	11	[26]
air conditioner	0.010399	0.41861	12	[26]
electric vehicle	0.002	0.23	27	[48]
refrigerator	0.0026167	0.21566	27	[26]
solar water heater	0.0001	0.1737	53	[49]

Table A.2
Model parameters.

Parameter	Meaning
P_{ik}	The probability that agent i is informed about the existence of technology k.
p_k	The probability that an agent is informed about the existence of technology k via mass media.
q_k	The probability that an agent is informed about technology k via the word-of-mouth effect in the social network.
b_k^i	The number of agent i's network neighbours who know the existence of technology k.
O_i	The optional technology set of agent i.
$tech_1$	The sustaining technology.
$tech_2$	The disruptive technology.
af_i	The affordability of agent i.
pr_k	The price of technology k.
u_i	The maximum perceived utility of agent i.
$\vec{\lambda}_i$	The preference vector of agent i.
$\vec{q}_{ik}$	The value vector of technology k for agent i
$h_k(\tau)$	The accumulative technological progress of technology k at time τ.
h_{0k}	The initial value of technological progress of technology k.
$\overline{C}_k$	The upper limit of technological progress of technology k.
r_k	The rate of technological progress of technology k.
ψ_k	New purchases of technology k within a time step.
T_1	The timing that $tech_1$ enters the market.
T_2	The timing that $tech_2$ enters the market.
p_{nd}	Network density.
Ms	Market share.
Ms_1	The market share of $tech_1$.
Ms_2	The market share of $tech_2$.
$mode$	The value of consumers' preferences with the maximum probability, given that consumers' preferences follow a triangular distribution.
th_i	The demand threshold of agent i regarding the second value dimension.
$mode_{th}$	The value of consumers' th_i with the maximum probability, given that consumers' th_i follows a triangular distribution.
$tech_k^1$	The first value dimension of technology k.
$tech_k^2$	The second value dimension of technology k.
λ_i^1	The preference of consumer i for the first value dimension.
λ_i^2	The preference of consumer i for the second value dimension.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A.1 shows the estimated values of parameters p and q in the Bass diffusion model from some existing studies. p ranges from 0.0001 to 0.0912, and q ranges from 0.1737 to 1.45. The innovation takes from 5 to 53 years to occupy 80% of potential markets (see Table A.2).

Appendix B

B.1. Model calibration

Given the fact that there is no wide consensus that there exists a single type of innovation representative enough for all kinds of innovation, and the purpose of this study is explanatory, we intend to find a set of parameters that are within a reasonable range instead of being accurate. Since the Bass diffusion model is well known for its good fitness with realistic data, we use it as an objective to cross-calibrate the agent-based model. This treatment is a common technique used in previous literature [28,33,50–52]. For the Bass diffusion model, $p = 0.005$ and $q = 0.18$ are used to let the diffusion rate of innovation reach 80% in the 29th year, which displays a stylised S-shaped diffusion curve (see Appendix A). Miller [53] proposed an approach called "Active nonlinear tests (ANTs)" to explore complex models with huge parameter spaces. The core idea of this method is to use global optimisation algorithms such as genetic algorithm, simulated annealing, particle swarm, etc., to find a parameter combination that can meet the requirements in the huge parameter space. The research uses the ANTs method and calibrates the model with a genetic algorithm. When calibrating the model, it is assumed that only $tech_1$ exists without being influenced by other factors. R^2 is used to evaluate the fitness between the model output and the target output, that is, to find the parameter combination that maximises R^2 within the search range:

$$\max R^2 = 1 - \frac{\sum (A_{Bass}(t) - A_1(t))^2}{\sum (A_{Bass}(t) - \overline{A_{Bass}})^2} \tag{B.1}$$

where $A_{Bass}(t)$ denotes the accumulative diffusion rate at time t according to the Bass diffusion model; $\overline{A_{Bass}}$ represents the average accumulative diffusion rate according to the Bass diffusion model; $A_1(t)$ is the accumulative diffusion rate from the agent-based model. After the parameter search, $R^2 > 96\%$ can be obtained when $p_k = 0.008$, $q_k = 0.024$, and $p_{nd} = 0.009$. The target data, experimental data, and fitness are shown in Fig. B.1. It can be seen that the model output under this set of parameters can stably generate a typical S-shaped diffusion curve, which has a high fitness with the Bass diffusion curve. The model can demonstrate different diffusion patterns of $tech_1$ and $tech_2$ given different entry timings of $tech_2$ and repeat purchase periods, while letting the total diffusion curve keep the S-shaped feature as shown in Fig. B.2. It can be seen that different entry timings and repeat purchase periods do not change the trends of the diffusion. For simplicity and to obtain comparable experimental results, we assume that $tech_2$ enters the system at the tenth time step, and consumers' repeat purchase periods follow a normal distribution $N(u = 10, \sigma^2 = 2)$.

B.2. Model validation

Rand and Rust [51] proposed four aspects of rigorous model validation: micro-face, macro-face, empirical input, and empirical output validation. Microscopically, the decision process of every consumer is built based on Rogers' innovation adoption model; meanwhile, two important effects on consumers in the real market were considered, namely the mass media and the word-of-mouth effect, according to the Bass diffusion model [26] and the innovation decision theory [25]. The perceived utility of each consumer is calculated according to the multiple-attribute decision-making theory, which matches the value dimensions of disruptive innovation [11,21]; The model introduced a complex network to describe the social relationships among consumers, and thus the word-of-mouth effect can be mimicked through the local interactions between the consumer agents, which is consistent with previous literature [33,54]. From the macroscopic aspects, mass media affects all agents according to a certain probability, which is consistent with the Bass diffusion model [26]. Regarding the input aspect, this model is calibrated with the Bass diffusion model and demonstrates a fitness over 96%, and the parameters are within reasonable ranges. The calibrated network density is 0.009, which corresponds to the fact that "complex networks in the real world are sparse" [55]. As

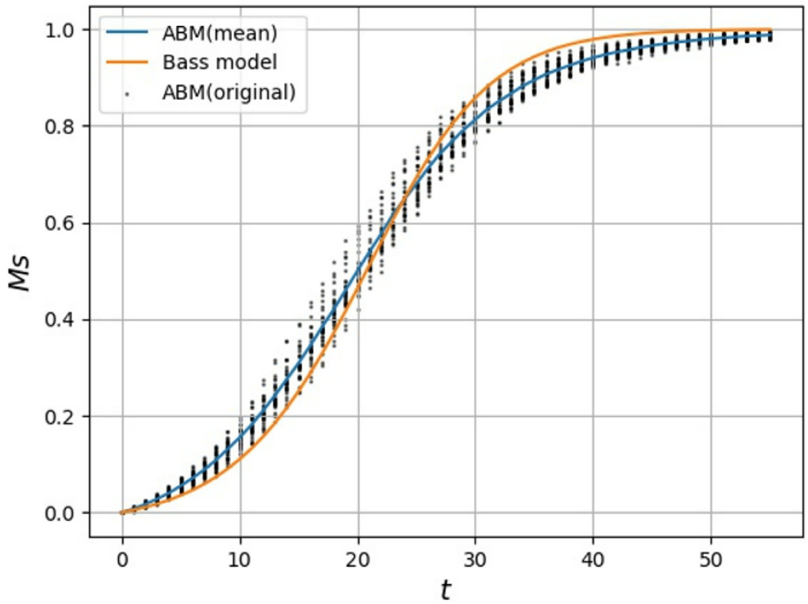

Fig. B.1. Model calibration.

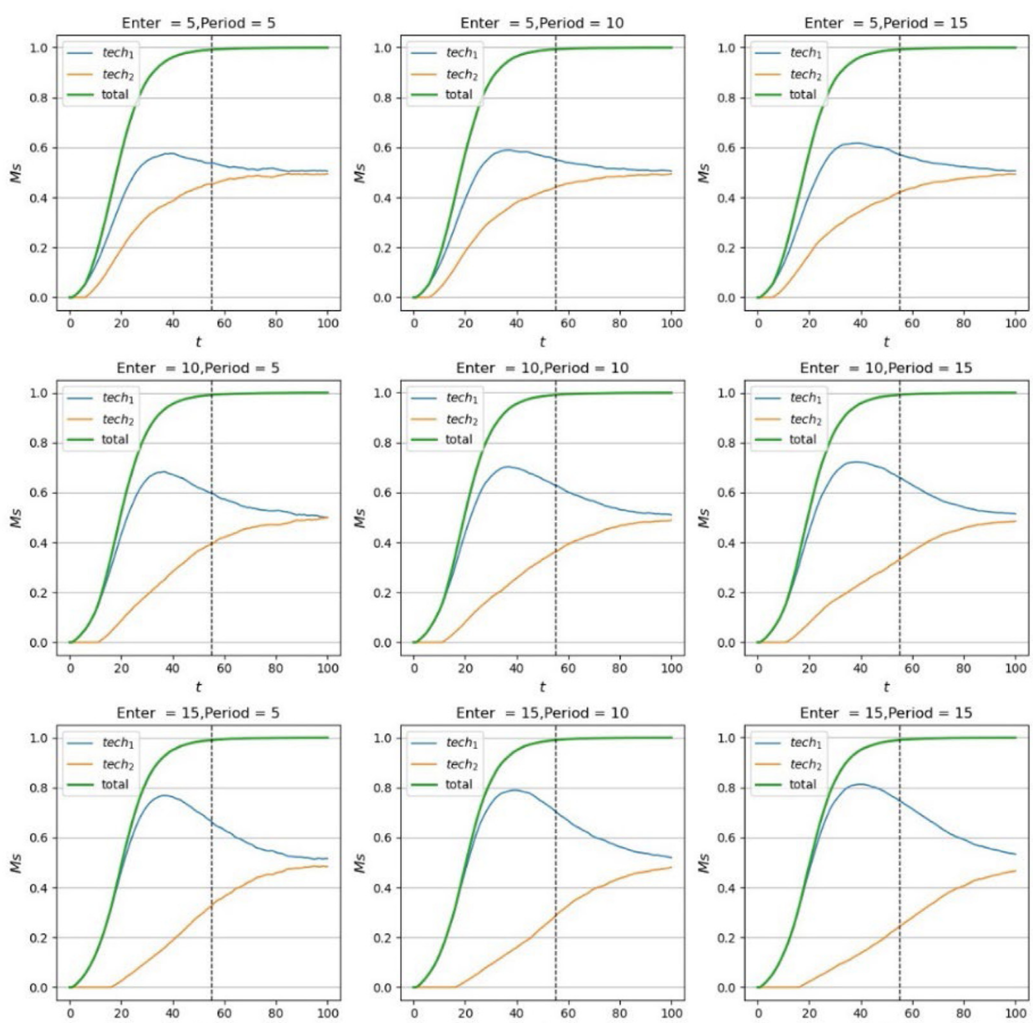

Fig. B.2. Diffusion curves given different enter timings of $tech_2$ and consumer repeat purchase periods.

to the output aspects, the calibrated model can reproduce the typical S-shaped curve of innovation diffusion. It should be noted that the validation approach in this study differs from empirical predictive models. This work follows a generative modelling paradigm, where validation is based on the ability to reproduce multiple stylised facts and known patterns, rather than out-of-sample prediction. The aim is mechanism identification rather than forecasting. More stylised facts regarding disruptive innovation reproduced by this model can be seen in the numerical experiment section. Therefore, this model can pass the validation tests mentioned above and has the credibility to serve the explanation-oriented research purpose.

Data availability

Data will be made available on request.

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