Chapter 11
Social Interactions in Post-design Phases in Product Development and Consumption: Computational Social Science Modeling

Russell Thomas and John Gero

Abstract This chapter presents a system to model social interactions between producers and consumers in the post-design phase. Producers form their expectations about consumer behavior during the pre-design and design phases. Consumers' behaviors are a result of their interactions with designs based on their experiences that form their value systems as well as their social interactions with other consumers. Because the post-design phase includes consumer behavior, producers reevaluate their plans and strategies for future designs. A subset of the system is implemented to model social interactions where the producers and consumers are modeled as computational agents. The agents' values that are used to guide their decision-making are modified through the agents' interactions with products and other agents. One of the goals of this work is to demonstrate the viability of agent-based modeling to study innovation ecosystems and their social aspects. Through computational experiments, we are able to test hypotheses regarding the mutual influence of producer and consumer values on the trajectory of design improvements. Exemplary results are presented.

Keywords Producers • Consumers • Social interaction • Agent-based modeling • Situated cognition • Producer–consumer interaction

R. Thomas (✉)
Krasnow Institute for Advanced Study, George Mason University,
4400 University Drive, MS 6B2, Fairfax, VA 22030, USA
e-mail: russell.thomas@meritology.com

J. Gero
Krasnow Institute for Advanced Study, George Mason University,
4400 University Drive, MS 6B2, Fairfax, VA 22030, USA

University of North Carolina at Charlotte, 9201 University City Blvd,
Charlotte, NC 28223, USA
e-mail: john@johngero.com

T. Taura (ed.), *Principia Designae – Pre-Design, Design, and Post-Design*,
DOI 10.1007/978-4-431-54403-6_11

11.1 Introduction

In the eyes of a producer or designer, consumers often react to a new product introduction in surprising and unexpected ways. These unexpected reactions in the post-design phase are both a source of risk—products may fail in the marketplace—and a source of innovation as new uses or new utility are discovered, which in turn create opportunities for new directions in product design. Both producers and consumers form their expectations during the pre-design and design phases, including their experience with previous designs. But their behaviors and interactions in the post-design phase are not simply a matter of having those expectations met or not. In other words, design does not sit only between product requirements and product generation in the pre-design and design phases. Design also spans the post-design phase where there is often a complex interplay between *cognition*, *value systems*, and *social interactions* that reshape the design landscape and, cause producers to reevaluate their plans and strategies for future designs. This can be illustrated as follows.

Over the course of several product design generations, a producer will probably develop design competency in some areas (e.g. high volume production, narrow tolerances, ergonomic design) and not in others (e.g. reliability in extreme environments, high performance, small runs of custom configurations). Reinforced by success in the market, this producer will tend to value future designs that utilize the producer's competencies and exclude the design characteristics where the producer has little or no competency. Essentially, these design preferences are the producer's value system, which is also reflected in the producer's preferred stream of new product designs. We can view a stream of new product designs as a trajectory within the space of possible designs or within the space of possible performance/cost ratios. From their viewpoint, the Producer prefers new product designs that are similar to those where the Producer has the most experience and expertise, where it has relatively good profitability, and also where the Producer expects Consumer demand to be high or at least adequate. If consumers behave as the producer expects based on pre-design and design work, then the producer's strategic choice becomes one of choosing the optimal design trajectory and then executing it effectively.

But if consumers do not always react as expected or if they engage creatively with new and existing products in the post-design phase, then producers must reevaluate their strategic choices. This might mean abandoning existing competencies and preferred design strategies in favor of new and untried paths. (This is a form of Schumpeter's "creative destruction" Schumpeter 1942.) It might also mean that the producer might benefit from serendipitous events—e.g. product characteristics that were previously not valued by consumers suddenly come into favor, allowing a marginal producer to rise to market leadership. Producers that successfully observe and learn from consumers in the post-design phase can then adapt their strategies and plans in the subsequent pre-design and design phases, including the possibility of making fundamental changes in strategy or architecture.

Therefore the behavioral focus of our research is on how producers choose from alternative new product designs where the alternatives might differ in performance along dimensions related to consumer utility. We are especially interested in settings where the performance dimensions emerge endogenously rather than being fixed or introduced exogenously. For example, this would arise when new uses are found for a product, a use case is dramatically altered, or when new classes of users enter the market place.

To study this class of behavior and phenomena, it is necessary to observe the value systems and behaviors of both producers and consumers during the post-design phase, and preferably over several generations of product design to record changes in design trajectories. It is also useful to explore various experimental treatments to understand how alternative conditions of cognition, value systems, and social interactions affect outcomes. The phenomena of interest arise through the dynamic social interactions between agents, and between agents and artifacts, far from equilibrium. Therefore, it is important that the research method allows for the study of the endogenous processes for learning (direct and indirect), social interactions and network formation, and be capable of rich emergent phenomena. For these reasons, we have chosen to build a computational laboratory with multiple agent types, artifacts that agents produce and consume, and social interactions between agents. One of the main benefits of this research method is that many different experimental treatments can be explored and the detailed internal state of all agents is fully available for examination.

There is also a broader spectrum of interactions and forces at work in the post-design phase, including influences of government policies (e.g. intellectual property institutions), social interactions between producers (e.g. communities of practice), the value-shaping influence of third-part agents such as market analysts and 'gatekeepers', and the upstream influence of funding organizations and research institutions. Though these are beyond the scope of our current research, the architecture of our computational laboratory is extensible to include these other types of agents, artifacts, and interaction types.

One of the goals of this paper is to demonstrate the viability of Agent-based Modeling (ABM) to study innovation ecosystems and their social aspects. We have implemented a multi-agent system (Ferber 1999; Weiss 2000; Wooldridge 2008). It is designed to be a computational laboratory (Casti 1999) to support a wide variety of experimental settings and tests. Using multi-agent systems to simulate social systems is part of an emerging interdisciplinary field called Computational Social Science (Epstein 2012; Epstein and Axtell 1996; Gilbert and Conte 1995; Miller and Page 2009). Briefly, agents and their micro-level behaviors are formalized using relatively simple rules and limited/plausible capabilities for reasoning and behavior. An open environment is provided for agent interaction, often in the form of a grid or network. Through interaction with other agents and the environment, each agent alters its internal state, learns and adapts. The general research strategy is to study emergent phenomena that are not simple aggregations of the micro-behaviors (Gilbert 2002; Goldstein 1999; Holland 2000).

11.2 Theoretical Context

11.2.1 Co-evolution of Technologies and Consumer Preferences

Dosi (1982) introduced the idea of viewing technology evolution as trajectories through the space of possible designs, and movement along a trajectory as the result of "normal problem-solving" and "progressive refinement" by producers as they find ways to improve trade-offs in design variables. Saviotti (1996) presents a more formal model of technological evolution through design space, where the space is defined by dimensions for each technical and service characteristic associated with a particular technology. 'Characteristics' are formalized as a vector of variables that specify both a product's internal structure ('technical characteristics') or services performed for its users ('service characteristics') (Saviotti and Metcalfe 1984). This "twin characteristics framework" is important for understanding both the producer's values, which center on technical characteristics and associated learning, and the consumer's values, which center on the service characteristics. We apply this method for modeling the space of possible designs and to specify the position of particular product designs within that space. Gero (1990) is a further elaboration of these ideas in the field of design science, specifically via Gero's Function-Behavior-Structure (FBS) ontology for designs. 'Structure' in FBS corresponds to Saviotti's 'technical characteristics', while 'Function' corresponds to Saviotti's 'service characteristics'. 'Behavior' provides the ontological linkage between Structure and Function, and thus are often the focus of attention of product designers in pre-design and design phases. Because our simulation does not include agents actually performing design acts or making explicit design decision, we do not explicitly include Behavior in our model of product designs.

Saviotti (1996) also proposes methods of analyzing population-level dynamics in design space such as movement along trajectories and changes to the 'technological frontier'. The latter is related to the 'adjacent possible', a phrase coined by Kauffman (1996) for the set of all the designs that are directly achievable from an existing set of competences. Thus, the technological frontier is the limit of what is producible with today's costs and capabilities, while the designs in the set of the 'adjacent possible' are decision alternatives for producers who choose to expand or extend the frontier.

Dosi and Nelson (2010) provide a recent survey of the state of research on technology trajectories and evolutionary processes that give rise to them. They describe the supporting evidence as "ubiquitous", adding that "trajectory-like patterns of technological advance have been generally found so far whenever the analyst bothered to plot over time the fundamental techno-economic features of discrete artifacts or processes." (p. 16) Technology trajectories are an example of emergent phenomena (Gilbert 2002; Goldstein 1999; Holland 2000) in that they arise from the collective action of individual agents but are not simple aggregations of agent behaviors. As Dosi and Nelson (2010) describe, technology trajectories

have a downward causal influence on agents, effectively circumscribing technological advances "within a quite limited subset of the techno-economic characteristics space. We could say that the paradigmatic, cumulative nature of technological knowledge provides innovation avenues (Sahal 1985) which channel technological evolution, while major discontinuities tend to be associated with changes in paradigms."

Compared to the large literature on technological evolution and trajectories, there has been much less research on the co-evolution of technologies and consumer preferences/values. Evidence of this is given the survey of the state-of-the-art in Dosi and Nelson (2010). They discuss research on how demand and other socio-economic factors shape the direction of technological advance, but they do not cite any research that specifically focuses on endogenous co-evolution of technology and consumer preferences. However, there has been research on specific topics related to co-evolution of technology and consumer preferences/values, for example: the role of experimental users and diverse consume preferences (Malerba et al. 2007), consumer resistance to innovations (Moldovan and Goldenberg 2004), compatibility and innovation (Sosa and Gero 2007), and innovation as changes in value systems (Gero and Kannengiesser 2009).

Separate from technological evolution, there is an extensive literature on consumer preferences, opinions, and consumer behavior. Liggett (2010) evaluates alternative methods for mapping consumer preferences as a population using perceived product characteristics and their 'ideal product' which can be formalized as a vector of values for each service characteristic of the product. Liggatt also uses Multi-dimensional Scaling (MDS) to create a 2D map of a population of consumers' ideal vectors relative to the available products. There is also extensive research on how consumers influence each other's values and opinions through social interactions, e.g. Friedkin and Johnsen (1999). This literature guided our design decisions for social influence mechanisms and patterns, including topology of consumer social networks, the behavior of opinion leadership, susceptibility to social influence, and homophily as a primary factor in the determining strength of social ties and thus the degree of influence between any two consumers.

11.2.2 Situated Cognition and Innovation

Situated cognition (Clancey 1997) provides the theoretical basis for our design of agent cognition. Any cognitive system operates within its own worldview and that worldview affects its understanding of its interactions with its environment (Clancey 1997; Gero 2008). In essence, what you think the world is about affects what it is about for you.

A person or group of people is 'situated' because they have a worldview that is based on their experience (Smith and Gero 2001). Situated cognition involves three ideas: situations, constructive memory and interaction. Situations are mental constructs that structure and hence give meaning to what is observed and perceived

based on a worldview. Constructive memory makes memory a function of the situation and the past. Memory is not laid down and fixed at the time of the original sensate experience. What is remembered is constantly being recreated and reframed. Interactions between agents trigger changes in situations and memories.

Through the lens of situated cognition, innovation in a social ecosystem is an emergent phenomenon that arises from the interplay of situations, constructive memory, and social interactions at the level of agents and networks of agents. Moreover, we believe that situated cognition is at the heart of social processes of creativity and inventiveness (Gero 1996; Sawyer and Sawyer 2012). This is especially relevant to emergent aspects of innovation (Finke 1996; Gero and Damski 1997; Gero 1996; Gero and Kannengiesser 2004; Sawyer and Sawyer 2012). For these reasons, situated cognition is foundational for any study of innovation in social ecosystems (Edquist 2005; Llerena 2006).

In the current implementation of our simulation, only Consumers are designed with features to support situated cognition. In future work, we expect to add situated cognition capabilities to Producers and other agent types.

11.3 Architecture of the Simulation System

There are two types of agents in the current implementation—'Consumers' and 'Producers'—and one type of artifact—'Products'. Throughout each simulation run the population size is fixed for Consumers, Producers, and Products. The population size is under experimental control and can range from ten to hundreds or thousands, limited only by computer capacity and processing speed. To date, our experiments have been run on a MacBook Pro laptop with 2.53 GHz dual core processor and 4 GB main memory, with a population of 100–200 Consumers and a similar number of Products.

Consumers seek to consume Products by moving around a geographic Consumption Space with micro-behavior similar to foraging, but with social interactions. Consumers are not endowed with any knowledge or map of the Consumption Space, nor do they have any memory of where they have been. The Consumption Space is a bounded rectangular grid with von Neumann neighborhoods, and the size of the Consumption Space is proportional to the population size of Products and Consumers so that the spatial density remains constant. This facilitates foraging micro-behaviors and minimizes behavioral artifacts that might result from a physical landscape that was either too dense or too sparse. In each clock cycle consumers can move to any neighboring point on the grid within the boundaries. At each time step Consumers move around the landscape looking for attractive Products to consume, or to maneuver out of crowded areas. Only one Consumer can occupy a given grid location at a given time.

Consumers are social, while Producers are not. The social network among Consumers is initialized as a 'small world' network with random assignments.

Once the simulation starts, Consumers form new social relations when they meet each other or by referral through their existing social network. The initial strength of a social tie is proportional to the similarity between the two Consumers. Strengths of social ties decay with time unless they are recharged by exchanges of information. While the structure of the social network evolves endogenously, when ever a Consumer has no social ties the simulation system intervenes and creates several new social ties.

Products are initially distributed randomly in the Consumption Space, where they remain until they are consumed or they expire. If they are consumed or expire, they are replaced by the Producer(s) but not necessarily with a Product of the same type. During simulation initialization, a relatively large number Product types are generated by the system and these comprise the 'Product Design Set', i.e. the set of possible new Products that may be introduced during the course of a simulation run. A small subset of these possible Products are selected as the initial set of 'active' Products. Each new Product type is selected from the 'adjacent possible' relative to the currently 'active' Product set. Each new product introduced expands the 'adjacent possible' to include Products that were previously not feasible for Producers. If the Product Design Set is large relative to the length of a simulation run and the rate of new Product introductions, then we are able to simulate a continuous stream of innovations.

Though Producers have several cost measures associated with each type of Product, there is no price to Consumers and thus no financial transaction between Consumers and Producers. This is because our research focus is on the interaction of Consumer and Producer value systems and not on profit-maximizing decisions given limited resources.

Producers only take action when a Product is consumed or expires. When that happens they make a decision to either replace it with an identical Product type, a different Product type in the portfolio of available types, or to introduce a new Product type that had previously not been available. Producers have no direct interaction with or knowledge of individual Consumers, therefore they make their decisions based on historical data regarding the consumption and expiration Products of various types. Also, in the current implementation, Producers have no social interactions with each other, nor any knowledge that there are other Producers. In the results presented in this paper, the simulation was configured to have a single Producer.

The population of Consumers initially have identical values and other initial conditions, and are spaced randomly with uniform distribution on the Consumption Space. The adaptive elements in their cognitive architecture are primed in two ways. During initialization Consumers repeatedly sense, perceive, and evaluate all of the products in the initial 'active' set. Then the simulation is started in a 'priming mode', which is fully functional except that experimental data is not collected. Priming is complete when all or nearly all Consumers are sufficiently adapted to make consistent valuation and consumption decisions. After priming is complete, the Consumption Space is reset to it's initial conditions for Products and Consumers, including the social network.

11.4 Computational Modeling of Agents and Artifacts

11.4.1 Products

Products are constructed as a graph structure with six nodes. During the construction process, edges between the nodes are formed at random, creating a single connected graph with between 5 and 14 edges. There are 112 unique six node connected graphs, yielding a design space for agent exploration that is small enough to be tractable for enumeration and complete analysis.

Products have both surface characteristics and functional characteristics. During their search and evaluation process, Consumers can only sense and perceive a Product's surface characteristics (its 'signature'). The functional characteristics are only experienced through the process of consumption. During consumption, Consumers gain utility based on the functional characteristics, relative to expectations. Higher than expected evaluations of functional characteristics yield positive utility, while lower than expected evaluations of functional characteristics yield negative utility. The surface characteristics of Products are related to their functional characteristics, but not identical. Consumers cannot directly perceive the utility of Products.

The Product's utility is a function of its topology, while its external appearance is a function of its physical layout. Physical layout (Fig. 11.1) is constructed on a circle with a relaxation method to equalize the length of edges. Distance from the centroid of this layout produces a signature in the form of a six-element vector. Four more elements are added based on other surface characteristics of the graph, for a total of ten elements in a signature vector.

Three dimensions of Consumer utility have been defined (Fig. 11.2) in a way that might be analogous to performance dimensions in a manufactured component. The first is the number of edges, which ranges between 5 and 15, and might be analogous to a property like weight or density. The second is mean clustering coefficient, which might be analogous to a property like stiffness/flexibility. The third dimension is the maximum distance between nodes in a spring-electrical embedding. This might be analogous to maximum span distance.

The construction process for Products yields a non-obvious relationship between the surface characteristics and the functional characteristics of Products. Products that are close in surface characteristics (i.e. close in Value Space) might have different utilities. This allows for a somewhat rugged landscapes.

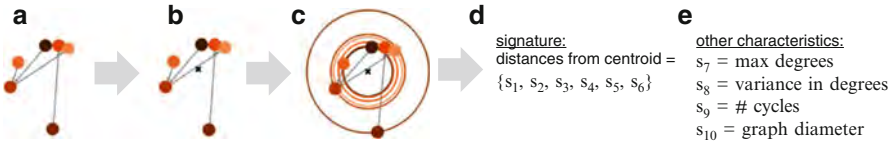
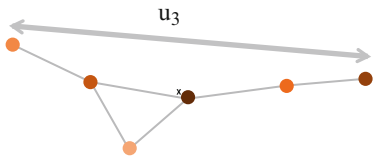


Fig. 11.1 Generation of surface characteristics for Products. (**a**) random placement of nodes on a unit circle and random generation of edges; (**b**) identification of a centroid; (**c**) and (**d**) distances of nodes from centroid determines the signature; (**e**) other physical characteristics available to Consumers through sensation and perception



u_1 = # edges
u_2 = Mean clustering coefficient
u_3 = max distance
in spring-electrical embedding

Fig. 11.2 Maximum spanning distance is the third of the three dimensions of utility, measured on the same Product as shown in Fig. 11.1. The normalized utility vector of this product is (0.1, 0.39, 0.46)

In addition to these two views that are relevant to Consumers, we also characterize Products in ways that are particularly relevant to Producers. This is an important feature to our design because of the need to model plural interests, perceptions, and value systems between Producers and Consumers. We have adapted the idea of 'production recipe' from (Auerswald et al. 2000), where it was used in an agent-based model of learning-by-doing on the shop floor. A production recipe is a vector of characteristics that related to the production or assembly process, and therefore to the costs and complexity of manufacturing and the challenges of learning through experience. We have defined the following eight-element vector for specifying recipes:

r_1 = Number of degree-1 nodes
r_2 = Number of degree-2 nodes
r_3 = Number of degree-3 nodes
r_4 = Number of degree-4 nodes
r_5 = Number of degree-5 nodes
r_6 = Log of number of cycles = $ln(c)$, rounded to nearest 0.5
r_7 = Length of longest chain
r_8 = Number of chains of degree-1 or degree-2 nodes

These are each normalized to a range of values between 0 and 6. There are 91 unique recipes for the 112 unique Products. The Hamming distance between any two recipes is a measure of accessibility from one to the other through learning-by-doing and also explicit design explorations.

The cost to manufacture a given design has two components. The first is material, which is a simple function of the number of edges. The second is assembly cost, which is a function of the recipe and the Producer's cumulative experience in each of the dimensions of the recipe. With zero experience, the cost function rises as the square of each recipe element value, summed across the recipe. Thus, initially most of the designs are too expensive to manufacture, rendering them infeasible. With experience the exponent of the cost function is reduced until it plateaus to yield a linear function of each recipe element value.

An important feature of the production recipe approach is that Producers can gain experience in one set of Products that lowers its costs for other Products in the 'adjacent possible' region of design space. However, because the Producer does not have full knowledge of the design space, the trajectory of design choices emerges through a series of local/limited decisions, adaptations, and also constraints of attention. It is not governed by foresight or planning.

11.4.2 Consumers

Consumers search the landscape for attractive Products to consume, and they form social networks in the process. Consumers modify their values through direct product interaction (evaluating and consuming Products) and through social interactions. Consumption decisions and subsequent learning are mediated by two independent variables—'value' and 'utility'. 'Value' is the Consumer's appraisal of a Product based on its surface characteristics, relative to that Consumer's ideal. Thus, valuation is performed prior to any consumption decision. Consumers choose to consume based on their perception of product signature, perception of proximity to their ideal type, and a rough expectation of utility. Generally, Consumers choose to consume when the Product they encounter is close to their ideal type. The space of possible Product signatures is called the Value Space. The value system for each Consumer centers on a single vector that represents the signature of its ideal product type. Consumers learn and adapt by adjusting this vector through experience and social interaction. Therefore, each Consumer's value vector can be represented as a point in Value Space, and their changing values as paths through Value Space.

In contrast, 'utility' is the benefit that the Consumer receives after consuming the Product. It can only influence future consumption decisions through agent learning and, indirectly, through social interactions. In the current implementation, there are three possible utility functions (Fig. 11.2).

Figure 11.3 shows a simplified block diagram of the agent architecture. Compared to other agents in the social network influence literature, these agents have a rich architecture that includes both symbolic and sub-symbolic reasoning. This was necessary to implement situated cognition, which was one the primary research goals. Due to space limitations, we will only describe perception, conception, situation, valuation, and social interaction functions.

Perception is the collection of functions that enable the agent to focus and organize their sensations according to their current situation, their expectations, and past experiences. Consumers perceive Product signatures using a Self-organizing Map (SOM, also known as Kohonen Networks). SOMs are a type of neural network that are trained via unsupervised learning. Essentially they perform a mapping from the sensed Product Signature to a condensed 2D internal representation of the Products. This is functionally equivalent to conceptual spaces, as described in Gärdenfors (2004). Perception is updated every step, but is only processed when new sensations arrive.

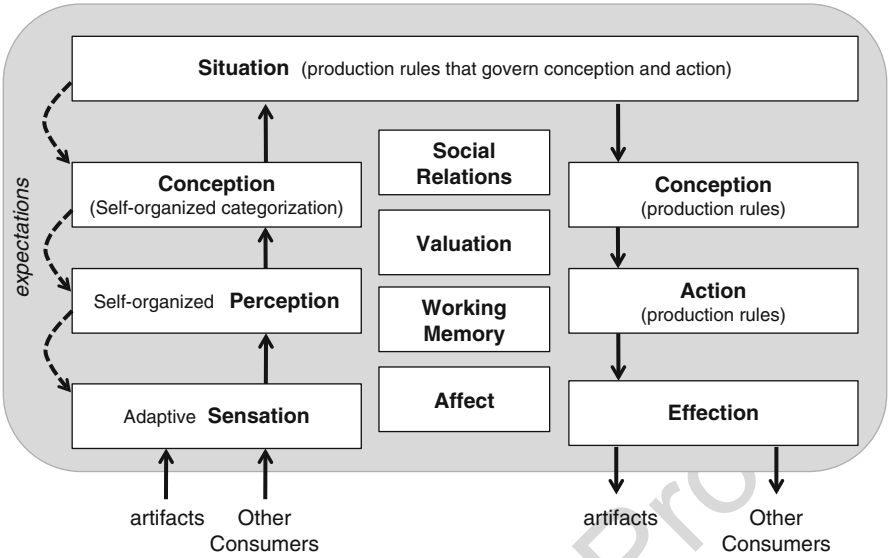


Fig. 11.3 Simplified agent architecture for Consumers

Perception of other agents is performed through a categorization and comparison procedure, where agents with direct social connections are labeled 'most similar', 'most dissimilar', 'most admired', 'least admired', etc.

Conception is the highest level of reasoning, including both tacit and explicit capabilities. Tacit conceptual reasoning is focused on deciding whether a given product should be considered attractive or not. This is implemented using a SOM that essentially creates a one-dimensional map of products that it has experienced and the value and/or utility that is perceived or realized from those products. A threshold value is used to trigger a decision that the product being inspected is attractive. The threshold value is adapted through learning by experience. Conception also includes explicit reasoning about actions, social interactions and goals. These are implemented symbolically as 'If-Then' production rules.

Situation has the function of cognitive orientation and focus. We implemented it using production rules that test for conditions that would change a Consumer's situation, and then fire actions to change their concepts accordingly. Overlapping situations can be active at the same time. Situations act as conditions on other conception rules so that each conception rule fires only when one of its applicable situations is active. Situation also activates other reasoning functions, as appropriate.

Social interactions are implemented using production rules. Generally, social interaction only occurs when the Consumer is both not in the act of consumption and is also frustrated by its consumption experiences. The exception to this occurs when a Consumer's social ties have been reduced to two or fewer and their strength has fallen below a threshold value. Here, conception rules fire that cause the agent to create new social ties. This is necessary in order to sustain social networks and

avoid disconnections. This was essential to maintain the distinction between 'social' and 'non-social' runs in paired experiments.

The targets of social actions and influences interactions are always defined by the perceptual categories mentioned earlier. In these experiments, Consumers are only influenced by a single neighbor at a time. They do not poll their local social network or perform any reasoning based on the range of values of other agents.

The utility function is a weighted sum of the three dimensions described above. However, the weights are adaptive and have a degree of random 'jitter' to simulate trial-and-error exploration of alternative utility functions. As mentioned previously, utility is only realized after a Product is consumed, but this result feeds back into Sensation, Perception, and Valuation via expectations.

In contrast, the valuation function operates on perceptions relative to an 'ideal product' vector. The closer the Product is to the consumers ideal the higher the valuation. It is measured as Euclidean distance between the sensed product and the ideal, both of which are filtered by Sensation. Also, there is an adaptive filter for valuation to model agent focus and prioritization, and also generalization.

In summary, at the task level the Consumer's problem is to find relatively more desirable Products to consume by searching the Consumption Space and adjusting their ideal product type. If they become dissatisfied during this process or if they are not able to find products to consume, they interact socially to either modify their value system or to move toward another agent in the Consumption Space.

At a social level, Consumers create and maintain social relationships through physical contact in the Consumption Space. However, if a Consumer is close to losing social connections, that Consumer interacts socially to build new connections through a referral process ('friends of friends'). The focus of social interaction is on soliciting or offering information about another Consumers' ideal product. We simulate the phenomena of opinion leadership and also susceptibility to influence from others.

11.4.3 Producers

In the current implementation, Producer agents have a simple architecture focused on two decision processes. They use simple decision rules based on local optimization and, unlike Consumers, do not have any other cognitive capabilities for sensation, perception, conception, or affect. The only decisions they make are (1) current production—choosing a replacement product from existing designs to replenish inventory in response to Consumer acts of consumption, and (2) new product introduction—choosing a new product designs to introduce from the designs that are in the 'adjacent possible'. To decide on current production, the Producer uses consumption statistics by region, and then makes their choice from existing designs based on weighted random choice. Weights are set to be proportional to consumption history in that region. Also, a fixed weight is given to recently

introduced products to encourage their selection and production, even though they may not have much history of consumption in that region.

New product designs are initially given a ranking according to their performance/cost ratio rank in three dimensions of performance. We assume that product designs are introduced in a sequence of improving performance/cost ratios, starting from the lowest and culminating in the highest, yielding a trajectory of product designs in the space of performance and cost. Since there are three performance dimensions, there are multiple possible trajectories for any given set of possible designs, and the trajectories may or may not be disjoint.

Because of feasibility and cost constraints, Producers will initially produce the designs with lowest costs (both design and manufacturing) and therefore relatively low (unattractive) performance/cost ratios. Subsequent new product introduction choices are made from the designs that are next in sequence of performance/cost on any of the performance dimensions. This defines the 'adjacent possible' for the Producer. When more than one product design is in the 'adjacent possible', Producers face a strategic decision to either stay on their current design trajectory or to move on to a new trajectory. Where design trajectories diverge ('branching points'), Producer choices for which new product to introduce determine which design trajectory is realized and which are not. This creates path dependence in Producer values and, indirectly, in Consumer values too.

11.5 Method

11.5.1 Experimental Design

Our goal is to study how Producer's choices from alternative designs are affected by evolving Consumer demand and preference (in the post-design phase) as revealed by their consumption behavior. Producer's choices should reveal how their post-design learning influences their actions in succeeding pre-design phases.

During the course of a run, Producers can only directly affect their costs by learning-through-experience. To increase product performance (i.e. to offer higher utility to Consumers) Producers must discover and offer new designs as they become feasible and cost-effective. On the other hand, Consumers can only influence their utility through consumption decisions, which may be satisfying or not, and by modifying their value systems so that the Products that are available are better appreciated (possibly).

The phenomena of interest are design trajectories in the space of Product types, as measured by performance/cost ratios over time. Divergences between alternative design trajectories represent discontinuous change and (potentially) disruptive innovations. The simulation system has been designed to allow, from identical initial conditions, different design trajectories can be realized depending on the co-evolution of Producer and Consumer values.

Therefore, our experimental approach involves comparing results across three experimental settings with identical initial conditions for the Product Design Set:

1. A single Producer acting in isolation from Consumers, with a deterministic consumption rule.
2. Consumers acting in isolation from Producers, with a deterministic Product replacement rule.
3. A single Producer interacting with a population of Consumers, with endogenous consumption and production/innovation processes.

The first setting allows us to measure the outcomes of Producer's decision process considering only the needs and values of the Producer. We expect to see design trajectories that are chosen based on local optimization and accumulated 'learning by doing', given the initial 'active' Product set and the topology of the Product Design Set. We can consider these realized design trajectories to be 'preferred' by Producers in the absence of other influences. Furthermore, we measure the Producer's value system by the weights they assign to the three alternative utility measures.

The second setting allows us to measure the outcomes of Consumers' decision processes considering their needs and values alone. We expect to see Consumer values—i.e. their 'ideal product' vector and their utility weights—adapt continuously as new products are introduced. However, Consumer adaptation will stop when they find Products that are repeatedly and sufficiently satisfying, and thus 'make up their mind' by resisting any further changes to their values. This should lead to two types of results. First, the population of Consumers will become segmented as sub-groups form with similar values that are resistant to change. This will be visible as clusters in Value Space and Utility Space. Second, there will be considerable path dependence in trajectories in Value Space and Utility Space depending on the initial 'active' Product set and also the sequence of product introductions. This will mean that if Products are introduced in the 'wrong' sequence, Consumers may not find them attractive enough to consume, even though they would do so in other, more favorable circumstances (Saunders and Gero 2004).

The third setting allows us to measure the value system changes that result from the mutual influence of Consumers and Producers. If design trajectory outcomes in this third setting resemble those of the first setting, then we can say that the Producer's values have not been significantly affected by the Consumer's behaviors and their changes in values. Likewise, if the trajectories and patterns of Consumer values in Value Space and Utility Space resemble those from the second setting, then we can say that Consumer values have not been significantly affected by Producer decisions and changes in their values.

However, we expect to see significant differences in the third setting compared to both the first and the second, which would provide evidence that both the Producer's and Consumers' values have a strong mutual influence on each other that is not predicted by their behavior in isolation. Furthermore, this sets the stage for possible emergent phenomena and 'collective intelligence' that arise from this mutual influence.

11.5.2 Treatments

The primary experimental treatments are different rules for the initial set of Products available for consumption (the 'active set') and the agent's rules for making changes. For the Producer, the key decision is when to introduce a new Product from the available alternatives. This depends on their value system—how much they value 'profitability' (i.e. high performance/cost ratio), how they weigh the three dimensions of Consumer utility based on consumption history, etc. For Consumers, the key rule is how quickly or easily they 'make up their mind' about what product characteristics and utility dimensions they prefer, and how open they are to change and influence after that. While we will initially experiment with a few alternatives, eventually we intend to run parameter sweeps across a range of Product Design Sets and agent value system rules.

For each run of the experiment, we run each of the three experimental settings with the same initial conditions for the Product Design Set, which includes both an initial set of Products available for consumption (the 'active set') and the set of possible new Products covering improvements in performance/cost in one or more dimensions. Each treatment will be run repeatedly with other initial conditions randomized. The resulting design trajectories and value system trajectories are analyzed statistically to identify differences between the three settings.

11.6 Results

We are in the early stages of experimentation and therefore we present preliminary and illustrative results in this paper.

11.6.1 Setting 1: Producer Acting in Isolation

The following describes illustrative results in the first experimental setting—Producer acting alone.

The initial 'active set' of products are those that have an initial manufacturing cost below a fixed threshold, chosen so that it would exclude all but a few products. Figure 11.4a is a histogram of initial manufacturing costs and Fig. 11.4b is a histogram from a single run after 3,000 steps. Costs are high initially because the Producer has no experience and thus faces a cost function that rises with the square of recipe element values.

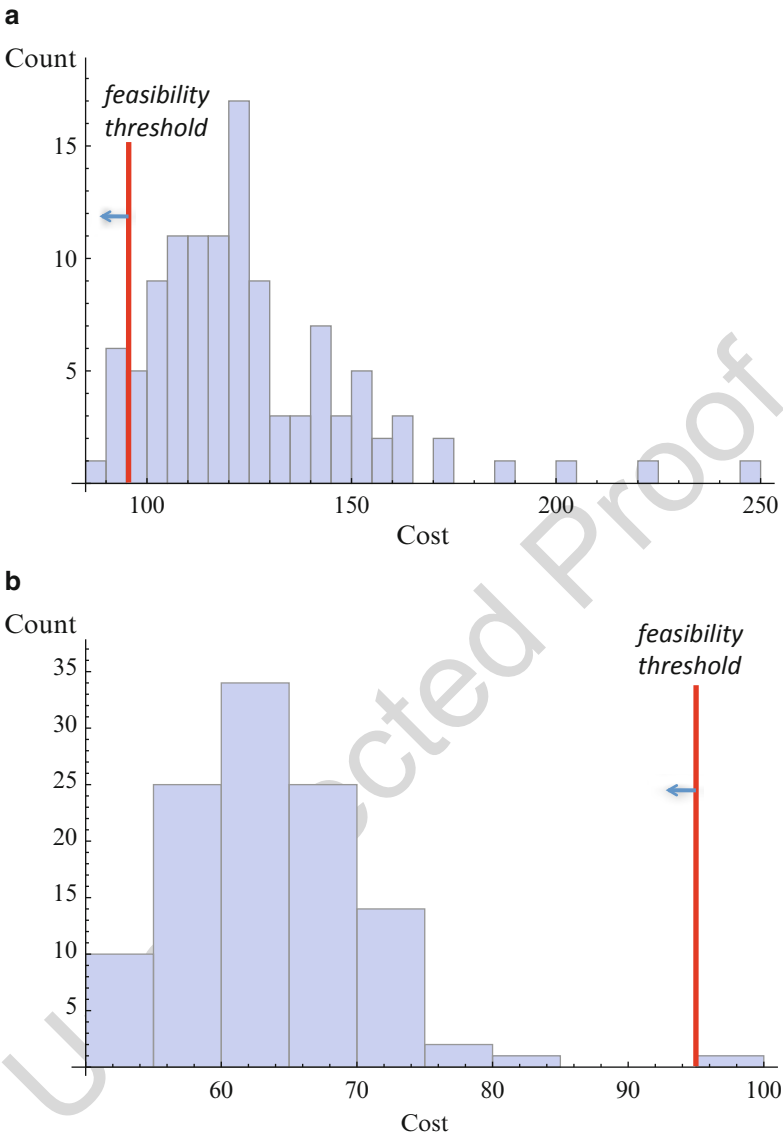


Fig. 11.4 Histogram of manufacturing costs for all possible designs with Producer using Rule 3—"Maximize performance/cost ratio" (**a**) $t = 0$ (**b**) $t = 3{,}000$

In this setting, the Producer manufactures a fixed quantity of product each step in the simulation, but that quantity is weighted across the 'active set' according to the Producer's value system. There are three weighting rules that we have explored:

1. *Minimize cost*—essentially focused on exploiting the benefits of learning-by-doing.
2. *Maximize performance*—a proxy for providing the most utility to Consumers without regard to cost as long as it is below the feasibility threshold.
3. *Maximize performance/cost ratio*—a middle ground between (1) and (2). This corresponds to profit maximization in micro-economic models.

The graphs in Fig. 11.5 show cumulative production by product design index for a single run for each of the three rules but with the same initial conditions. The stopping condition for each run was either 3,000 time steps or producing 500 units of the design with maximum utility under that rule. Thus the production quantities are different between runs because they reached the stopping condition at different times.

The diagrams in Fig. 11.6 show how design trajectories differ under the three Producer rules. All 112 possible designs are shown in the space as a grey dot (potential), or other dot as described in Fig. 11.6. The layout of the space is suggestive of proximity between designs from the Producer's point of view—i.e. proximity of production recipes. This layout was created using distance to 12 nearest neighbors and a graph layout algorithm—spring-electrical embedding. Other methods were tried, including Multi-dimensional Scaling, but none produced

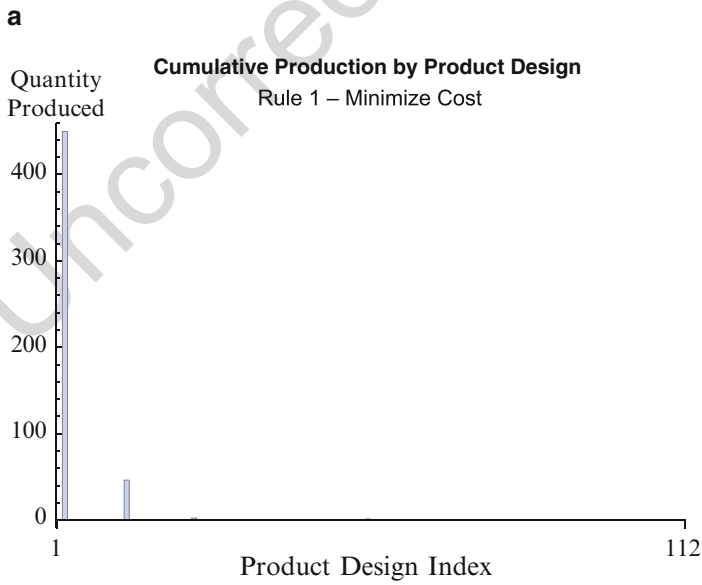
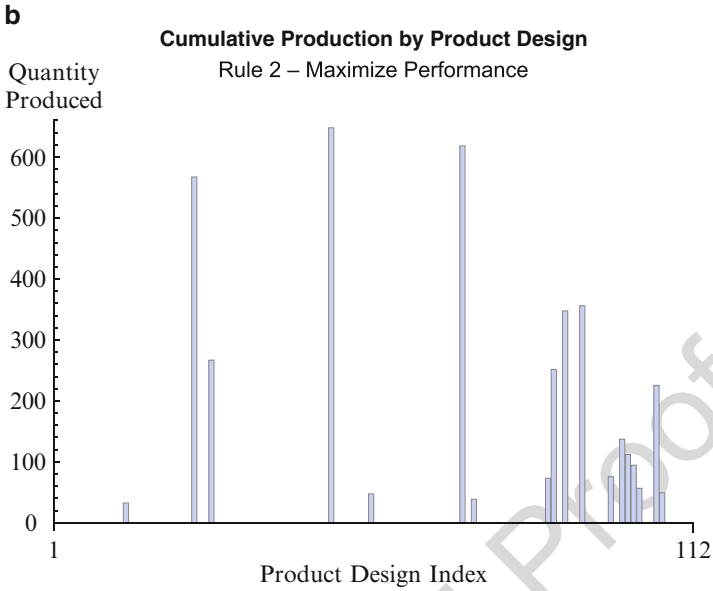


Fig. 11.5 Results of three runs with different valuation rules for Producer acting alone (Setting 1) (**a**) Rule 1 (**b**) Rule 2 (**c**) Rule 3



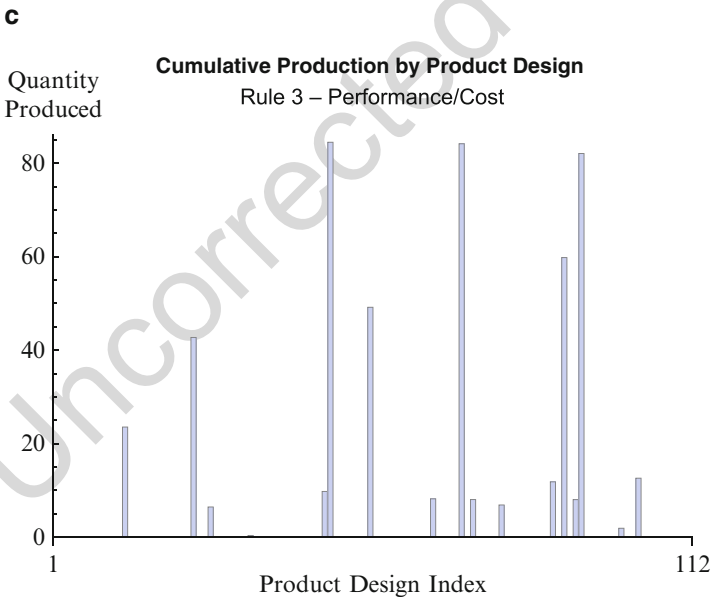


Fig. 11.5 (continued)

results that were as good as this for visual clarity. The light blue lines and dots show the relevant neighbor relations for the 'active set', i.e. the adjacent possible. Notice that many of these lines span a long distance indicating that the true dimensionality of the design space is high.

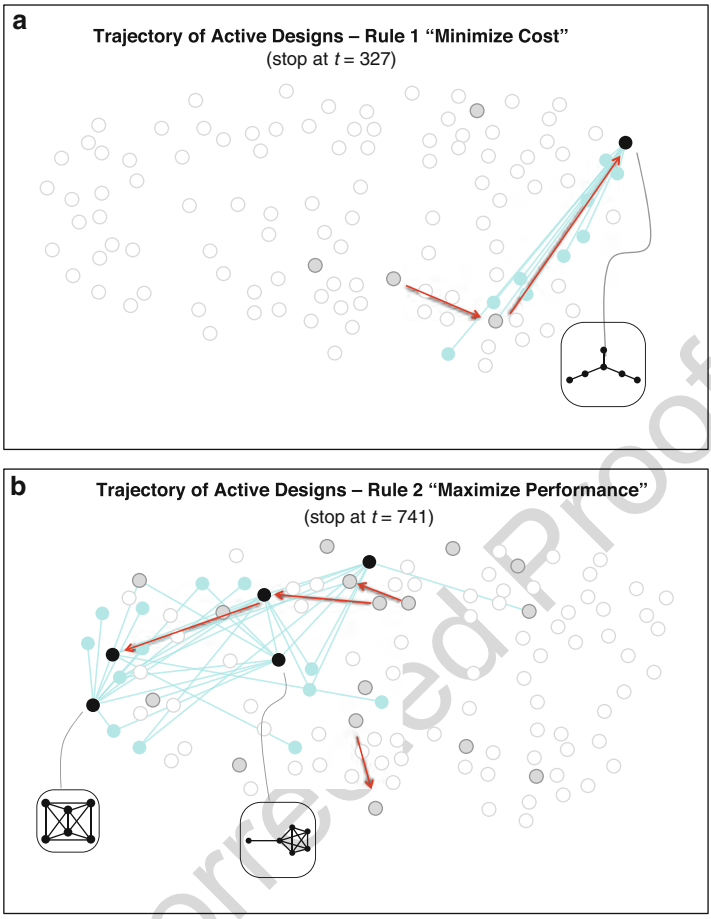


Fig. 11.6 Design trajectory from a single run for three different Producer rules. Key: *black dot* = active set; *grey dot* = previously active but no longer produced; *light blue dot* = 'adjacent possible' designs; *hollow grey dots* = all possible designs; *red arrows*: the main trajectory (**a**) Rule 1. *Inset*: Product design #2 (**b**) Rule 2. *Inset*: Product design #108 (*left*) and #100 (*right*) (**c**) Rule 3. *Inset*: Product design #105 (*left*) and #28 (*right*)

These diagrams reveal three broad differences in trajectories. First, the speed of movement along the trajectory is very different. Rule 1 moves very quickly to a fixed point where it only produces Product #2. We suspect that this pattern will be repeated with many other initial conditions, though maybe not all. Rule 2 moves fairly quickly toward the region of design space that is populated by the most complex designs. But Rule 3 meanders and moves more slowly, even oscillating between brand new designs and revivals of previous designs.

Second, the destination of the trajectories are clearly different. Rule 1 seems to gravitate toward simple designs, while Rule 2 does the opposite. As might be

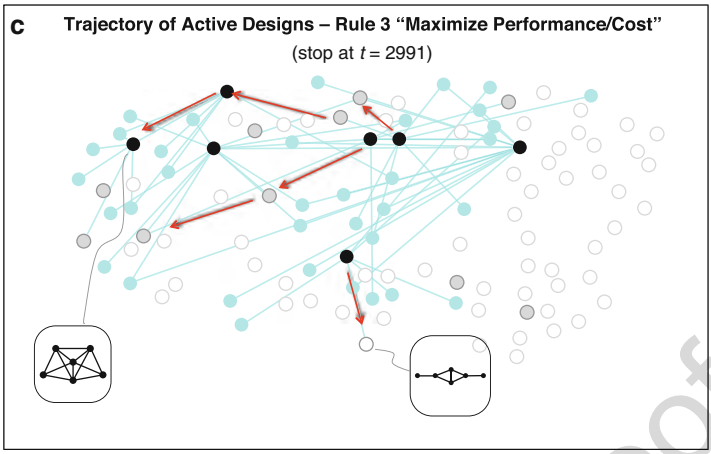


Fig. 11.6 (continued)

expected, Rule 3 seems like a hybrid, with predominant preference toward the high complexity region but also persistent preference for simpler designs.

Third, the number and diversity of product designs varies. Rule 3 is the most diverse, and seems to have a strong inclination to diversify and try many designs simultaneously, even previous designs. Rule 1 is the least diverse, and Rule 2 is in between. In our future experiments we will be measuring these differences in trajectories to test our hypotheses statistically.

11.6.2 Setting 2: Consumers Acting in Isolation

When testing Consumer behavior separate from Producer behavior and decision rules, our goal is to present them with relatively simple patterns of change and look for endogenous and emergent responses. Thus, we are presenting them with somewhat arbitrary design trajectories and we are looking for general patterns regarding how they respond to or resist the changes.

To analyze Consumer behavior and changes in their value system, we use two representations not present in the analysis of Producers. The first is 'Value Space'—a Multi-dimensional Scaling (MDS) map of Consumer ideal product vectors along with the characteristics vector of each Product (both active and potential) (Liggett 2010). In the graphs shown below, these are unfiltered by Sensation. The second representation is 'Utility Space'—a simple three-dimensional map of each Consumer's utility weights in a triangular barycentric coordinate system.

One interesting general pattern is clustering of values and preferences. We would be interested in knowing if clusters (a.k.a. 'market niches') form

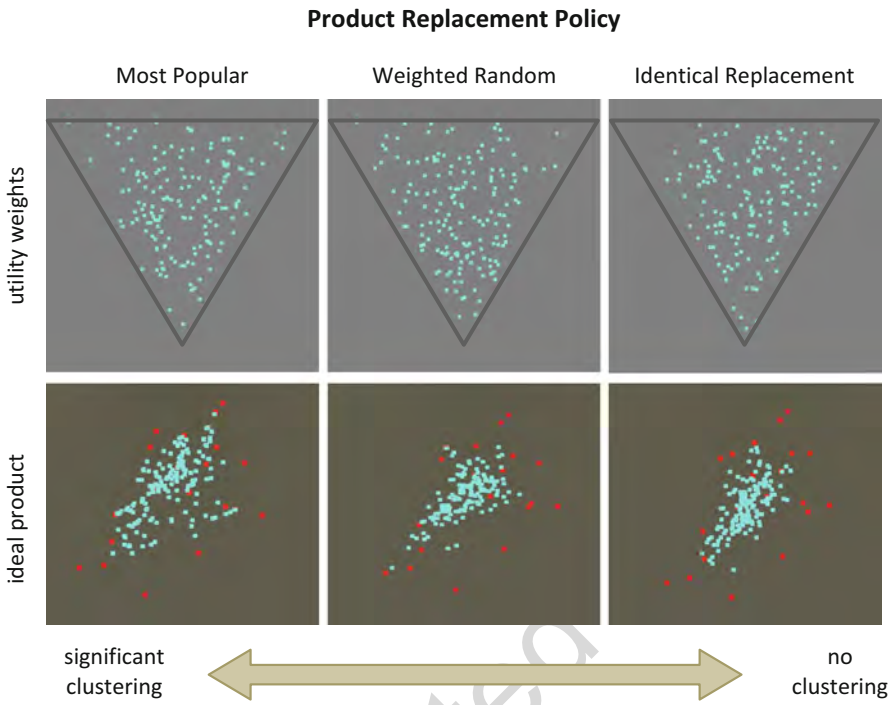


Fig. 11.7 Results from three runs with different treatments but otherwise identical initial conditions. Clustering of Consumer values is only sustainable if Producers are responsive to their initial preferences. Key: *Blue Dots* are individual consumer ideal vectors (*bottom*) or utility weights (*top*). *Red dots* are Products in the active set

endogenously and are sustained. To test for clustering, we implemented three simple production rules (really, product replacement):

1. *Identical Replacement*—the same Product replaces a Product that is consumed. Thus the mix of Products never changes.
2. *Weighted Random Replacement*—replacement products are chosen by random draw with the probability being proportional to past consumption in that broad region.
3. *Most Popular*—the replacement product is chosen to be what ever the most popular product (most consumed) in that region.

The images in Fig. 11.7 show the results of these three alternative treatments for a given random realization, for Steps = 6,000. The three treatments differ in how responsive the Producer is to Consumer demand patterns. 'Most Popular' is the most responsive policy, followed by 'Weighted Random', which is somewhat responsive, and followed by a non-responsive policy of 'Identical Replacement'. The most significant result is the degree of clustering in Value Space (bottom row) for the responsive policies. These clusters persist over extended time periods (∼100

steps) and establish themselves in niches in Value Space far from the centroid. In contrast, the dispersion of ideal products in the 'Identical Replacement' treatment appears to be ephemeral movement of individuals without persistent clustering. The clustering behavior is not as visible or apparent in the space of Utility Weights (top row), but other analysis or visualization methods might reveal some effects.

11.6.3 Setting 3: Producers and Consumers Interacting

Figures 11.8 and 11.9 show the mutual influence of Producers and Consumers. This is the only one of the three rules that show significant mutual influence. For Rule 1—Minimize cost, adding Consumers interaction made no difference since it didn't alter the cost function. For Rule 2—Maximize performance, adding Consumer interaction also had no influence because Consumer demand did not directly influence the Producer's performance metric.

The situation is different for Rule 3 because variations in Consumer demand can change the performance/cost ratio as measured by Producers. Comparing Figs. 11.8 and 11.9, it can be seen that movement along the design trajectory is slower when Consumer values are dynamic and situated (Fig. 11.9), compared to the setting when there are no interactions with Consumers (Fig. 11.8). Importantly, for these particular parameter settings for Producer and Consumer learning, the design trajectory is not altered by Consumer interaction. However, that does not rule out the possibility that there are parameters values that can result in a dramatic shift in trajectories. Using full parameter sweeps, we will look for critical parameter values in future research.

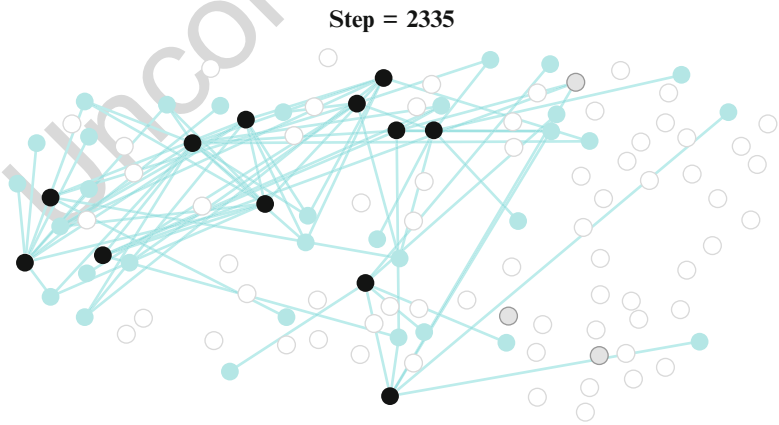


Fig. 11.8 A snapshot for Setting 1—Producer only, showing the active set of designs (*black dots*) using Rule 3—Maximize performance/cost ratio, recorded when the target metric reached 25

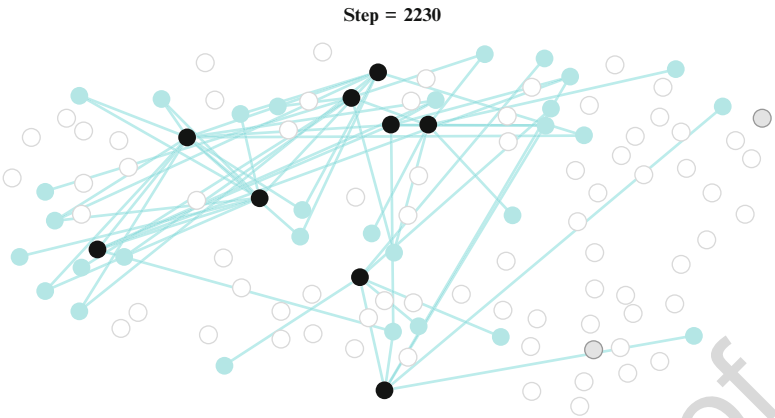


Fig. 11.9 A snapshot for Setting 3—Producer–Consumer interaction, showing the active set of designs (*black dots*) using Rule 3—Maximize performance/cost ratio, recorded when the target metric reached 25. Compared to Fig. 11.8, the pace of movement along the design trajectory is slower

11.7 Discussion

The results substantiate the argument that interactions between Consumers and Producers in the post-design phase are essential to the process of innovation. Producers need to combine several types of learning in order to shape the post-design outcomes and to feed into the pre-design and design activities to follow. First, they need to gain tacit knowledge to achieve improvements in performance/cost ratio. In a sense, the design phase only offers the promise and potential for a certain performance/cost goal to be achieved. Whether that promise and potential is realized depends on whether the Producer has sufficient persistence and follow-through to avoid excessive diversification, and also sufficient flexibility and openness not to get stuck in a narrow range if it precludes other, more promising paths. Second, the Producer must continually learn and adapt to what the marketplace defines as 'value'. Certainly, market research and testing can help here, but this learning mostly happens through engagement with the market and Consumers through post-design activities of selling, servicing, and customizing.

Consumers, too, engage in post-design 'work' of a sort. Through their shifting and emergent preferences and surprising discoveries of new functions and new significance, they reshape the value landscape both for Producers and also other Consumers. In future experiments, we expect to see patterns of reinforcing interactions between Producers and Consumers, but maybe also inhibiting interactions, too, maybe in surprising ways.

While the results in this paper are illustrative and suggestive, we believe they begin to show value of Computational Social Science methods in studying

innovation processes that span social and technical domains and diverse social groups. The architecture of the simulation system demonstrates that it is feasible to build rich computational models to study the simultaneous influence of several factors at once, and across different social levels. This is especially important when we are studying how agents react to and even generate novelty. In particular, our agent architecture for Consumers includes a comparatively rich set of capabilities to model situated cognition, both with artifacts and also with other agents. Also, our artifact architecture for Product demonstrates that it is possible to design an environment that is rich in possibilities without requiring the designer to (necessarily) plan or explicitly design all those possibilities ahead of time. For example, we chose three utility dimensions for Products based on the characteristics of graphs (i.e. degree count, clustering coefficient, and longest span in an embedding). But the simulation system could be greatly enriched if the utility dimensions were open-ended and endogenously created and diffused by agents. This is an example of the benefits of the computational approach.

Another significant benefit of computational modeling is the ability to run both exploratory and controlled experiments that have demonstrable relevance to real-world settings. The results presented for Setting 1—Producer Acting in Isolation—are still exploratory at this stage. However we were able to identify three qualitative distinctions between design trajectories. In future work, we aim to quantify and measure these distinctions so that we can do more rigorous experiments involving design trajectories as dependent variables.

The results presented in Setting 2—Consumers Acting in Isolation—take us closer to controlled experiments and statistical hypothesis testing. We were able to identify conditions where our Consumers were and were not able to endogenously form clusters of values. Clustering has a significant effect on the diffusion and adoption of innovation, both in the form clusters of early adopters and also clusters of resistance to change.

Another contribution of our research is demonstrating how to measure and evaluate changes in value systems in the context of innovation, both at the level of an individual, in a group, and in a population. In this paper we have presented and discussed three different analysis and representation methods—(1) design trajectories in the space of possible designs, (2) Value Space for populations of Consumers and their ideal product vectors; and (3) Utility Space for populations of Consumers (and Producers) to monitor and measure how their utility function changes over time. One of our most significant lessons from this research so far is the value of multiple simultaneous measurements and representations, because value systems is inherently multi-level, multi-dimensional, and even pluralistic, even within an individual agent.

With further experiments and results, we expect that our experiments will reveal emergent patterns of organization that shape the Producer's design choices. In particular, we believe that experiments will reveal self-reinforcing processes (both direct and indirect) where early Consumer learning and preference formation influences Consumer receptivity to new Products that have similar surface characteristics or offer similar performance dimensions, and this in turn influences

Producer decisions on the trajectory of new product introduction. We suspect that this behavior will appear at critical values of parameters that govern the rate of learning and adaptation by Producers and Consumers.

Acknowledgements This research is based upon work supported by the US National Science Foundation under Grant Nos. SBE-0915482, CNS-0745390, CMMI-116715 and CMMI-1400466. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

References

Akintoye A, Beck M (2009) Policy, management and finance for public-private partnerships. Wiley, Oxford

Archibugi D, Howells J, Michie J (1999) Innovation policy in a global economy. Cambridge University Press, New York

Asimov M (1962) Introduction to design. Prentice-Hall, Englewood Cliffs

Auerswald P, Kauffman S, Lobo J, Shell K (2000) The production recipes approach to modeling technological innovation: an application to learning by doing. J Econ Dynam Contr 24(3):389–450

Avermaete T, Morgan EJ, Viaene J, Pitts E, Crawford N, Mahon D (2003) Regional patterns of innovation: case study of small food firms. In: DRUID summer conference 2003 on creating, sharing and transferring knowledge. Copenhagen, Denmark, June 12–14, 2003

Bower JL, Christensen CM (1996) Disruptive technologies: catching the wave. J Prod Innovat Manag 13(1):75–76

Castelfranchi C (2001) The theory of social functions: challenges for computational social science and multi-agent learning. Cognit Syst Res 2(1):5–38

Casti JL (1999) The computer as a laboratory. Complexity 4(5):12–14

Clancey WJ (1997) Situated cognition: on human knowledge and computer representations. Cambridge University Press, Cambridge

Cooke P (2001) Regional innovation systems, clusters, and the knowledge economy. Ind Corp Change 10(4):945–974

Danneels E (2004) Disruptive technology reconsidered: a critique and research agenda. J Prod Innovat Manag 21(4):246–258

Dooley K (1997) A complex adaptive systems model of organization change. Nonlinear Dynam Psychol Life Sci 1(1):69–97

Dosi G (1982) Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Res Pol 11(3):147–162

Dosi G, Nelson RR (2010) Technical change and industrial dynamics as evolutionary processes. In: Handbook of the economics of innovation. Elsevier, Amsterdam, pp 51–127

Edquist C (2005) Systems of innovation: perspectives and challenges. In: Oxford handbook of innovation. Oxford University Press, Oxford, pp 181–208

Epstein JM (2012) Generative social science: studies in agent-based computational modeling. Princeton University Press, Princeton

Epstein JM, Axtell R (1996) Growing artificial societies: social science from the bottom up. Brookings Institution Press, Washington, DC

Feldman DH, Csikszentmihalyi M, Gardner H (1994) Changing the world: a framework for the study of creativity. Praeger, Westport

Ferber J (1999) Multi-agent systems: an introduction to distributed artificial intelligence. Addison-Wesley, Harlow

Finke RA (1996) Imagery, creativity, and emergent structure. Conscious Cognit 5(3):381–393

Friedkin NE, Johnsen EC (1999) Social influence networks and opinion change. Adv Group Processes 16(1):1–29
Gärdenfors P (2004) Conceptual spaces: the geometry of thought. MIT Press, Cambridge
Gero JS (1990) Design prototypes: a knowledge representation schema for design. AI Mag 11(4):26
Gero JS (1996) Creativity, emergence and evolution in design. Knowl Base Syst 9(7):435–448
Gero JS (2000) Computational models of innovative and creative design processes. Technol Forecast Soc Change 64(2–3):183–196
Gero JS (2008) Towards the foundations of a model of design thinking. DARPA Project BAA07-21
Gero JS, Damski JC (1997) A symbolic model for graphical emergence. Environ Plann B Plann Des 24(4):509–526
Gero JS, Kannengiesser U (2004) The situated function–behaviour–structure framework. Des Stud 25(4):373–391
Gero JS, Kannengiesser U (2009) Understanding innovation as a change of value systems. In: Proceedings of growth and development of computer aided innovation third IFIP WG 5.4 working conference, CAI 2009, pp 249–257, Harbin, 20–21 Aug 2009
Gero J, Maher M (eds) (1993) Modeling creativity and knowledge-based design. Psychology Press, Florence
Gilbert N (2002) Varieties of emergence. In: Proceedings of agent 2002 conference: social agents: ecology, exchange, and evolution, pp 11–12, Chicago
Gilbert N, Conte R (1995) Artificial societies: the computer simulation of social life. Psychology Press, Florence
Goldstein J (1999) Emergence as a construct: history and issues. Emergence 1(1):49–72
Grace K, Saunders R, Gero J (2008) A computational model for constructing novel associations. In: Proceedings of the international joint workshop on computational creativity. Madrid, Spain, September 17–19, 2008
Holland JH (2000) Emergence: from chaos to order. Oxford University Press, New York
Hybs I, Gero JS (1992) An evolutionary process model of design. Des Stud 13(3):273–290
Kauffman S (1996) At home in the universe: the search for the laws of self-organization and complexity. Oxford University Press, Oxford
Kuhn TS (1996) The structure of scientific revolutions. University of Chicago Press, Chicago
Leydesdorff L (2000) The triple helix: an evolutionary model of innovations. Res Pol 29(2):243–255
Liggett RE (2010) Multivariate approaches for relating consumer preference to sensory characteristics. Ph.D. dissertation, The Ohio State University
Llerena P (2006) Innovation policy in a knowledge-based economy: theory and practice. Springer, Berlin
Macy MW, Willer R (2002) From factors to actors: computational sociology and agent-based modeling. Ann Rev Sociol 28:143–166
Malerba F, Nelson R, Orsenigo L, Winter S (2007) Demand, innovation, and the dynamics of market structure: the role of experimental users and diverse preferences. J Evol Econ 17(4):371–399
Miller JH, Page SE (2009) Complex adaptive systems: an introduction to computational models of social life: an introduction to computational models of social life. Princeton University Press, Princeton
Moldovan S, Goldenberg J (2004) Cellular automata modeling of resistance to innovations: effects and solutions. Technol Forecasting Soc Change 71(5):425–442
Pahl G, Beitz W, Feldhusen J, Grote KH (eds) (2007) Engineering design: a systematic approach. Springer, London
Repenning NP (2002) A simulation-based approach to understanding the dynamics of innovation implementation. Org Sci 13(2):109–127
Sahal D (1985) Technological guideposts and innovation avenues. Res Pol 14(2):61–82

Saunders R, Gero JS (2004) Situated design simulations using curious agents. AIEDAM 18(2):153–161

Saviotti P (1996) Technological evolution, variety, and the economy. Edward Elgar Pub, Aldershot and Lyme

Saviotti PP, Metcalfe JS (1984) A theoretical approach to the construction of technological output indicators. Res Pol 13(3):141–151

Sawyer RK, Sawyer RK (2012) Explaining creativity: the science of human innovation. Oxford University Press, Oxford

Scherer FM (1986) Innovation and growth: schumpeterian perspectives. MIT Press, Cambridge

Schumpeter JA (1942) Capitalism, socialism and democracy. Harper, New York

Smith GJ, Gero JS (2001) Emerging strategic knowledge while learning to interpret shapes. In: Gero JS, Hori K (eds) Strategic knowledge and concept formation III, Key Centre of Design Computing and Cognition. University of Sydney, Sydney, pp 69–86

Smith GJ, Gero JS (2005) What does an artificial design agent mean by being 'situated'? Des Stud 26(5):535–561

Sosa R, Gero JS (2004) A computational framework to investigate creativity and innovation in design. In: Gero JS (ed) Design Computing and Cognition '04. Springer, New York

Sosa R, Gero JS (2005) A computational study of creativity in design: the role of society. AI EDAM 19(4):229–244

Sosa R, Gero J (2007) Computational explorations of compatibility and innovation. In: León-Rovira N (ed) Trends in computer aided innovation, vol 250. IFIP, The International Federation for Information Processing, Springer, New York, pp 13–22

Taura T, Nagai Y (2005) Primitives and principles of synthesis process for creative design. In: Gero JS, Maher ML (eds) Reprints of international conference of computational and cognitive models of creative design VI, pp 177–194, Key Centre of Design Computing and Cognition Heron Island, Australia, 10–14 Dec 2005

Weiss G (2000) Multiagent systems. MIT Press, Cambridge

Wooldridge M (2008) An introduction to multiagent systems. Wiley, Chichester

Preprints

Editor's Proof

Metadata of the chapter that will be visualized online

Chapter Title	Modelling (pre-)Design Activities With a Multi-Stakeholder Perspective	
Copyright Year	2014	
Copyright Holder	Springer Japan	
Corresponding Author	Family Name	**Cascini**
	Particle	
	Given Name	**Gaetano**
	Suffix	
	Organization	Politecnico di Milano, Dip. di Meccanica
	Address	Via La Masa 1, 20156, Milan, Italy
	Email	gaetano.cascini@polimi.it
Author	Family Name	**Montagna**
	Particle	
	Given Name	**Francesca**
	Suffix	
	Organization	Politecnico di Torino, Dip. di Ingegneria Gestionale e della Produzione
	Address	C.so Duca degli Abruzzi 24, 10129, Torino, Italy
	Email	francesca.montagna@polito.it
Abstract	The paper proposes an extension of the Gero's Function-Behaviour-Structure (FBS) framework aimed at representing Need and Requirements and their relationships with the Function, the Behaviour and the Structure of an artefact. Needs and Requirements can be modelled as further types of variables to describe with the same formal approach of the situated FBS model the transformation processes which occur in the earlier stages of design, when the requirements still need to be specified. Furthermore the external world where needs are situated is split into the complementary perspectives of the different stakeholders influencing the adoption process of a new product, i.e. into buyers, users, beneficiaries and other outsiders. The extended model aims at supporting a more careful and detailed investigation of the processes that occur in the earliest stages of design, and specifically what happens in new product development activities. As carefully discussed in the introduction of the paper, such a shift in the designer's perspective appears as a crucial step to build an efficient design methodology for innovation.	
Keywords (separated by "-")	Design for innovation - FBS framework - Multi-stakeholders analysis - Needs identification	