Complex systems models for strategic decision making

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A number of simulation techniques may be applied to strategy and decision-making. In using such techniques it is important to understand the role of models, in the context of the wider decision-making process which is largely a communal and political process; the choice of a particular approach or technique depends not only on the type of decision being considered, but also on the stage of the decision-making process (which in turn affects the type of problem under consideration).

Models which take into account the dynamics of a system can give insight into possible outcomes and indications of unintended consequences. Such models may not necessarily reproduce all aspects of a complex adaptive system; there is a continuum of modelling techniques, ranging from static equilibrium models through to agent-based approaches which can incorporate evolution and learning. The trade-offs between alternative approaches is discussed.

1. Introduction

Complexity provides a starting point for discussing both the environment in which a corporation is operating, and its own internal structure. Complexity concepts can be used to develop robust strategies in a rapidly evolving environment, highlight the possible impact of emergent properties, and identify the organisational capabilities that will ensure corporate survival in the 21st century. Modelling techniques developed for complex adaptive systems are being applied to a wide variety of business problems, including market demand forecasts, industry evolution and strategy development. Although many techniques are still in their infancy, such models are expected to be key to effective management in the future.

In this paper, the role of models in supporting strategic decision-making is discussed; of particular interest are those techniques developed to support the study of complex adaptive systems.

1.1 Complexity and models

Intuitively, the study of complex adaptive systems and the concept of complexity is readily applicable to strategic decision-making within companies. If the economy is a complex adaptive system [1], a proper understanding of complexity theory should provide a better basis on which to build strategic models. To some extent this is true, in that models built to study complex systems often require fewer abstractions. However, the advantage of a model is that it is a simplification of reality which enables people to understand key aspects of a situation. There is a danger that a more realistic model is, in fact, too complex, so that it is no longer possible to understand the output or to decide how to act. Simple models, based on an equilibrium system, may be preferred because of the illusion of prediction and certainty they give the user.

1.2 Models to understand/simulate complex systems

Complex systems of interest are often described as being on the 'edge of chaos' and displaying self-organised order. Such systems are continuously changing, but preserve some degree of structure at all times[1]. Such change is varyingly described as learning, evolution or adaptation, depending on context. From the modelling viewpoint we are dealing with systems which are dynamic in nature and for which static models, based on equilibrium or stasis, are inappropriate. One result of this emphasis on dynamic systems, is that we can no longer expect models to predict. Because the systems are continually changing, outcomes of changes are path dependent and may be multi-valued. The object of a model is no longer to predict but to understand. Some authors question the extent to which a model can aid understanding, as similar results or outcomes can be the result of a number of different dynamical processes — the fact that a model can reproduce observed behaviour does not guarantee that the underlying assumptions are correct: 'Computational models are particularly good at developing theory [and] suggesting the logical consequences of a set of assumptions...[But]..computational models do not prove these theories they help develop....Expectations that

[1] This is in many ways a self-fulfilling observation: systems which are either static, or display total randomness, are rarely identified as being 'complex'.

computational models can demonstrate or prove anything beyond theory building is asking too much of them and will lead to disappointment' [2]. This is consistent with Schrage's view that '... models are most useful when they are used to challenge existing formulations rather than to validate or verify them' [3].

There is a deeper link between models and complex systems highlighted by Holland [4] who suggests that complex adaptive systems anticipate the future by means of various internal models which are simplified representations of the environment. Holland distinguishes between a 'tacit internal model' which prescribes current action under an implicit prediction of future state and an 'overt internal model' which provides a basis for explicit (internal) exploration of alternatives. This distinction provides an admirable means of describing the use of models in strategic decision-making. A successful modelling approach involves taking tacit internal models (held by individuals) and turning them into overt internal models which can be debated, criticised and simulated.

1.3 Strategic decision making — role of models

A number of simulation techniques may be applied to strategy and decision making. In using such techniques it is important to understand the role of models, in the context of the wider decision-making process which is largely a communal and political process; the choice of a particular approach or technique depends not only on the type of decision being considered, but also on the stage of the decision-making process (which in turn affects the type of problem under consideration).

1.4 The need for models

Although many models adopt a relatively static view of the world (consistent with a determinist, positivist view of the world), complex systems models highlight the dynamics of change. It is assumed that organisations and industries are complex systems characterised (typically) by high numbers of component entities, and a high degree of interconnection (and hence, interaction). In this context, the outcome of any change to the system (such as an investment decision or policy change) cannot always be predicted. To some extent, this reflects the cognitive limits of human beings; humans find it difficult to understand the behaviour arising from mutually interacting entities. As de Guess [5] notes: '... most people can deal with only three or four variables at a time, and do so through only one or two time iterations'. Similarly, Larichev and Moskovitch [6] suggest that '... decision makers completely apprehend only those decision problems in which a maximum 5-8 structural units interact in the knowledge representation.'

In practice, managers make simplifying assumptions. Typically, simple cause/effect relationships are assumed, rather than multiple interactions; systems are simple and independent of each other, and there are no delays in the system.

This has implications for the way companies develop strategies. Mintzberg [7], for example, is highly critical of strategic planning as a concept and Rosenhead [8], in a critical review of complexity and management, highlights the tendency of some writers to reject a role for analytic methods in management, emphasising instead the importance of political processes in determining strategy.

Van der Heijden [9] identifies three approaches to strategic planning:

- rationalists, who aim to plan an optimum strategy in a forecast environment,
- evolutionists, who emphasise the complexity and uncertainty of the world and the way companies' strategies emerge through political processes (and may deny any value to analytical approaches),
- processualists who recognise the uncertainty of the future, but also hold that it is not entirely unpredictable — the processualist will recognise the political processes at work in the formation of strategy, but also accepts the value of analytical and rational techniques (e.g. simulations and scenarios planning) in helping to structure the political debate.

The processualist approach is adopted in this paper. Models are developed to improve strategy development, but it follows from the above that model building should not be seen as an end in itself, but as part of a wider decision-making process which is essentially social in nature, involving negotiation and debate.

1.5 The modelling context

Earlier work [10, 11] has emphasised the need to take into account the political context in which a model is developed and used. In particular, a framework of procedural intelligence developed by Humphreys [12] was used to formalise the role of modelling in decision-making and strategy development. Humphreys argues that in order to resolve initially unstructured problems (typical of a business environment), the decision-maker must introduce constraints on the problem in order to identify an appropriate course of action. He identifies five levels of constraint setting, each of which involves a different way of representing knowledge. The levels represent different cognitive activities, and any decision problem will involve all five levels in turn. These are:

- level 5 — setting boundaries,
- level 4 — choice of frames,
- level 3 — problem structuring (within framework),

- level 2 — interpreting structure,
- level 1 — assigning referents.

Table 1 is an attempt to locate some commonly used management tools and processes within Humphreys' framework.

Table 1 Tools to support cognitive processes at different procedural levels.

Procedural intelligence level	Support
5 — Setting boundaries	Scenarios planning
4 — Choice of frames	Scenarios planning Cognitive mapping
3 — Problem structuring within frame	Conceptual models Enterprise models Influence diagrams
2 — Interpreting structure	Exploration of conceptual model — alternative scripts 'What-ifs' Econometric models Game theory Simulations Expert systems Sensitivity analysis
1 — Assigning referents	Market surveys/analysis Competitor analysis Data-mining Setting targets

As one moves from higher to lower levels there is a narrowing of focus. It can be seen that conceptual models are associated with level 3 and simulations with level 2. This does not diminish the value of modelling, but does highlight the fact that model development is carried out in a wider decision-making context. Too often, managers leap to a model as a solution without properly considering what the problem is.

1.6 What do models tell us?

There is still the question of what information can be derived from a model or simulation. As we saw above, one school of thought is essentially negative — models are confined to the role of theory development or for challenging existing formulations. A more positive view is that: '... models allow us to broaden our viewpoint beyond our fixed notions, based on current reality, of what can transpire. These scenarios help expand our linear expectations to include all the possible futures we may encounter' [13]. Both viewpoints reflect the idea that models allow one to explore the outcomes of alternative strategic choices, rather than providing a forecast of a predetermined future. Thus, the type of knowledge coming out of complex systems models is itself 'complex' (or at least, complicated!) — not single-valued answers (this is what you should do), but rather a statement of options which place limits on the extent to which control can be exercised. This pushes much of the decision making back to the higher cognitive levels in Humphreys' model, where objectives and values dominate. In reality, of course, decisions have always been made on the basis of the decision-makers' values. Schrage [3] points out that the types of model produced by an organisation reflect the values and perceptions within the organisation.

1.7 Multiple models

In general terms, models [3]:

- act as tools for negotiation,
- create/unearth choice,
- define a context for trade-offs.

In this list we see a clear departure from the idea of a single objective model which predicts an optimal strategy. This is implicit in Humphreys' framework discussed above. By the time a model is developed there has been a considerable narrowing down of the original problem. Yet, the choice of different boundaries (level 5) or different frameworks (level 4) would inevitably result in a different model. This reflects a general characteristic of social systems. Such systems are undoubtedly complex and adaptive but, unlike the physical sciences, there is no complex, coherent body of theory to describe them. Instead, a number of different and independent theories co-exist. Models of social systems — often conceptual — represent tentative theories providing one view of an issue. Such models are rarely interlinked and are not necessarily mutually incompatible[2]. For these systems, the post-modernist view, that truth and knowledge are subjective, social constructs, seems to make much more sense.

Thus, different models give different views of a problem and reflect choices made earlier in a decision process. There is no single model which will incorporate all aspects of a strategic problem. This implies that there could be advantages in developing multiple models of a particular decision to reflect different viewpoints. This is Schrage's view: '... the companies that want to see the most models in the least time are the most design sensitive; the companies that want ... one perfect model are the least design sensitive' [3].

2. Modelling in practice

The preceding discussion has emphasised the dynamic nature of complex systems and hence the needs for modelling techniques which can handle dynamics and change. Because the systems are dynamic, equilibrium models which imply predetermined and forecastable

[2] For example, consider the different schools of thought in politics, sociology, psychology as well as debates between neo-classical and other breeds of economists.

futures or predict a 'correct strategy' are misleading. Instead of models as forecasting tools, we emphasised the use of models as tools to aid understanding and critical debate. The discussion also highlighted the value of applying different modelling techniques to a single problem as a means of identifying the range of issues which can influence outcomes. In the remainder of this paper, a number of dynamic modelling techniques are applied to two strategic issues: understanding market growth for a new service or product (product diffusion), and strategic choice in a competitive market.

We consider three techniques which may be used to study aspects of dynamic systems:

- system dynamics [14],
- agent-based models [4],
- evolutionary game theory [15].

The discussion illustrates how models can aid understanding of a strategic issue and the way different techniques give different insights. The models often work at different levels of detail. However, in most cases a key issue is the type of cognitive model used to describe agent behaviour.

3. Modelling product diffusion

The telecommunications industry continues to change rapidly in every aspect of its business. To succeed in this fluctuating environment, products and services must be innovative and quick to market. Increasing competition has led to a reduction in product lifetimes in many industries and as the number of potential telecommunications services increases, similar pressures will reduce the development cycle of new services. New products and services must address customer needs and enter the market quickly to recoup investment. Managing an organisation's portfolio will therefore require a deep understanding of the factors determining a product's life cycle.

The diffusion of an innovation (knowledge or actual take-up of a new product or service) is the process by which that innovation is communicated through channels over time among the members of a social system [16]. The key aspects required to understand the diffusion process and the adoption of a new product are therefore the methods and nature of communications and the cognitive process involved in assessing the utility or profitability of that product.

Conventional diffusion models, such as the Bass model [17] describe the diffusion process by a formula such as equation (1):

$$\frac{dN(t)}{dt} = g(t, N)[N_T - N(t)] \qquad \text{...... (1)}$$

where $N(t)$, $g(t, N)$, N_T, are the number of adopters, the coefficient of diffusion at time t and total number of potential adopters in the social system. This shows that the rate of change in adopters with respect to time is proportional to the number of people who have not adopted. The conventional diffusion modelling technique is simply the fitting of a suitable mathematical form to empirical data.

The coefficient g describes the characteristics of the diffusion process and is determined by the nature of the innovation, the communications channels used and the social network. Variation of this parameter allows tailoring of the model; g can be a constant, a function of N or a combination. With the coefficient as a constant, it describes the external influences, i.e. outside of the social system, such as the effect of mass media. With the coefficient g as a function of the number of adopters, the diffusion is influenced by factors internal to the social system, i.e. imitation by consumers is represented.

This basic form is observed in quantitative studies in real life. It can be considered as an observed macroscopic property of the diffusion system. However, the equations are essentially phenomenological. They provide little insight into the diffusion process and hence offer little guidance for managing product life cycles. Both system dynamics and agent-based models offer a means of investigating the diffusion process in detail and offer an ability to explore the impact of different marketing strategies.

3.1 System dynamics approach

There are a large number of factors that influence a potential customer's decision to purchase a product. These factors could include the quality of a product/service, or consumer awareness of the product. The influence that these factors will have on the purchase decision and on the other factors will vary with time. Thus, product sales are inherently dynamic. Given these considerations, a system dynamics approach was adopted to build a model which generates product life cycles from the influence certain factors have on a prospective customer's purchasing decision [18]. For example, advertising expenditure and customers' perceived need for a service can both influence new service diffusion [14].

3.1.1 Customer choice model (cognitive model)

The decision-making procedure a customer goes through when electing to purchase a new service was broken down into a number of stages (Fig 1).

The major factors determining a customer's decision to buy are an understanding of the service, its utility and its acceptability. The service provider will have an influence

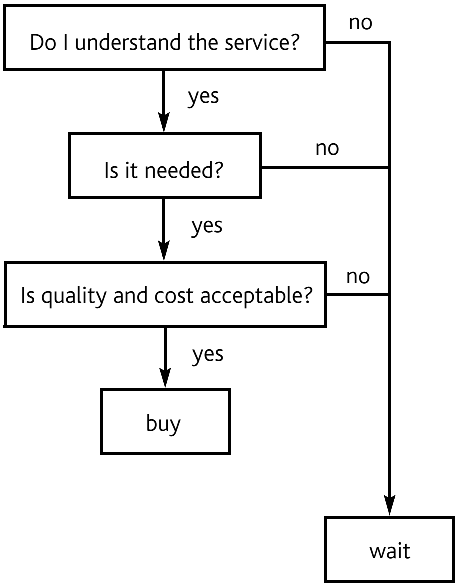

Fig 1 Model flow diagram.

over each of these factors depending on its commercial strategy, as shown schematically in Fig 2.

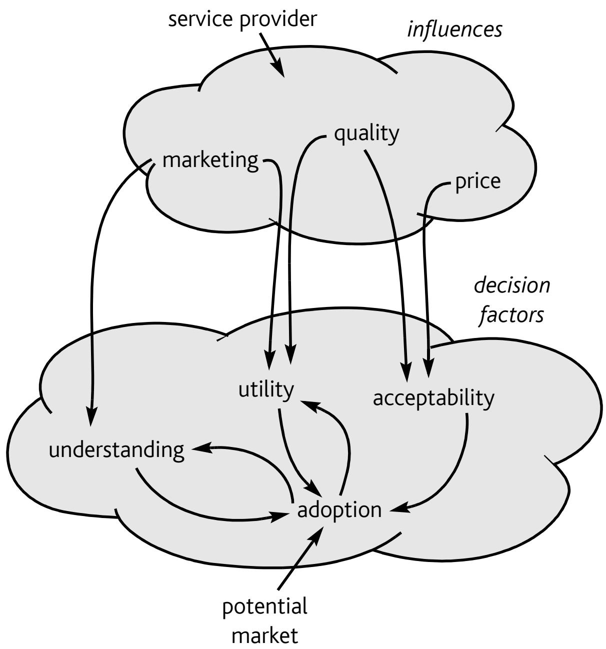

Fig 2 Overview of the customer choice model.

The model itself incorporates a number of decision-making sectors which run simultaneously — understanding, utility, acceptability, and adoption.

Decisions will be dependent on the values of the influencing factors: marketing, quality and price. Understanding is influenced by a service provider changing the amount of marketing and word of mouth from new adopters in the adoption sector. Utility, or the value of the service to the customer, is influenced by quality and marketing which are controlled by a service provider and by changes of cumulative adoption in the adoption sector. The acceptability of a service is influenced by price and quality which are assumed to be controlled by a service provider. System externalities, such as changes in price and quality of input products to the service provider, are outside the scope of this paper.

Output from each decision-making sector is a fraction which represents the probability a customer understands the service, has a need for the service or finds the service acceptable. These fractions are passed into the adoption sector where the overall probability of purchase is calculated. The probability of purchase is then applied to the potential market and annual adoption calculated.

3.1.2 Results 1 — Development of fax market (with/without postal strike)

In order to provide a basis for the modelling exercise, the historical launch of Group 3 fax machines in the UK was considered. The exercise illustrates how models can be used to test hypotheses.

Adoption of fax in the UK began in the late seventies and followed a slow but steady growth until the late eighties when there was a significant increase. This is believed to have been due to the one-off event of the 1987 UK postal strike, although there are suggestions that new consumer services often take-off when the price falls below a critical threshold.

To produce the effect of the UK postal strike, the actual utility and price acceptability were significantly increased for the duration of the event, demonstrating that the model can be used to explore the knock-on effects of events occurring in the past.

Figure 3 illustrates the actual and calculated adoption of fax from 1980. When considering the two plots in Fig 3, it can be seen that the diffusion figures derived from the model, which include the effect of the postal strike, compare extremely well to the actual historical data. By 1994 approximately 59% of the potential market had

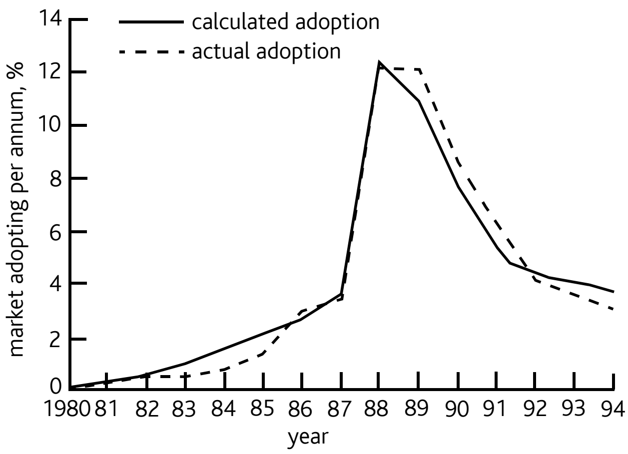

Fig 3 Graph of adoption of fax machines versus time.

actually adopted fax compared to the calculated figure of 60%. Thus, the model supports the postal strike hypothesis.

3.1.3 Results 2 — Alternative marketing/product development strategies

A second use of the model is to investigate alternative strategies. By applying a number of commercial strategies to maximise fax adoption, different life cycles were generated. Figure 4 shows three different life cycles generated by different strategies concerning investment in quality and marketing over time.

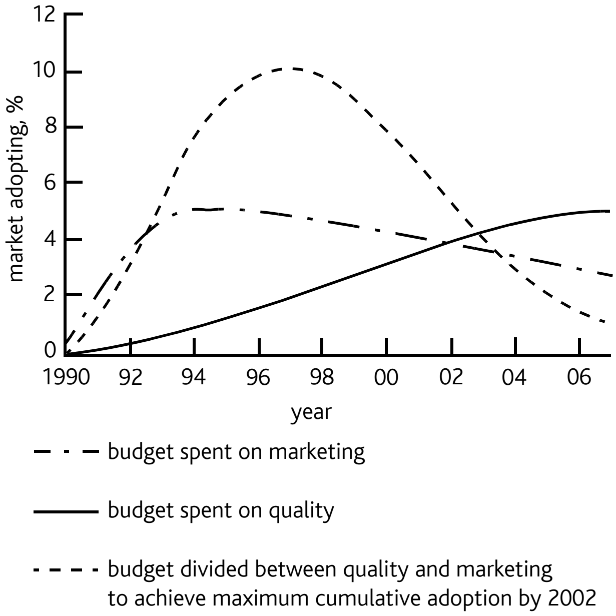

Fig 4 Graph of adoption versus time showing effect of varying marketing and quality spend.

It can be seen that investing in quality or marketing, although changing the product life cycle, does not produce maximum cumulative adoption for the case of fax. When investing the entire annual budget into marketing, the service produces a plateau life cycle. This plateau shape is the result of the market becoming aware of the service very early and a number of innovators adopting the service very quickly. After approximately 5 years, adoption levels off and remains at an approximately constant level. New purchases are made as utility increases — a result of the steady increase in the fax base.

Investing the entire annual budget into improving the quality of service produced a very slow-developing growth curve. The market is unaware of the service and therefore unaware of any increase in quality. Gradually diffusion accelerates as satisfied customers, through word of mouth, make more people aware of the service.

Adoption is greatly improved by the annual budget being invested on the factor that has the greatest influence in both present and future time periods. To achieve this a number of scenarios must be applied and an understanding gained of the influence each variable has and when this influence will have its maximum effect.

The product life cycle generated by applying a strategy to maximise adoption was symmetric and produced by the market initially being made aware of the service by the entire annual budget being spent on marketing. Subsequently, the annual budget was invested on a combination of marketing and quality according to the marketing growth requirements. After 12 years, the difference in market development for the three scenarios is significant (Table 2).

Table 2 Market development for the three scenarios.

Curve (Strategy)	Cumulative diffusion after 12 years (% of saturated market)
Budget spent on marketing	57
Budget spent on quality	27
Budget divided between quality and marketing	90

Greater cumulative adoption could have been achieved with the strategic use of price reductions, but for simplicity only two influences were used to give an indication of the type of results that could be produced.

This type of model could be used to explore a number of possible future scenarios. It is not a predictive device but can lend insight into the impact of different investment strategies.

3.2 Agent-based approach

The system dynamics approach still treats populations as if all members were identical and gives no insight into the processes by which information is transferred at the micro-level. In order to produce a more realistic model of the diffusion process, the agent-based modelling approach can be adopted [19, 20]. This technique involves creating a population of discrete entities, or 'agents', each representing an individual member of the real population of consumers in question. Each of the agents contains a set of goals, beliefs and actions and can interact with other agents or the environment in which the population exists. Agent-based modelling enables the problem to be addressed using a bottom-up approach. The goals, beliefs, actions and interactions are microscopic attributes of the system. The overall, macroscopic, behaviour appears as a result of the combined effect of all the microscopic attributes and the complex interactions between them and the accuracy of the model comes from the description of the behaviour of the individual agents.

In constructing an agent-based model (ABM) of the diffusion of an innovation within a population of consumers, we need to create a conceptual model of a consumer's cognitive behaviour and create an accurate and detailed picture of the social network within the population. The key elements of an ABM of a population of consumers are the process by which a consumer decides to adopt a product, the cognitive process, and the network of connections that exist within the population through which information about the product or service is passed, the social network.

3.2.1 Cognitive process (learning)

There are a number of theories from the social sciences that shed light on to the problem of describing the cognitive process. These include theories on human need, social comparison theories, conditioning theories, decision and choice theories among others [21].

Individuals can be influenced by the information passed by other individuals and by the observed actions of other individuals. The theories describing these processes are known as bandwagon theories. Essentially these are feedback processes where an increase in the number of adopters in the population generates information which is passed back to the rest of the population and, either directly or indirectly, affects the pressure on individuals to adopt the innovation. The external process effectively acts to alter the profitability or perceived profitability of the adoption.

There are three main bandwagon processes. In any single diffusion process the bandwagon process will in general be a combination of the three with different weights and be different for each individual.

- Fad theory

  This theory describes the situation where the profitability of the innovation is ambiguous and where the information concerning the profitability does not influence the adoption decision. It is a question of who within the population has adopted that generates the pressure to adopt. The pressure can be negative or positive (following or avoiding trends) and the influencing members of the population can be highly specific or general. Examples of this phenomenon are threats of lost legitimacy, i.e. needing to demonstrate conformity or non-conformity, and competitive pressures, i.e. individuals must adopt or potentially lose out.

- Increasing returns

  Increasing returns theories of bandwagons [22] describe the situation where the profitability of an innovation is not ambiguous and as the number of adopters increases, the profitability of an adoption increases, e.g. as more people bought fax machines, the profitability of buying one increased as they became a more useful device since the user could communicate with a larger number of people. This is an example of what is known as a positive 'network externality'. There can also be examples of negative externalities where the returns decline. Increasing returns are not usually influenced by the nature of the social networks since the profitability of the innovation, and any increase in it, is obvious from the innovation itself and information passed by the members of an individual's social network are not relevant.

- Learning theories

  Learning theories of bandwagons refer to the situation where there is incomplete information concerning an innovation. The profitability of the innovation is considered ambiguous. Before adoption, the individuals need to acquire more information about the innovation from other individuals in the social network. The profitability is then revised up or down depending upon the information received concerning the innovation.

In the ABM implementation described in this work, we have taken a learning theory described by Rogers [23] and a separate mechanism to describe fad or trend following.

Rogers' theory was developed independently of the needs of a computer-based simulation, however its structure lends itself well to implementation in an ABM. The model describes a multi-stage process which can be represented by the flow chart in Fig 5. In the simulation, each individual follows its own instance of this process. It has its own, in general unique, values for the parameters within the flow chart. Comparison with Figs 1 and 2 indicates that Rogers' model is focusing on the understanding element of the cognitive model used in the systems dynamics work described above.

The four stages have been interpreted as described below.

- Knowledge

  This is considered to be how an individual acquires information about the function of the product which is then used by the individual to assess how well it satisfies their needs from a rational point of view. Knowledge is acquired from the members of the social network and from advertising.

- Decision

  The individual makes the choice of adopting or not which depends on whether the individual has acquired enough knowledge about the product and has a sufficiently high attitude towards it.

- Implementation

  This is the explicit process of adopting the product.

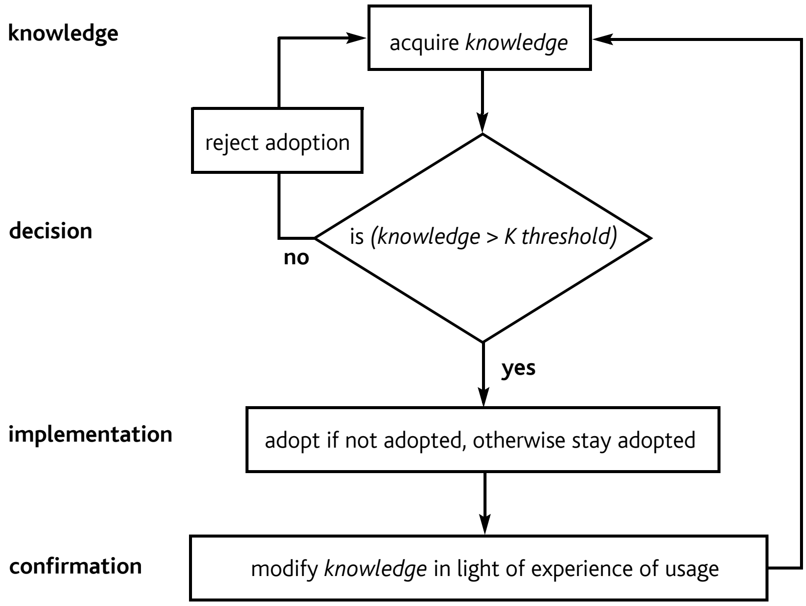

Fig 5 Flow chart of implementation of multi-stage adoption process. The stages are represented in bold and the variables are italicised.

- Confirmation

  This is the process by which the values of knowledge and attitude are adjusted in the light of the experience that the individual has after using the product.

Each individual follows this flow chart at each arbitrary time step. Knowledge is passed to and fro between individuals within the social network of each individual and can also be injected directly by means of advertising.

In an ABM, the fad process of adoption can be implemented as follows. At each arbitrary time step, the individual goes through its social network and looks to see how many of the population, with whom the individual is in contact, have adopted. If the proportion of the acquaintances that have adopted exceeds a threshold value that is a characteristic of that individual, then that individual itself adopts. This is the process used by Watts [24].

3.2.2 Social networks

The form of the social network is crucial to drive the adoption process. An accurate description is therefore very important. Although survey data provides a guide to the structure of the network, it is, however, necessary to use theoretical constructs since the survey data, if not incomplete, will be imprecise to a certain degree. Recent theoretical work on networks [25] has produced many interesting results relating to the understanding of the nature of the structures that exist in social systems and their theoretical properties. These results can be used to construct appropriate theoretical networks, and the knowledge of their properties acts as a guide to the important characteristics, such as when cascading adoptions occur and the extent of the cascades.

The social network refers to the linkages that exist between individuals, along which information passes. Networks have been modelled, abstractly, using graphs — a collection of nodes with links connecting them. These have, in the past, been either completely ordered or completely random. The ordered graph has nodes with the same number of links between neighbours and the random arrangement has links between nodes connected to other nodes within the entire population at random. Most networks that exist in the real world appear to be somewhere between these two extremes. From empirical work by Milgram [26], the mean acquaintance distance between any two people in the USA was determined to be around six. Recent work by Watts and Strogatz [27] has considered ordered networks with additional randomness introduced. These new structures are known as 'small world' networks with reference to the phenomenon described above (see Fig 6). Two important parameters associated with these networks are the length of the shortest path connecting two individuals (the characteristic path length), and the average probability that two nodes with a mutual acquaintance will be connected (the

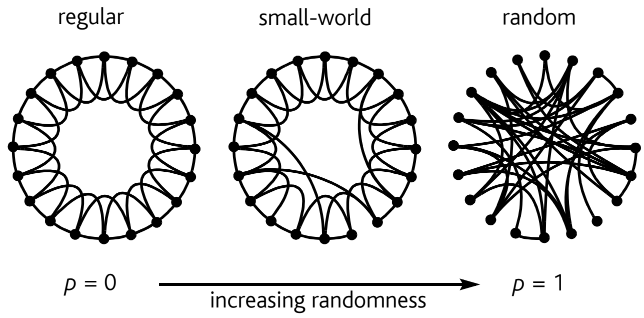

Fig 6 Showing a one-dimensional network and the transition between an ordered system and a random one, after Watts and Strogatz [27].

clustering coefficient). Starting with an ordered lattice and introducing random short cuts, the path length, falls while the clustering coefficient remains high. We observe clustering and short global separation between nodes, i.e. a small world character with local groupings.

It appears that the small world model is an appropriate abstract network to use in modelling a social network. It allows us to characterise real data from surveys, using the length scale and cluster coefficient, or to permit us to construct linkages in a realistic way when exact data for a population is absent. For a simulated set of links, we still have to have a realistic idea as to what kind of distribution of connectivities we expect for a network of consumers.

Amaral et al [28] considered empirical data for a network of movie actors (where the network was derived from the collaborations in particular films) and also for acquaintances of 43 Utah Mormons and 417 high school students, indicating best friends — both first two friends and first three friends. For the actor networks, connectivities were described by a power law for collaborations between 30 and 300 and truncated for higher values. In contrast, most friendship and acquaintance distributions in normal populations appeared to be distributed in a Gaussian fashion.

3.2.3 Experiments

The cognitive process and the social network described above were used to create a simulated population of consumers. A series of experiments were carried out with the intention of identifying and isolating the most important parameters involved in the diffusion process — which parameters most affect the speed and extent of diffusion and in what way? In modelling a system as complex as a social system, the level of sophistication can be increased, almost without limit; however, the parameters and processes included were purposefully chosen to give a realistic yet manageable system to identify and interpret the key factors involved in the diffusion process.

The computer simulation was designed to allow full control of all the parameters chosen. These include parameters that a marketer may or may not have control over in real life but the parameters were included to understand the limitations marketing strategies may face. The simulations were composed of 5000 agents or customers. The social linkages were created using a small world algorithm, with parameters giving a Gaussian distribution of connectivities for the individuals. The key parameters were:

- *phi* — probability of the random links in the population,
- *knowledge seed* — determines extent to which population was seeded with knowledge in a random fashion, simulating the effect of advertising or prejudice,
- *know SF* — the parameter knowledge scale factor, whereby weights are given randomly to the significance attached to information passed between individuals within the population,
- *know SF sd* — variable standard deviation of above,
- *know th* — the thresholds for knowledge and attitude, that need to be exceeded before adoption can occur, can be seeded randomly, simulating the profile anticipated in a population, ranging from early adopters to laggards,
- *know th sd* — variable standard deviation of above,
- *p seed* — determines random seeding of the population with actual adoptions, as this is required for pure fad processes but is optional for processes that include learning (the learning and fad processes can be turned on or off for each experiment).

Details of the experiments have been published elsewhere [20]. Although all simulations showed the characteristic ‘S-shape’ diffusion curve, both the delay in diffusion and the time over which diffusion occurred were sensitive to key parameters. Here we present a synopsis of the result which summarise the trends of the effects on the speed of the diffusion process in the cases in the exchange of knowledge processes shown above.

- *phi*

  An increase has little effect on the duration of the diffusion process. However, the process occurs earlier after initiation.

- Knowledge scale factor (*know SF*)

  An increase decreases the duration of the diffusion process and also makes it occur earlier after initiation.

- Knowledge scale factor standard deviation (*know SF sd*)

  An increase leads to a decrease in duration of the diffusion process but the process occurs later after initiation.

- Knowledge threshold (*know th*)

  An increase leads to a small decrease in the duration of the diffusion process but significantly delays the process after initiation.

- Knowledge threshold standard deviation (*know th sd*)

  An increase leads to an increased duration but the process occurs earlier after initiation.

These trends are shown in Table 3.

Table 3 A summary of the effects, as the stated parameters are increased, on 'duration' and 'delay' to the start of the diffusion process (up and down arrows indicate increase and decrease respectively).

	duration	delay
phi	—	↓
know SF	↓	↓
know SF sd	↓	↑
know th	↓	↑
know th sd	↑	↓

When considering the fad process defined in this work, the parameter that has the greatest influence on the extent of the diffusion process is the knowledge threshold that needs to be exceeded in order for adoption to occur. The degree of linkage appears not to have a strong effect. Below a certain level of fad threshold, the average penetration suddenly increases from around 30% to around 100%. This behaviour is highly reminiscent of rapid changes in state of physical systems. Empirical simulations are currently the only means to determine this transition in systems with the topology chosen to represent the social system. The agent-based technique is therefore vital to investigate this phenomenon for the development of marketing strategy. The challenge for marketing strategists is to determine this threshold and to try to reduce it to the critical level. The results of this sort of simulation could be applied to products that have a high fashion appeal or products that have increasing functionality the larger the number of people an individual interacts with who have adopted. The technique presented here permits the anticipated success of such a product to be determined.

4. Strategic options

The models above are looking at the growth of new markets and have neglected the presence of competition. However, companies now operate in an increasingly competitive environment and it is not possible to ignore the impact of other players on the success or otherwise of a chosen strategy.

In principle, game theory provides a means for optimising strategies in a complex environment. However, in practice, many analyses are based on simple idealised two-player forms (such as the prisoner's dilemma) which ignore two key features of real situations: lack of knowledge of pay-offs for different strategies and the fact that when there are many players the number of options becomes so large that optimisation is no longer a feasible approach [29]. In fact, '... the theory of games demonstrated how intractable a task it is to prescribe optimally rational action in a multiperson situation where interests are opposed' [30].

Here we use two approaches:

- a strategic simulator (based on a system dynamics model),
- evolutionary game theory (an extension of classical game theory that applies when games may be endlessly repeated and have no obvious end-point).

A feature of both models is that they are built around a specific strategic situation and do not assume some sort of generic problem space: '... there is no over-arching theory of complexity that allows us to ignore the contingent aspects of complex systems. If something really is complex, it cannot be adequately described by means of a simple theory. Engaging with complexity entails engaging with specific complex systems' [31].

The two models look at similar issues relating to market entry and competitive strategy. However, the specific details are slightly different and outlined below. The interest in the comparison is the different type of information which can be gained by the alternative approaches.

4.1 Strategic simulator — BT business game

4.1.1 Overview of model — description of strategic issue

The BT telecomunications business game [32, 33] is based on a competitive market model of the telecommunications industry in a fictitious country. The current version of the game has four players — three operators and an industry regulator. The operators offer telephony products to a market of business and residential customers and the players make decisions on tariffs, workforce levels, marketing effort and network infrastructure investments. In addition, the game includes a wholesale market including indirect access and interconnect agreements as well as opportunities for operators to lease plant from each other. The regulator has powers to control the tariffs set by the operators as well as a range of powers within the wholesale area. Typically, the model is set up so that the three operators represent an incumbent, a second operator and a new entrant.

The configuration of the game is illustrated in Fig 7. The central 'referee' computer plays host to a system dynamics model, implemented using Powersim, which models the retail and wholesale markets. This is linked dynamically to a Microsoft Excel workbook which enforces the regulatory constraints on operator decisions and manages the communications with game players, receiving

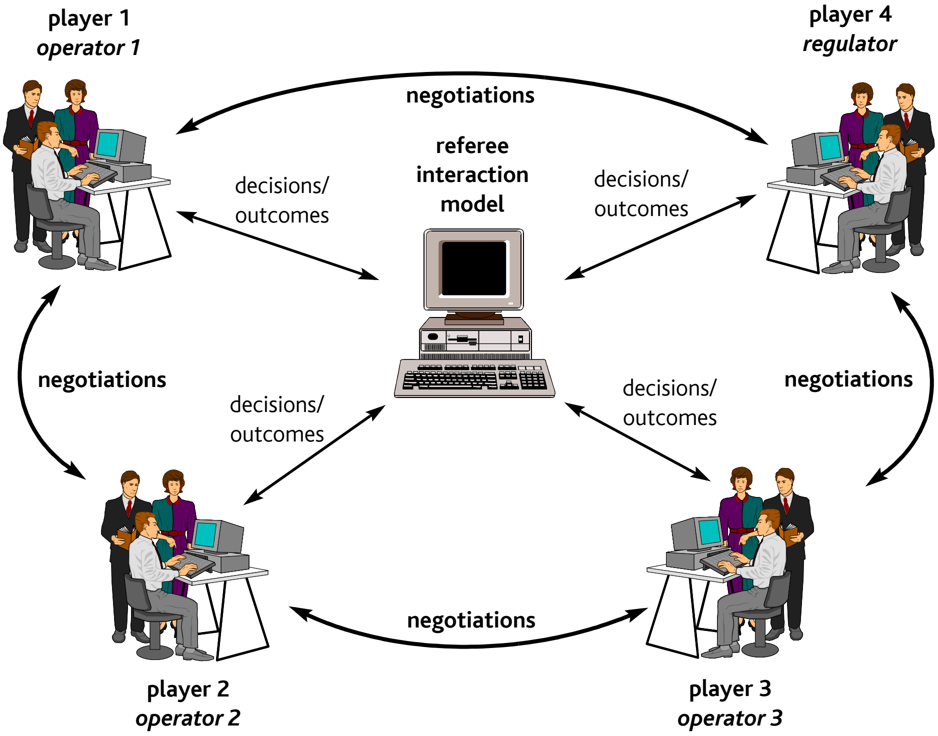

Fig 7 Game configuration.

decisions and transmitting results. Each of the players use a front-end implemented in Microsoft Excel residing on computers networked to the central computer. The players interact through the decisions they make and the results they receive from the game model. However, we encourage negotiations between the players during the course of the game; this interaction is as important as, if not more than, those mediated by the computerised aspects of the game.

The game is aimed primarily at industry experts who are able to cope with not only a large decision space (approximately 30 decisions per round are required) but also a significant amount of complexity, which is needed for the game to be seen as a sufficiently realistic model of a real industry and to enable them to explore the issues with which they are concerned.

The decision was made not to try to model any specific country, since, if we did, minor inaccuracies might distract from the real issues and it would make the game less versatile.

One of the main objectives was to make a game for strategic exploration. This was successful — participants indicated that the game did make them discover and experiment with strategies they had not considered before.

4.1.2 Knowledge — what do we learn?

A number of points relating to knowledge emerge from this model:

- the model itself is an embodiment of knowledge, derived in this case from experts consulted during its development[3],
- the 'knowledge' emerging from use of the model is many valued and no single 'optimum' strategy emerged from playing the game, or could emerge, since any successful strategy will reflect the strategy of the other players — this is one source of our inability to predict the future,
- the number of possible outcomes is huge since 30 decisions per round are made — even if these were just binary decisions, there are ~1 billion different decision sets possible, with the game being played, typically, for 6-8 rounds; any knowledge of strategies and outcomes is necessarily incomplete.

In the BT business game, the core model is systemic, but deterministic. There is no learning or cognitive model built into the simulation, as these capabilities belong to the players. The complexity arises because the human players are capable of developing a rich set of strategies and changing these in the light of events. Over a period of time (repeated workshops), some general rules of behaviour were identified, i.e. some general guidance of what can be successful strategies and under what circumstances.

However, as discussed above, only a fraction of the possibility space can be explored. In principle, the game

[3] Strictly speaking it reflects the beliefs of those individuals. Whether, and in what way, those beliefs are 'true' is another issue, and reflects the problems of 'validating' strategic simulations.

could be built as an agent-based model. The agents can then be given a set of rules for decision-making and the model run many times to see whether there are typical outcomes (this is a similar approach to Allen [34] in his fishing model). There is a trade-off here — the agent-based model can explore much more of the possibility space, but with only a limited set of strategies; the workshop-based game offers much richer strategies, but only a limited exploration of the possibility space. In both cases, the knowledge produced is likely to be a set of guidelines or decision-rules. The complexity of the system modelled ensures that knowledge of a single 'optimum' strategy is impossible. Furthermore, there are likely to be trade-offs. In a world where competitor and customer responses are uncertain, it may be better to find a 'robust' strategy, giving reasonable returns for a number of different possible futures, rather than optimising for one assumed future. For a more detailed coverage of the business game, see Jensen [32, 33].

4.2 Evolutionary game theory

Any agent-based approach must have a method for choosing between strategies. Evolutionary game theory provides one such approach. 'Classical' game theory is largely based on the assumption that the players are rational agents maximising in a complete and perfect information environment. Due to the linear nature of such models, the equilibrium solution has frequently been a matter of simple calculus. However, the unrealistic and restrictive assumption of rational agents in a complete and perfect information environment limits the use of 'classical' game theory in many real-life situations where players are boundedly rational and many real-life phenomena such as seemingly irrational behaviours cannot be explained using 'classical' game theory. Evolutionary game theory came as an alternative, assuming that the system is in perpetual evolution where players are adaptive learning agents who are liable to make mistakes (behaving in seemingly irrational ways) due to the lack of complete information about the environment.

The work described here is concerned with how rational players update their beliefs about their opponents and how they use these beliefs to aid strategy choice. This is in contrast with the traditional evolutionary approach, which analyses the evolution of sophisticated behaviour through trial and error (or natural selection) in a population of players. It follows that a major aim was to investigate the different learning mechanisms that may be used in evolutionary game theory (EGT) and consider their relative importance when constructing economic models.

4.2.1 Description of strategic issue

Although there have been many strong results published in various areas of EGT, the common theme is that instructive analysis must be context specific. This means that care should be taken when results are applied to a business situation. With this in mind, a particular scenario was chosen in which to conduct the investigation.

As with the BT business game, the evolutionary game has four players — a regulator, a market leader firm, a market follower firm and a potential entrant. In contrast to the business game, where players were free to choose and change their own strategic objectives, in the EGT model, strategic objectives are assumed for the players (see the Appendix).

Players also had a limited set of strategies (see Table 4). These strategic options were also open to players of the BT business game, with the exception of 'aggregator'.

Table 4 Strategic options for players — see the Appendix for interpretation.

Market leader	Aggressive, expand, consolidate.
Market follower	Aggressive, expand, consolidate.
Potential entrant	Don't enter, rent, build, and aggregate.
Regulator	Punish, don't punish.

The aggregator buys call minutes to certain destinations in bulk from the network operator who is offering the cheapest wholesale price to such destinations and then sells the call minutes to the customer at prices cheaper than the retail prices offered by network operators. The aggregator is thus able to earn profits by exploiting the difference between wholesale and retail prices.

4.2.2 Static and dynamic games

Each of the dynamic models were formulated from the same static (one-shot) game which is represented in normal form in which the pay-off function for the various combinations of player strategies is represented by a pay-off matrix, whose dimension is equal to the number of players. Thus, the pay-off matrix represents the cognitive decision model of the agents. As there are four players in the scenario, cross sections of the matrix could be displayed by fixing two of the player's strategies. For example, when the potential entrant chooses to enter and the regulator chooses to punish, the pay-offs can be displayed as:

ML's strategies

$$
\begin{array}{ll|c}
 & & \quad A \qquad\qquad\qquad\quad E \qquad\qquad\qquad\quad C \\
\hline
\text{MF's Strategies} & \begin{array}{c} A \\ E \\ C \end{array} & \begin{pmatrix} (a_{11}, b_{11}, c_{11}, d_{11}) & (a_{12}, b_{12}, c_{12}, d_{12}) & (a_{13}, b_{13}, c_{13}, d_{13}) \\ (a_{21}, b_{21}, c_{21}, d_{21}) & (a_{22}, b_{22}, c_{22}, d_{22}) & (a_{23}, b_{23}, c_{23}, d_{23}) \\ (a_{31}, b_{31}, c_{31}, d_{31}) & (a_{32}, b_{32}, c_{32}, d_{32}) & (a_{33}, b_{33}, c_{33}, d_{33}) \end{pmatrix}
\end{array}
$$

Each entry is a four-dimensional vector displaying the pay-offs to each of the players.

The game becomes dynamic after the introduction of time and by considering players as agents with the ability to 'learn' but the dynamics of the game are dependent on the values in the pay-off matrix and any particular scenario is represented by a particular choice of pay-off matrix.

4.2.3 Learning models

The learning mechanisms all take the same basic form. At various points in time the players go through the cycle shown in Fig 8.

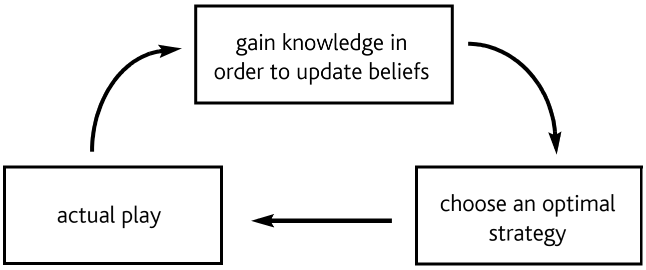

Fig 8 Basic learning mechanism.

Three basic models of the learning mechanisms were developed:

- repeated games with pure strategies and best responses,
- best response models with discrete time and mixed strategies,
- models based on the replicator dynamics.

Repeated games

Repeated games are simply finite repetition of the static game. Each player is assumed to have full knowledge of its own pay-off function, to calculate their best response given their beliefs about other players' strategies and to start the game with prior beliefs. Each round consists of the players simultaneously playing their best responses. Variants to this approach included:

- memory — updating beliefs using the last *n* rounds,
- sampling — updating beliefs using a sample of the last *n* rounds,
- mutation — players randomly change beliefs, equivalent to gaining false beliefs,
- updating beliefs at random intervals.

Best response games

In these models, time is represented as a discrete variable. At regular intervals the players simultaneously play a mixed strategy (representing probabilities of their playing each of the pure strategies) depending on their current state and calculated best response, given their beliefs. Each player updates their beliefs by naively assuming the other players will stay playing the same mixed strategy. Again, variants to this approach are possible:

- Poisson updating — each player only updates beliefs at particular points in time,
- mutation.

Replicator models

These are similar to best response games — at regular intervals the players simultaneously play a mixed strategy depending on their current state and their expected pay-off from each of their pure strategies (given their beliefs). However, in these models, players evolve strategies according to a fitness criterion, rather than simply playing the best response. Variants are similar to best response.

4.2.4 Results

The behaviour of the various games has been studied in some detail. Perhaps the most important conclusion of this work is that, in general, the system does not reach equilibrium. Figures 9 and 10 show results for a repeated game.

An equilibrium is reached for the repeated game when agents have longer memories (last 5 rounds) (Fig 10).

Cyclical behaviour is also observed with repeated games and replicator models (Fig 11), but in the case of replicator models the changes occur over long time periods reflecting the more gradual evolution of strategy in these models.

Comparison of Figs 10 and 11 show that choice of learning model can have a radical effect on players' fortunes — in Fig 10 (best response), the equilibrium strategy for the potential entrant is 'don't enter'. In contrast, in Fig 11, the potential entrant's strategy evolves to a mixture of 'rent' and 'aggregate'.

5. Looking to the future

Complexity science is often presented as a way of 'improving' policy making. In much of the discussion on complexity and strategy or policy making, it is assumed that it is possible to make 'better decisions' using rational processes. Indeed, this is often a key justification in research applications. The promise of both complex systems theory and simulation is that of 'better control' — better control of organisations, better control of economies, better control of markets and better control of societies[4]. Thus, James W Herriot (VP, BiosGroup) is recently quoted as stating: 'Complexity science is the structural engineering of organisations'. These are big claims, and it is important to understand the capabilities and limitations of both 'complexity science' and the simulation techniques used to study complexity.

[4] Such objectives clearly have ethical implications, but there is not space to discuss these in this paper. Fortunately, one of the messages of complexity is that there are limits to the extent to which complex systems can, in practice, be controlled.

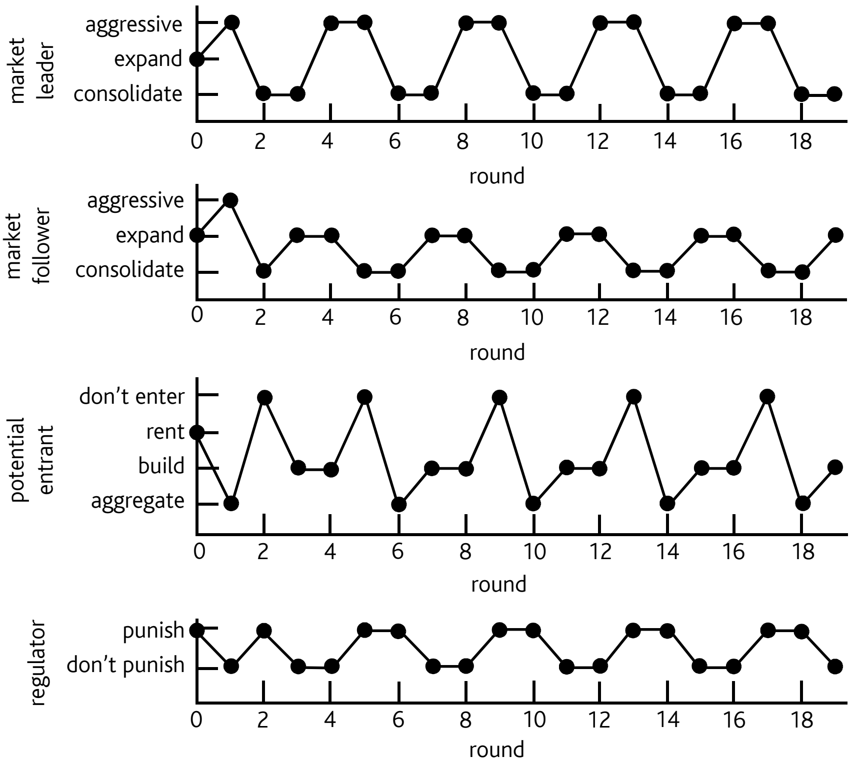

Fig 9 Showing periodicity of strategies when only previous round remembered.

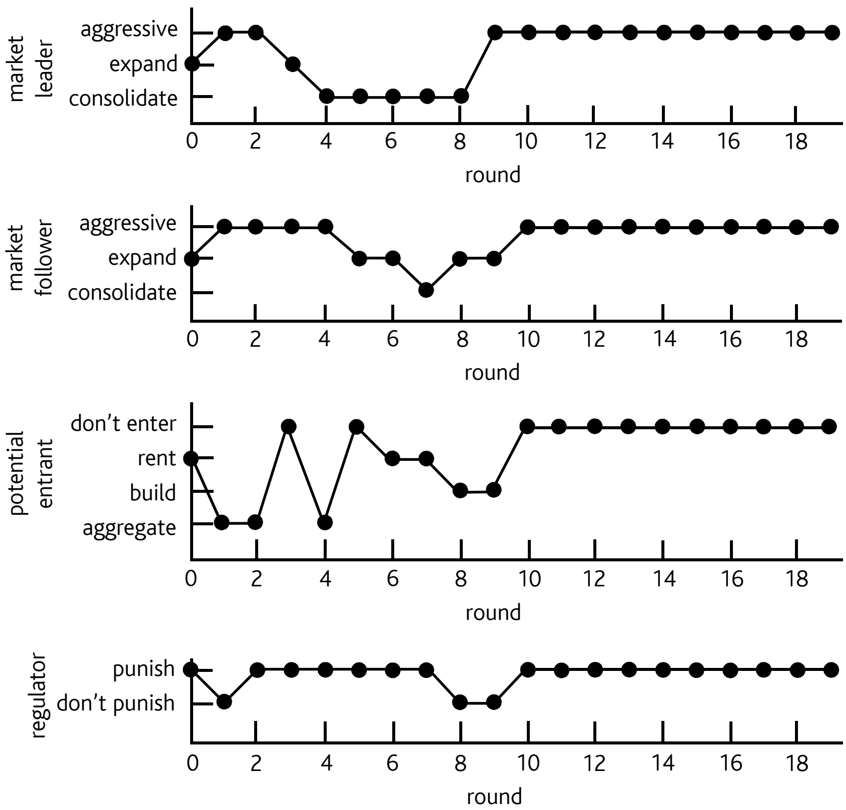

Fig 10 Equilibrium outcome reached when memory increased to last 5 rounds.

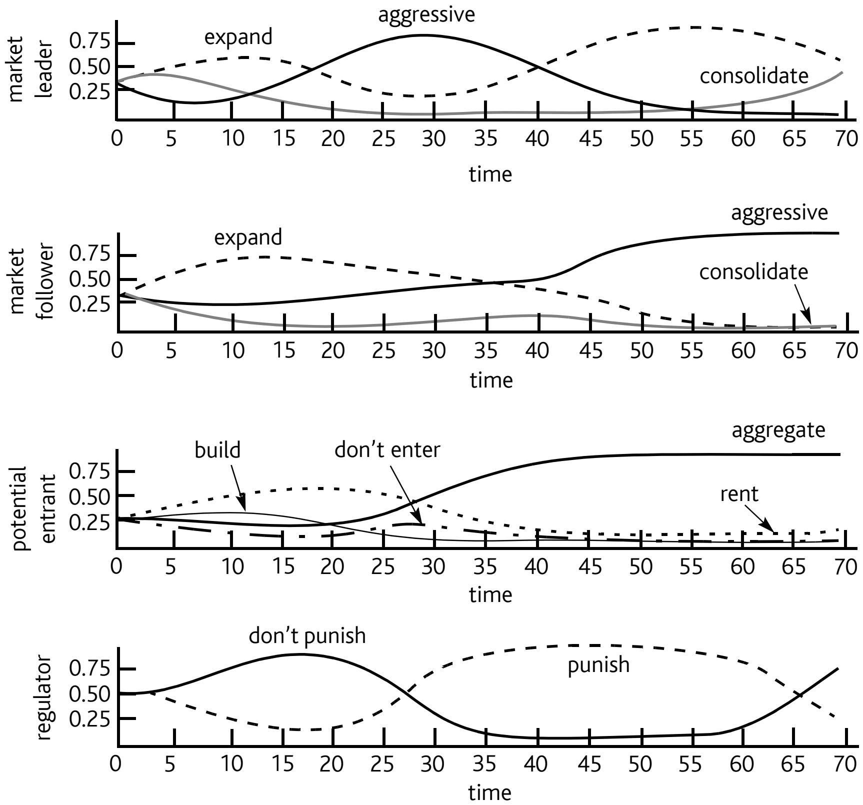

Fig 11 Evolution of strategies using replicator model.

This paper has discussed the role of modelling in strategic decision making, and the types of information obtained from different modelling techniques. Decision making is best seen as a process, of which modelling forms a part. Models allow users to investigate alternative strategies and understand implications of specific courses of action. A key role therefore is 'hypothesis testing'.

However, a specific model provides just one view of the entire problem, and different models reveal different issues. Thus, in looking at product diffusion, a system dynamics model enabled us to develop a top-down view of key issues, and to investigate alternative growth strategies based on advertising and quality improvement. However, the system dynamics approach gave little insight into the way information actually spread within a population. For this, an agent-based model was required. Similarly, in looking at decision-making in a competitive environment, a computer-based game gives a rich experience of the problem and can reveal some complex strategies, but it is not possible to explore all possible options. Evolutionary game theory uses a much simpler set of strategies, but revealed the complex way these can interact together to give a constantly changing market-place.

If simulations are to live up to the claims made for them much work needs to be done. The discussion above shows clearly the importance of identifying appropriate cognitive and learning models. We saw in the discussion of evolutionary game theory how the choice of learning model could radically alter the preferred strategies of some players.

The issue of competing models needs to be considered more carefully. Some work (for example, Arthur [35]) has shown how a near optimal solution is obtained by the interplay of different (evolving) decision-making models within a population. In this context, no single model can be considered right or wrong; the outcome is an emergent property.

Finally, the decision-making process in organisations should be looked at more carefully. For simplicity, we usually assume managers have just one problem to look at, and the decision-making process is one of seeking options (alternative solutions) and by some cognitive process choosing the 'best' solution. This is a rational choice model. However, in messy reality, managers are faced with a constant stream of problems and alternative courses of action. We can no longer think of a 'problem' in isolation, but have to consider the many competing demands for managers' attention [36].

All three issues (cognitive models, the interaction between competing models and the competition between problems for managers' time) undermine a simplistic view of a simulation providing an answer to a problem. Simulation models, of the type developed to study complex systems, have the potential to greatly improve both the design of organisations and the basis on which decisions within those organisations are made. However, in the field of social systems there is still much work to be done, not only in constructing realistic models, but in understanding how such models can be used effectively in a decision-making process.

Appendix

Strategic objectives of players

Market Leader

- Uphold strong position by maintaining or increasing market share
- Market growth
- Deter potential entrants
- Prevent the market follower from expanding
- Avoid punishment from the regulator

Market Follower

(Possibly interpreted as the aggregate behaviour of smaller firms)

- Increase market share, preferably at the expense of the market leader
- Market growth
- Deter potential entrant unless co-operation can be established

Potential Entrant

- Enter the market in a profitable manner

Regulator

- Market growth
- Increase competition
- (Rather optimistically) to decrease its own role in the future

Interpretation of strategies

Aggressive	A combination of marketing tactics and more forceful methods of keeping potential entrants out of the market.
Expand	Building and investing in the future, possibly by leasing out services to competitors.
Consolidate	Consolidating the current market position.
Don't enter	Defer entry to a later date.
Rent	Using existing services to gain a foothold.
Build	Develop own networks and services.
Aggregate	Exploit the price difference between consumers and suppliers.
Punish	Employ methods such as limiting price bands, using fines.
Don't Punish	Leave the market to regulate itself.

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