

Computational Explorations of Creativity and Innovation in Design

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A thesis submitted in fulfilment of
the requirements for the degree of

Doctor of Philosophy

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2005

Acknowledgments

According to the main assumptions of this work, ideas can be better understood when the creator is considered as part of the social group in which it operates and in relation to existing knowledge. In this vein, I wish to acknowledge the individuals and Institutions that have contributed to my doctoral studies.

The research presented in this thesis was supported by an International Postgraduate Research Scholarship from the Australian Government and a University of Sydney International Postgraduate Award. Computing resources were provided by the Key Centre of Design Computing and Cognition.

I wish to thank my supervisor John Gero for his generous support and constructive challenges throughout the course of this research at the University of Sydney and as a visiting student to the Design and Computation group at the Massachusetts Institute of Technology. Thanks go to staff and fellow students from both research groups for contributing to a stimulating research environment with enriching discussions, in particular Julie Jupp and Rob Saunders.

My appreciation goes to the organisers, editors, reviewers, and attendees of the workshops, conferences, and journals where I was able to present early stages of this research for their effort and valuable feedback, especially Andy Dong, David Brown and Linda Candy. Key figures who provided brief but timely direction and encouragement include Herbert Simon, Robert Axelrod, and Howard Gardner.

This work would not have been possible without the incessant support from my family, my partner and my friends. For their unqualified trust and their continuous encouragement I am grateful. For their love I will always be humbled.

My initial approach to design research was nurtured by lecturers and colleagues at Universidad Autonoma Metropolitana and Centro Nacional de las Artes in Mexico and at the National University of Singapore.

This thesis represents my highest personal academic achievement and, as such, I wish to dedicate it to all the people who are marginalised, excluded, and have no access to formal education and training. The world, and our understanding of it, would certainly be much better if opportunities were available to all.

Summary

This thesis addresses creativity in design as a property of systems rather than an attribute of isolated individuals. It focuses on the dynamics between generative and evaluative or ascriptive processes. This is in distinction to conventional approaches to the study of creativity which tend to concentrate on the isolated characteristics of person, process and product. Whilst previous research has advanced insights on potentially creative behaviour and on the general dynamics of innovation in groups, little is known about their interaction. A systems view of creativity in design is adopted in our work to broaden the focus of inquiry to incorporate the link between individual and collective change.

The work presented in this thesis investigates the relation between creativity and innovation in computational models of design as a social construct. The aim is to define and implement in computer simulations the different actors and components of a system and the rules that may determine their behaviour and interaction. This allows the systematic study of their likely characteristics and effects when the system is run over simulated time. By manipulating the experimental variables of the system at initial time the experimenter is able to extract patterns from the observed results over time and build an understanding of the different types of determinants of creative design. The experiments and findings presented in this thesis relate to artificial societies composed by software agents and the social structures that emerge from their interaction. Inasmuch as these systems aim to capture some aspects of design activity, understanding them is likely to contribute to the understanding of the target system.

The first part of this thesis formulates a series of initial computational explorations on cellular automata of social influence and change agency. This simple modelling framework illustrates a number of factors that facilitate change. The potential for a designer to trigger cycles of collective change is demonstrated to depend on the combination of individual and external or situational characteristics.

A more comprehensive simulation framework is then introduced to explore the link between designers and their societies based on a systems model of creativity that includes social and epistemological components. In this framework a number of independent variables are set for experimentation including characteristics of individuals, fields, and domains. The effects of these individual and situational parameters are observed in experimental settings. Aspects of relevance in the definition of creativity included in these studies comprise the role of

opinion leaders as gatekeepers of the domain, the effects of social organisation, the consequences of public and private access to domain knowledge by designers, and the relation between imitative behaviour and innovation.

A number of factors in a social system are identified that contribute to the emergence of phenomena that are normally associated to creativity and innovation in design. At the individual level the role of differences of abilities, persistence, opportunities, imitative behaviour, peer influence, and design strategies are discussed. At the field level determinants under inspection include group structure, social mobility and organisation, emergence of opinion leaders, established rules and norms, and distribution of adoption and quality assessments. Lastly, domain aspects that influence the interaction between designers and their social groups include the generation and access to knowledge, activities of gatekeeping, domain size and distribution, and artefact structure and representation. These insights are discussed in view of current findings and relevant modelling approaches in the literature. Whilst a number of assumptions and results are validated, others contribute to ongoing debates and suggest specific mechanisms and parameters for future experimentation.

The thesis concludes by characterising this approach to the study of creativity in design as an alternative ‘in silico’ method of inquiry that enables simulation with phenomena not amenable to direct manipulation. Lines of development for future work are advanced which promise to contribute to the experimental study of the social dimensions of design.

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Chapter 1

Introduction

This chapter presents an introduction to the area of inquiry and the problem addressed in this thesis. The aim, objectives and scope of this research are presented. The chapter ends with an outline of this thesis.

Design is an important social activity. Artefacts specified by designers respond to the needs and problems of social groups. Buildings are conceived for housing, objects and tools are developed for work and entertainment, and visual displays are created to support communication. Design practitioners are delegated by societies the fundamental task of transforming their environment. To that extent, design is seen as a social activity in which various stakeholders interact.

Designers may become change agents of their societies. They may propose new physical solutions or artefacts that trigger social transformations. The artefact specification is the immediate, tangible outcome of the design process. When artefacts are built and made available, their impact and ensuing consequences in a society are the final outcomes of design activity. Social and environmental changes are the ultimate products of design.

Creativity and innovation are possible outcomes of design. Design artefacts may be considered by social groups or by experts to address appropriate requirements in novel and unexpected ways. Certain artefacts may also influence the design of future solutions opening possibilities that were not available until then. When these types of conditions occur, both the artefact and the designer may be regarded as creative by their social group. The process by which a target group or population evaluates, adopts and adapts to creative solutions is considered the process of diffusion of an innovation. This research addresses some aspects of the fundamental relationship between individual generation and collective evaluation of design artefacts.

1.1 Research Problem

The fundamentals of creativity and its relation to innovation are not well understood (Runco 2004; Simon 2001). There is a clear gap in the current understanding of how individual action and social change integrate. An explanation for this divergence in the literature is that for the most part methods of inquiry tend to focus separately on individual or collective units of analysis without

considering their interaction within a system (Anderson 1972). The micro-macro link between individual action and collective change is an important interdisciplinary question today (Alexander et al. 1987; Sawyer 2001).

Undoubtedly, the most important contribution of the last sixty years of research in this area has been the demystification of creativity (Simon 2001). An emerging consensus exists today that creativity is the property of a system where individual and environmental conditions interact (Feldman et al. 1994; Sawyer et al. 2003). It is characterised as an ascribed property that is not entirely contained within the person or artefact in isolation but takes place in the interaction between a person or artefact and a socio-cultural context (Csikszentmihalyi 1997). Under this view, there is a complementary relationship between generative and evaluative processes, i.e., how creative solutions are produced cannot be understood in isolation of how they are evaluated (Csikszentmihalyi and Epstein 1999). A possible approach to the study of creativity as a social construct (Amabile 1993; Saunders 2002) is to examine the role of the environment and its interpretation by individuals. These types of situational factors have been addressed across a number of disciplines (Argyle et al. 1981; Ross and Nisbett 1991; Sternberg and Vroom 2002). The underlying assumption is that factors that sit outside the individual may be important determinants of behaviour and emphasis is given to the understanding of behaviour as a result of the individual interacting with an environment (Clancey 1997).

Examples can be drawn to support the dominance of both person and situation-based accounts of creativity. However, there are no clear reasons to over-emphasise either. It seems more appropriate instead to explore the informative range between the two extremes.

Treating creativity as a product of complex human interaction, computational agent models are presented as a convenient method of inquiry (Gilbert and Doran 1994). Such approach provides means to implement and experiment with individual and situational components. Individual factors refer to the internal characteristics of subjects under study. Situational factors are defined as the combination of external conditions and their interpretation by individuals and groups of subjects. Examples of situational factors include time schedules, environmental conditions, emergent group effects and interaction rules with which social groups operate.

This thesis presents computational explorations into the twofold problem of creativity and innovation. Experimental frameworks are developed to support explorations of artificial systems that exhibit target phenomena (Simon 1995). Verbal statements regarding theoretical principles and hypotheses are extracted from these programs. The intent is therefore explorative rather than to model a particular theory in an area where theorisation is limited and evidence inconclusive (Mayer 1999; Runco and Albert 1990). The use of computers to this end seems appropriate since the outcome of a system is not necessarily deducible at initial time (Epstein and Axtell 1996). Computers can be appropriate laboratories where phenomena and structures of interest are ‘grown in silico’ with the aim to discover and understand resulting patterns and principles.

1.2 Aim and Objectives

The aim of this research is to develop an understanding of individual and situational factors in creativity and innovation in design. The approach is to present experimental evidence from computational simulations that demonstrate interaction principles behind phenomena associated to creative design. The following objectives are considered necessary to achieve this aim:

- 1) To identify a series of components and mechanisms at work in a systems view of creativity and innovation.
- 2) To develop an elementary model that captures key principles of interaction between these components.
- 3) To investigate change agency by studying the roles of individual behaviour and social influence in the emergence of group change.

- 4) To develop a more comprehensive model to address aspects of design as a social activity that includes the individual generation and social evaluation of design artefacts.
- 5) To define a range of computationally applicable parameters in this model that are likely to determine the interactions between system components.
- 6) To design experiments with these parameters focusing on individual and situational experimental conditions. In experimental systems one independent parameter at the time is manipulated and its effects over a period of time and over a number of cases are investigated.
- 7) To collect data and use statistical analysis to study the effects of these experimental parameters in determining patterns of group change.
- 8) To analyse insights from these studies in order to understand the mechanisms that determine the behaviour of the system.
- 9) To discuss results and implications in view of current related empirical evidence from the literature and to elaborate a future research program.

1.3 Overview

This thesis continues in Chapter 2 with background analysis. A general overview is presented of the current literature with special emphasis on approaches that shift the focus on creativity to a systems view (Csikszentmihalyi 1988; Rathunde 1999). The DIFI framework, Domain-Individual-Field Interaction (Feldman et al. 1994), is presented as a promising approach to the study of design as a social activity. Related work in the computational modelling of creativity and discovery is followed by a review of multi-agent simulation in social sciences. The background chapter concludes with an analysis of situated behaviour.

Chapter 3 presents an initial approach to the modelling of emergent structures of convergence and divergence in stochastic cellular automata (CA). This is presented as an introductory study of the relation between individual action and collective change. It illustrates some aspects of change agency at a general level. Several extensions to CA of diffusion are discussed including dissent, displacement, and individual differences. Limitations of this modelling approach are discussed and the case is made for a more comprehensive framework of computational agency to study patterns of design behaviour.

A computational framework of design as a social activity is introduced in Chapter 4. The conceptual model of a multi-agent system is described in detail. This approach is shown to support a rich interpretation of a design system including designer agents (i.e., individuals), populations of adopters and opinion leaders (i.e., field), and a design domain. Some of the mechanisms represented in this framework include processes of social influence, experts' evaluation, learning and imitative behaviour. The system is shown to simulate some aspects that have been related to the definition of creativity and innovation in the literature including: diffusion, gatekeeping, peer influence, prominence, popularity, productivity, and quality.

In Chapter 5 a number of individual and situational variables are selected for experimentation with the agent framework. These two classes of experimental designs are described and results are presented for each experiment. The relationships between variables and the significance of the patterns that emerge from this experimentation are discussed within the particular assumptions of this framework.

Chapter 6 presents discussion of our results and assumptions in view of current knowledge in the field. The aim of this discussion is to provide analyses of our insights that advance our understanding of the problem and serve to reformulate long-standing questions in the area. Published empirical and experimental evidence is used to validate our results. Comparisons with other models are also included in this discussion.

Lastly, conclusions from this approach to the study of creativity and innovation in design are presented in Chapter 7 with short and long term extensions to our inquiry. Responses to controversial issues of this type of research are advanced.

Chapter 2

Background

This chapter presents a review of the literature from a number of complementary areas of inquiry. Current trends in creativity research and innovation studies are analysed. The areas within design research that address these two processes are then reviewed. Next, the enterprise of computational modelling is considered with emphasis on the study of artificial societies. Lastly, an overview of situatedness in creativity is summarised. The chapter concludes with a summary of the main concepts and open questions from this multi-disciplinary literature review.

The term creativity refers to make or bring into existence something new (Liu 2000; Sternberg 2001). Historically, the act of creation has carried theological implications that in contemporary reasoning about creativity still linger (Coyne 1997; Novitz 1987). On the other hand, the present usage of the term *innovation* refers mainly to the diffusion of technological advances. In design, the social ascription of creativity to individual practitioners can be associated to the origins of intellectual property (Fellner 1995), which formalises the evaluation of novelty and appropriateness. Patenting systems reinforce the connection between individual action (invention) and the potential change at the collective level (innovation). Creativity and innovation are fundamental in the practice of *design*, defined in this thesis as the synthesis of graphic, industrial and architectural artefacts.

2.1 Creativity

2.1.1 Definition

Definitions of creativity vary between researchers and across research fields (Cropley 1999; Dacey et al. 1998; Goswami 1999) This background analysis includes studies of creativity as a cognitive, social and epistemological construct. An operational definition of creativity as the precursor of innovation is: *Creativity is a property socially ascribed to individuals that generate solutions considered as novel and useful, and are adopted by members of their society.*

2.1.2 Anecdotal Accounts

The systematic inquiry of creativity is relatively recent and neglected in comparison to the study of other human phenomena (Feist and Runco 1993; Sternberg 1999). Anecdotal accounts were an early approach to understanding creativity (Poincaré 1914; Wallas 1926). They put forward the idea that creative processes follow a series of stages, of which 'illumination' accounts for the exceptional time at which a solution is made conscious (Roskos-Ewoldsen et al. 1993). The framing of these stages does little more than suggest that ideas that are considered creative require motivation, learning, hard work and a degree of serendipity. However, these requirements are desired for good performance in general and fail to characterise creativity. Further, the stages account is not supported by experimental evidence (Weisberg 1993), which suggests that different types of motivation, knowledge and intelligence affect creative behaviour in contradictory ways (Eisenberger and Rhoades 2001; Hennessey and Amabile 1998; Houtz 2003; Niu and Sternberg 2001).

A further widespread account is the isolation of creative/routine brain hemispheres. This idea implies that brain activity associated to creative behaviour is processed in the right hemisphere, whilst analytical thinking takes place on the other half. The empirical evidence simply does not support such specialisation of hemispheres (Fuster 2003; Simon 2001). Today the consensus is that creative behaviour, like most complex cognitive activities, is likely to require the confluence and integration of different brain functions to analyse and reformulate problems, and to generate and examine solutions (Atchley et al. 1999; Katz 1997; Runco 2004).

2.1.3 Individual Focus

The question of creativity -as the more general issue of human agency- is generally approached from two extremes: on one hand, creative behaviour is externalised and 'depersonalised', attributing the renewal of ideas to historical and social circumstances or contingencies, i.e., the *zeitgeist* (Simonton 1999). At the other end, causality is driven inward and is 'dissocialised', locating the determination of behaviour within the isolated individual (O'Sullivan and Haklay 2000; Young 1998). A small number of interactionist views take into consideration both the social nature of behaviour and individual differences (Gruber and Wallace 2001). Nonetheless, the speech by JP Guilford to the American Psychological Association in 1950 is the landmark reference to the beginning of the dominant research approach in the following six decades (Guilford 1950; Runco and Pritzker 1999).

The systematic study of creativity since Guilford (1950) has taken place largely within the realm of psychology (Sternberg and Grigorenko 1997). As a result, a view of creativity from an individualistic stance has dominated. Three main lines of inquiry have contributed to this programme: studies of physiological, cognitive, and personality differences (Runco 1993). These approaches share the assumption that the study of isolated individual characteristics provides the means to distinguish creative from non-creative brains, thoughts, and people, respectively.

Other approaches that fall within these categories and tend to share an individual focus include: clinical, developmental (Runco 1999; Sawyer et al. 2003), psychometric (Eysenck and Eysenck 1985), and historiometric studies (Simonton 1984).

Evidence from these studies remains inconclusive and no universal set of characteristics that consistently distinguish creative from non-creative people, products, or processes has been formulated (Amabile 2001; Simon 2001). Some definitions at the cognitive level tend to conflate creativity with learning, i.e., both are considered to provide new information (Indurkha 1998) and be instances of conceptual expansion (Thornton 2002; Ward 2001). Additional cognitive processes associated to creativity include: defocused attention and oversensitivity (Martindale 1999); associative thought (Mednick 1962); fluctuations in level of arousal (Eysenck and Eysenck 1995); unstructured thinking styles (Finke 1996); analogy (French 1995; Hofstadter 1995); and multiple simultaneous mental representations (Atchley et al. 1999; Martindale 1999).

Other researchers avoid explicit associations to any particular cognitive process and prefer to draw in complementary cognitive skills (Finke et al. 1992; Lubart 1999).

A consistent conclusion from these studies is that creative behaviour requires flexibility and the integration of seemingly different characteristics. The creative personality can be characterised in one word by its ‘complexity’, i.e., the combination of characteristics that are segregated in most people (Csikszentmihalyi 1996). A tendency for broad interests and greater versatility has also been summarised as the difference between highly influential creators and their non-creative colleagues (Simonton 2000; Sulloway 1997). The main conclusions from the study of individual differences can be summarised as:

- 1) The confluence of several brain functions is necessary for creativity (Simon 2001)
- 2) Complementary cognitive processes that enable analysis, reformulation, synthesis and evaluation are necessary for creativity (Finke et al. 1992)
- 3) Creative figures show different personality traits and patterns of behaviour (Gardner 1993)

The individualistic paradigm typically assumes that there are generative processes that yield creative output. This implies that creative value is an inherent property of objects and exists independently of evaluation by other people (Schön 1967; Weisberg 1993). In contrast, an alternative view gaining consensus suggests that ‘nothing is, or is not, creative in and of itself; creativity is inherently a communal or cultural judgment’ (Gardner 1993).

2.1.4 Evaluation

The essence of historical H-creativity (Boden 1995) or creativity with a capital C (Gardner 1993; Runco and Pritzker 1999) is that creativeness is evaluated and negotiated by a social group (Amabile 1983). It is generally agreed that such assessment is based on the combination of objective and subjective criteria that include peer influence, endorsement by experts, productivity, popularity, quality, aesthetic appeal, and other contingent factors (Amabile 1983; Getzels and Csikszentmihalyi 1969).

Whilst social acceptance need not conflate creativity with popularity, the latter can have a strong correlation (Gardner 1993; Simonton 2000). Alternatively, creative solutions or creators that are virtually unknown to the public may receive that ascription by peers and critics. A third criterion is the productivity of the creator (Simonton 2003). These evaluation criteria are central in the ascription of creativeness by the public or by the field. Thus, a measurement of creativity can be established as a function of the number and relevance of evaluators who agree on the ascription (Amabile and Hennessey 1999). Whilst at one extreme is the isolated individual who believes that his or her work is creative (p-creativity), on the other are historical achievements that revolutionise the world (H-creativity) (Boden 1994). Between these ends are solutions considered creative by groups or communities of varying sizes such as the circle of collaborators, the discipline, critics, and across multiple disciplines (Kuhn 1962, 1974). When evaluation is considered in the definition of creativity, it necessarily acquires a cultural and historical dimension (Amabile 1983) as a socio-historical process (Gero 1994), and in the eyes of the beholder (Goldenberg and Mazursky 2001; Navinchandra 1991).

A type of evaluation has been addressed in the psychometric tradition (Mednick 1962; Torrance 1984). However, this approach tends to isolate general individual abilities from the task and measures reasoning styles that may or may not be conducive to creative output in different fields (Amabile 1996; Sternberg 1998). There is no convincing evidence that practitioners considered creative in their discipline necessarily excel on the kinds of divergent and associative thinking skills that are the trademark of such tests (Gardner 1993).

2.1.5 Paradoxes

Some of the paradoxes revealed by studies of creativity include the following:

- 1) Whilst creative ideas are valued by society, obedience and compliance is preferred over behaviour associated with creativity (Hennessey 2003; Raina 2000; Torrance 1965, 1977)
- 2) Creativity requires novelty and utility (Cropley 1999), yet these two criteria are not universal: they are relative to changing standards set by evaluators. What at one moment is considered revolutionary may later be viewed as orthodox (Simonton 2000)
- 3) Novelty is essential but not sufficient to define creativity (Liu 2000). Some ideas are considered creative a long time after their introduction and therefore are not strictly novel
- 4) Although original ideas require freedom, constraints can actually benefit creativity (Partridge and Rowe 1994)
- 5) Creative solutions are often surprising, yet once presented they have a sense of obviousness and inevitability (Cohen 1999)
- 6) New ideas and artefacts tend to be adapted as they mature. High quality may come not from creative solutions but from subsequent modifications (Petroski 1992)
- 7) Creative behaviour is exceptional, yet most researchers and educators agree that it can be cultivated in everybody (Cropley 1999; Csikszentmihalyi and Epstein 1999)
- 8) People that are considered as creative exhibit varying levels of extroversion, productivity and skills (Gardner 1993)
- 9) Creativity is not equivalent to intelligence (Sternberg 2001), yet it is not completely different (Cropley 1999)
- 10) Even practitioners who produce solutions that have been considered creative may fail to do so consistently (Gardner 1993; Simonton 2003)
- 11) The way people are creative across different domains and eras is significantly different (Coyne 1997; Simonton 1998)
- 12) Creativity can be a curvilinear, inverted-U function of education or training; excessive domain specialisation can undermine creative development (Simonton 1988)
- 13) Talent is largely a putative property. Young people who are attributed innate talents are likely to receive the help and encouragement that high levels of competence require (Howe et al. 1999)
- 14) In everyday discourse explanations of creativity are often circular: people tend to attribute exceptional performance to talent and to explain talent by exceptional performance (Howe et al. 1999). To say that what makes a person creative is his or her creativity is a tautology (Csikszentmihalyi 1997)
- 15) Research provides no evidence for innate talent but shows that exceptional abilities are acquired often under optimal environmental conditions (Ericsson and Charness 1995)
- 16) Creative individuals contradict social norms, yet the latter are indispensable to establish the value of new ideas and to regulate their use
- 17) Creativity is present in all cultures, yet it is conceived and valued differently in each culture (Rudowicz and Yue 2000; Westwood and Low 2003)
- 18) Internal motivation generally leads to creativity and external motivation generally goes against creativity (Amabile 1983; Kohn 1999). Yet in some cases, external motivation may actually increase creativity (Amabile 1996; Eisenberger and Cameron 1996)
- 19) Creativity may be unpredictable in respect to the future and subjective in terms of the present; yet it is apparent, well interpretable, and even logical in retrospect (Kryssanov et al. 2001)
- 20) Evaluation is often based on whether a person of ordinary skill in the field would have found a new idea to be obvious. However, it is widely accepted that creative solutions are

surprising because of their obviousness and inevitability once presented (Bruner 1979; Cohen 1999). This is expressed in the typical reaction: ‘of course, why didn’t *I* think of that!’.

Many of these paradoxes suggest complex relationships between components of a complex system that can yield unexpected consequences.

2.1.6 Social Psychology

A general agreement in the field is that individual behaviour is influenced by the environment or the context (Gruber 1980; Kirton 1994; Sawyer et al. 2003; Wagner and Sternberg 1994). However, key debates exist on what counts as the context and the degree of influence (Sawyer et al. 2003). Interpretations range from immediate surroundings to general global structures (Sawyer et al. 2003). In nearly all accounts, context is regarded as an adjunct rather than a constituent of behaviour (Wagner and Sternberg 1994). Alternatively, social aspects of creativity have been considered more than subsequent externalities to the generative process (Amabile 1983, 1996; Hennessey 2003).

One of the leading researchers in this field is Dean K Simonton. His approach consists of historiometric studies where the role of social factors is often considered in the work of creative artists and scientists. These factors include: social reinforcement (1975); competition and productivity (1977); role-modelling (1975); formal education (1976); parenting influences (1976); political and social stability (1975); age and life span (1976, 1980); and domain experience (2000). Other social aspects of creativity investigated in the field include: family structure (Albert and Runco 1990); reward and effects of motivation (Hennessey and Amabile 1998; Maslow 1970; Thomas and Velthouse 1990); affective support (Gardner 1993); authoritarianism (Adorno et al. 1950); evaluation; peer support; and surveillance (Amabile 1983).

Findlay and Lumsden (1988) present an evolutionary framework where creative activity arises from a combination of innate and experiential subsystems. The former is concerned with mental properties whilst the latter with socio-cultural mechanisms. In general, a systems view of creativity (Rathunde 1999) defines creativity beyond personal qualities to include specific socio-cultural contexts. Other ecological models of creativity include the individual, external resources, and the relation between creative and non-creative people (Barron 1995; Harrington 1990). A related approach by Gruber (Gruber 1980; Gruber and Wallace 2001; Wallace and Gruber 1989) develops the intensive, contextualized study of individual cases where social factors influence individual responses and their social impact.

The DIFI framework (Domain-Individual-Field Interaction) by Csikszentmihalyi (Csikszentmihalyi 1988; Csikszentmihalyi 1997; Feldman et al. 1994) locates creativity outside the individual creator and into the interrelations of three main parts of a system: domain, field and individual. The domain consists of the set of shared knowledge, beliefs, techniques, and evaluation criteria shared by the members of a given community (Kuhn 1969, 1977). Fields include groups of individuals who share a common domain. The key implication of the DIFI model is that creativity is not reduced to individual behaviour. Situated in a dynamic environment and in balance between external and personal factors, creative individuals are said to generate ‘the right product at the right place and at the right time’ (Simonton 2000) where ‘rightness’ is largely defined by the society.

Figure 2.1 depicts the DIFI model where creativity occurs in the relationship between the components of a system (Feldman et al. 1994). The individual who does something creative receives information from the domain and adapts to the constantly changing conditions of a particular field. It follows that there is no way to evaluate the creativeness of a generative process produced by a person independent of social validation.

However, as Liu (2000) points out, the DIFI framework resolves the issue of *where* to locate creativity but offers no details of *how* interaction may take place between person, field and domain. In general terms, the domain is assumed to transmit information to the person, the person to produce a variation, and the field to include the selected variation to the domain (Csikszentmihalyi

1990). These mechanisms are analogous to the evolutionary functions of variation, selection, and transmission implying that creativity is an instance of cultural evolution (Boyd and Richerson 1995; Ziman 2000). A cautionary note from Csikszentmihalyi (1990) is that the casual chain is not a linear progression from individual variation to social selection to cultural retention and transmission. Whilst he advises that the system ‘is more intimately connected than that’, no further details are given suggesting that any real understanding of creativity is to come from investigating the interaction among all three subsystems. In a general-systems view of creativity the focus is on the linkages of its components where strong complementarities can be expected (Bossel et al. 1976; Skyttner 2001).

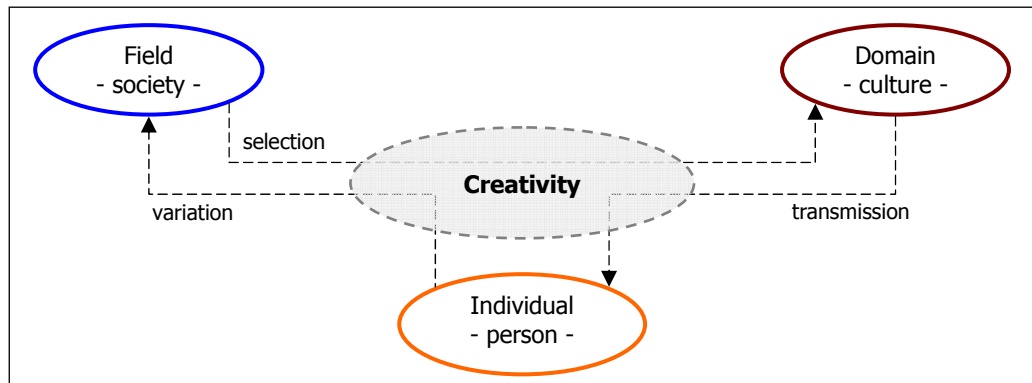


Figure 2.1 DIFI map: creativity as a property of Domain-Individual-Field interaction

At present the most important challenge for the study of creativity is the need for more appropriate methodological tools that enable observation and experimentation of interactions within a complex system perspective where creativity is multi-dimensional and adaptive in nature (Rudowicz 2003; Sawyer et al. 2003).

2.1.7 Towards a Theory of Creativity

The last fifty years of research have been rich in speculation and generalisations only loosely related to empirical evidence and a vague level of theorising (Mayer 1999). The present challenge is to use a combination of research methodologies to move from speculation to specification and explanation (Sternberg 1999). Whilst systems views of creativity in general are promising, its real value will be measured by its potential contributions to a theoretical model of creativity (Amabile 1983). A theory of creativity is not likely to be predictive due to its contingent nature (Boden 1999). Instead, creativity as an evolutionary system is likely to render explanatory theories only (Dasgupta 1994). These theories are expected to account for the dynamics of a socio-cognitive system as a whole rather than the linear relations of the elements (Findlay and Lumsden 1988). These types of inquiry are likely to be advanced by computational simulation (Byrne 1998).

2.2 Innovation

2.2.1 Definition

Innovation is defined in this thesis as a type of social change triggered by ideas or objects adopted by social groups. This adoption process is likely to cause changes in the practices and beliefs of adopters (Fagerberg et al. 2004). The study of innovations centres in the diffusion process, generally of technological developments and public health programmes (Grossman 1974). Diffusion is the process by which adoption increases over time in a social system (Baptista 1999; Freeman and Soete 1997). Two complementary aspects of diffusion are a) the ability of the generator to introduce and communicate new solutions, and b) the response of conspecifics to adopt available solutions.

This definition shows that, particularly from a systems standpoint, creativity and innovation can be difficult to distinguish. In this thesis we adopt the view that they characterise two phases or levels of a continuum of individual and social change.

2.2.2 Unit of Analysis

Innovation studies take the social group as the unit of analysis. The generative process is dissociated from the diffusion process. This is seen in the usage of the term ‘innovator’ in the literature to refer to the initial category of adopters followed by early, mainstream, and late adopters or to those who initiate the spread of a solution rather than its generation (Fagerberg 2003). Diffusion studies analyse the adoption of new solutions but circumvent their synthesis (Baptista 1999; Freeman 1982).

Factors that facilitate innovation include advantage over and compatibility with existing solutions (Petroski 1994), observability, complexity, and testability (Rogers 1995). However, objective features are in general less important than features perceived by adopters mainly originated from those who have adopted the innovation (Rogers 1995). Diffusion proceeds between similar people, i.e., have frequent exchange, share beliefs and opinions, or have geographic or social proximity. However, some degree of difference is necessary to reach across diverse groups as implied in the theory of the strength of weak ties (Granovetter 1973) and by more recent studies of social network structure (Wasserman and Faust 1994; Watts and Strogatz 1998). Connectors or individuals that bridge different groups are considered important to diffusion (Gladwell 2001).

2.2.3 Adoption

Adoption decisions have been characterised by five steps: knowledge, persuasion, decision, implementation, and confirmation (Rogers 1995). A number of studies investigate the role that bottom-up (word-of-mouth) and top-down (mass media) communication play in diffusion (Kautz and Pries-Heje 1996; Proykova and Stauffer 2002). It is widely accepted that top-down communication facilitates initial knowledge about a new solution whereas bottom-up interaction plays a fundamental role in decision and implementation. An important aspect in the adoption decision process is opinion leadership defined as the degree of influence that an individual has over the decisions of others (Bass 1990; Grossman 1974).

Some generalisations of earlier adopters include: they are not different from later adopters in age but have more years of formal education, have higher social status, have a greater degree of upward social mobility, and have larger social units (Rogers 1995).

The opposite of adoption is rejection, which can be active when the decision to not adopt follows evaluation or passive when evaluation does not take place (Rogers 1995). Discontinuance is a type of rejection after having adopted and can be due to replacement or disenchantment (Petroski 1992; Rogers 1995). Consequences of innovations are categorised along three dimensions: desirable versus undesirable, direct versus indirect, and anticipated versus unanticipated (Boudon 1982; Rogers 1995).

The main theoretical foundation in innovation studies is the sigmoid or S-shaped curve of adoption that results when the cumulative number of adopters is plotted over time as shown in Figure 2.2.

The S-shape of the diffusion curve is explained by the rate of adoption taking off once sufficient adopters accumulate and influence the adoption decision of others. Analytical models of the diffusion curve include Bass (1969), Floyd (1962), and Jeuland (1981).

The point at which the process of diffusion takes off has been called the ‘tipping point’ (Gladwell 2001) or critical mass of adoption (Ball 2004). This concept is relative to the cumulative curve shape, i.e., it is identified by an increase of adoption rate.

The point of inflection is defined as the time at which the rate of adoption starts to decay (Mahajan and Muller 1979). Curves of diffusion have been shown to fit symmetrical linear models

(Bass et al. 1994) and non-linear models where influence varies over time (Easingwood et al. 1983).

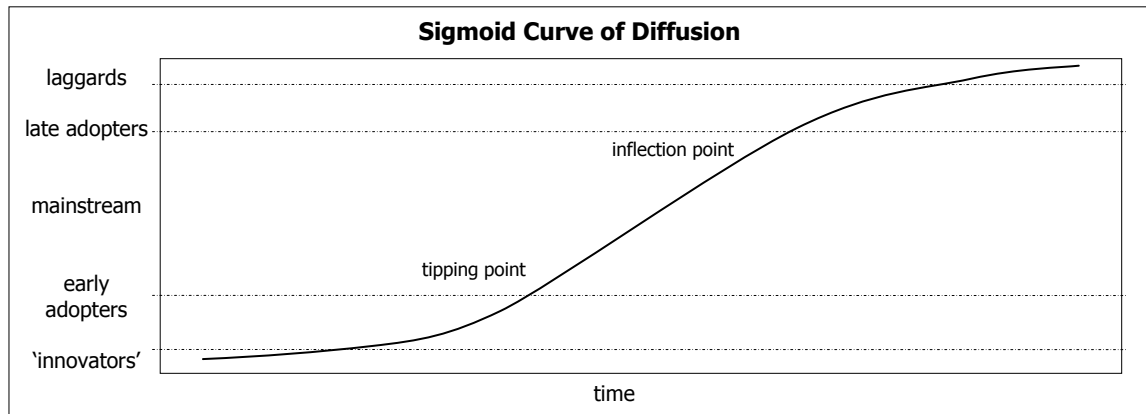


Figure 2.2 The S-curve of cumulative adoption over time. Types of adopters include innovators, early, mainstream, late adopters, and laggards.

2.2.4 Cycles

Early analysis of innovation cycles replaced 'black box' accounts with the notion of competition through innovation as the driving force of capitalist development (Schumpeter 1939). In economic terms, innovation has the function to destroy equilibrium by introducing new products, new production methods and new ways of organisation that increase profit margins by raising the price above the prevailing cost or lowering the cost below the prevailing price (Iwai 2000). As an innovation is introduced and assimilated, it is increasingly imitated by competitors rendering the original advantage obsolete and gradually diminishing the profit margin.

On the other hand, since imitators are likely to improve on the original innovation, economic structures are continually transformed from within, repeatedly creating and destroying advantage (Fagerberg 2003). Routinisation in general occurs when novel solutions are incorporated into regular activities and lose their separate identity (Rogers 1995).

Innovations have been categorised within two ends of a range: continuous improvements characterise incremental innovations, whereas radical revolutions impact across several domains (Freeman and Soete 1997; Helpman 1998). A more detailed categorisation of innovations has been formulated according to the type of motivation (intrinsic vs. extrinsic), the source of implementation (top-down vs. bottom-up), and the challenge (minor vs. major) (Glor 2001).

Figure 2.3 and Table 2.1 show the resulting innovation patterns: reactive, imposed, active, necessary, proactive, continuous and buy-in. Reactive innovation is defined by top-down initiation of change, minor challenge, and motivated extrinsically, i.e., demand or competition. In contrast, proactive innovation is initiated in a bottom-up direction and is intrinsically motivated.

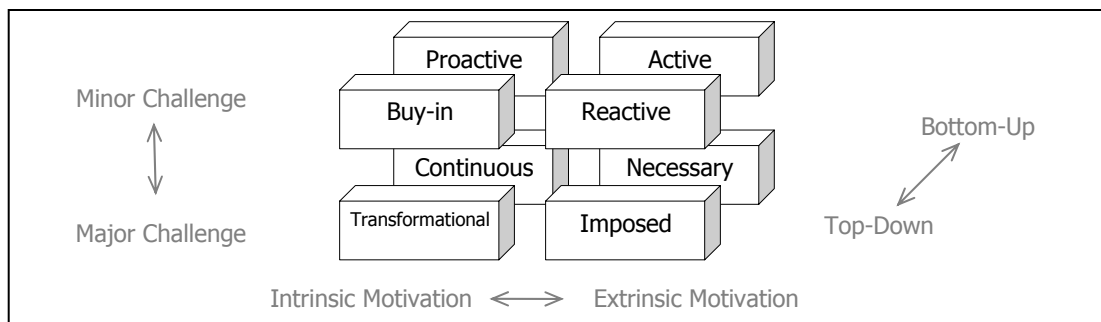


Figure 2.3 Types of innovation (Glor 2001) along degree, direction, and source of motivation to change.

Empirical evidence has been used to distinguish the process of creativity needed for each innovation pattern as a function of number and diversity of ideas (Glor 2001). Table 2.1 shows that combination of extrinsic motivation and top-down implementation with an innovation that presents a minor challenge is characterised as a reactive innovation aimed at solving an existing problem and is assumed to produce few and similar ideas (Glor 2001). Whilst insufficient information is generally available to validate this model, it is an interesting approach to the micro-macro link that calls for further investigation.

Table 2.1 Categories of Innovations (Glor 2001)

Innovation Pattern	Motivation Type	Implementation Source	Challenge	Creativity	
				Number of ideas	Diversity of ideas
Reactive	Extrinsic	Top-down	Minor	Low	Low
Imposed	Extrinsic	Top-down	Major	Low	Medium
Active	Extrinsic	Bottom-up	Medium	Medium	Low
Necessary	Extrinsic	Bottom-up	Major	High	Medium
Proactive	Intrinsic	Bottom-up	Minor	Medium	Low
Continuous	Intrinsic	Bottom-up	Variable	High	Variable
Buy-in	Intrinsic	Top-down	Minor	Low	Low

A key finding in the literature is that innovations need not originate from individual firms or actors in isolation but usually depend on extensive interaction with their environment (Fagerberg et al. 2004). This interaction has been studied in innovation clustering or the emergence of groups of innovations in geographic regions or industrial sectors (Avermaete et al. 2003; Cooke 2001; Gertler et al. 2002) and innovation spillovers or benefits acquired by a firm or a person not responsible for the initial investment (Adams 2002; Cohen 2002; Verspagen and De Loo 1999).

Innovation cycles are not treated as well-defined periods that can be identified by a precise event. Most innovations have a marginal initial impact and go through severe transformations until their full benefits are understood and applied in mature products. These subsequent improvements can be more important than the original solution (Rosenberg 1982).

2.2.5 Towards a Theory of Innovation

With most aspects known about innovation being treated independently, the direction for future research has been defined in the confluence of different multi-level factors of diffusion (Wejnert 2002). A comprehensive theory is likely to explain important aspects of social change (Boudon 1986). Four types of theories of social change can be distinguished by their aim: a) to show the existence of general and irreversible trends; b) to formulate conditional laws or if-then propositions where the condition may describe a system of variables; c) to separate the form from the content of change and address whether change in a field is continuous, discontinuous, linear, or cyclical; d) to reveal the causes or factors of change where change is generally characterised by interdependent actions, reactions and interactions rather than of a cause or even a group of causes. The latter type directly addresses the interaction between individuals and groups, i.e., the ‘entrepreneur’ or change agent and social forces where entrepreneurship is defined as the introduction of novelty into the economic system (Kuhn and Horwich 1993; Schumpeter 1939). Nonetheless, such role is often seen as a ‘necessarily unpredictable and extra-rational activity’ (Langlois 2002).

Rogers (1995) identifies a pro-innovation bias in the literature, i.e., the implication that innovations in general should be adopted by a majority. Due to this bias empirical studies have focused more on rapidly diffusing innovations, more on adoption than on rejection, and more on continued use than on discontinuance.

Changes in the methods of inquiry to overcome the pro-innovation bias include: alternatives to after-the-fact data gathering, i.e., analysis of on-going diffusion processes; to consider unsuccessful innovations; to study rejection, discontinuance, and re-invention; and to include the broader

context, i.e., how an innovation is related to existing solutions and the practices that it replaces (Petroski 1992). These objectives are amenable to computational exploration.

2.3 Creative Design

2.3.1 Definition

Design is defined in this thesis as a social activity in which individuals transform human needs into the specification of physical objects (Rosenman and Gero 1998). The aim of creative design has been defined to innovate, to propose new solutions (Christiaans 1992; Langdon and Rothwell 1985; Walsh et al. 1992). Design relates to human needs directly since it transforms socio-cultural requirements into the description of artefacts. Evaluation criteria are largely socially defined as well. An important aspect of design is to propose new ways to solve these collective problems. For this reason design has been defined as a means to address complex social problems (Rittel 1984) and can be regarded as the link between individual generative processes and collective change cycles.

2.3.2 Individual Level

Studies of creativity in design have inherited the dominant individual focus from the literature. The design process is usually defined in cognitive terms (Cross 1999; Cross et al. 1996; Margolin and Buchanan 1995). Consistent with this view, the outcome of the creative process is the specification of the design artefact (Akin and Akin 1996).

A number of general observations have been formulated in regards to creative design as a cognitive process: the goal and the problem space in design are incomplete (Buchanan 1995); constraints can be nomological or negotiable (Goel 1994, 1995); problem reformulation is required (Getzels 1982); problem decomposition is complex (Goel 1994); limited right or wrong answers but degrees of appropriateness; delayed evaluation and feedback until artefact is constructed and used; no definite stopping criteria (Goel 1994); contradicting requirements (Petroski 1996); requirements need to be reinterpreted (Lawson 1997); designers adopt a solution-focusing strategy (Cross 1990); and problem and solution co-evolve during the designing process (Dorst and Cross 2001; Poon and Maher 1997).

Creative design processes can be distinguished from routine design through the concept of search spaces. Representing design as search, creative design can be defined as the transformation of the existing space of possible designs (Gero 1996). This transformation may add or replace regions of the design space and is equivalent to ‘conceptual expansion’ (Ward 2001). In the new region or subspace a potentially creative solution is initially presented, i.e., a creative exemplar (Kuhn 1970). Subsequent search processes in the new space of possible designs yields further solutions, some of which may be of higher quality than the original exemplar.

This definition captures the paradox that creative solutions are ‘impossible’ to derive from the usual mental processing in the domain (Boden 1994; Ruiz Collantes 2000) or the given problem formulation (Einstein and Infeld 1961).

Design studies have also addressed the relation between generative phases where preinventive structures are built and exploratory phases in which the designer seeks to reinterpret these structures in meaningful ways (Finke et al. 1992). It has been shown that reinterpretation increases when the component parts and the interpretive category are restricted and when the interpretive category is unknown in advance (Finke 1996; Roskos-Ewoldsen et al. 1993). Tang and Gero (2002) observe that novelty and unpredictability increase when cyclic shifts occur between phases. They further use the ratio of preinventive structures in exploratory phases to total preinventive structures as an index of potential creativity.

Technical quality and creativity in design seem to have no significant correlation; however, there is a close relationship between creativity and aesthetic attributes (Christiaans 1992). Whilst

many tools and techniques have been proposed to support creative designing, at present the main open question in the field is understanding (Bonnardel 2000; Fischer 2000; Leiva-Lobos et al. 1997). A general consensus in the field is that more studies of creativity in design are necessary in order to develop a better understanding of how creative design occurs (Dorst and Cross 2001; Edmonds and Candy 1998).

Since creativity is considered to require social evaluation, generative processes can only be said to produce potentially creative solutions. Once generated, design artefacts are evaluated by a series of social mechanisms implemented to reach agreement on what constitutes creative design. Such evaluation mechanisms include patent examination, publications, awards, and competition juries.

2.3.3 Social Level

Research on design as a social process has been scarce (Bucciarelli 2003). At the discourse level the social role of design professions is revised periodically (Jacobs 1962; Margolin and Margolin 2002; Popov 2002; Sommer 1983). The general implication is that beyond aesthetic and physical consequences, design artefacts are part of a social system where different stakeholders interact and where personal and social experiences are importantly shaped by mediating artefacts. In this regard design behaviour can be defined as the task of shaping the physical environment seeking a fit/congruence with the social environment (Popov 2002).

Much of the work on social interactions in design, however, concentrates on the immediate surroundings of the design team, in particular in the investigation of Computer Supported Collaborative Work (CSCW systems) (Rosenberg and Hutchison 1994). The broader impact of artefacts is mainly addressed by studies of sustainable design, life-cycle modelling, and participatory design.

The social dimension of design projects has been analysed under the assumption that product development is an interdependent activity comprise clients, suppliers, venture capitalist, manufacturers, competitors, and critics (Holt and Radcliffe 1991). A 'Social Dimension - Event Scale' framework maps design projects by social complexity (from individual to cultural dimensions) against time scale. Within this framework innovations are located at high levels of social complexity.

A key role of design at the social level is the initiation of innovation (Archer 1999; Langdon and Rothwell 1985). This can occur in different stages of the life cycle of a technology: from the application of new technologies into new artefacts, to the optimisation of layouts, materials, features, resources and production methods. The role of design can be associated to both radical and incremental innovations (Petroski 1992; Walsh et al. 1992). Whilst solving *wicked* problems has been defined as fundamentally a social process, design has been approached comparatively less from a social science perspective than technological innovation or R&D (Walsh et al. 1992).

2.3.4 Design Computing

Computational methods of inquiry in design research can be characterised in three types according to their aim: exploration, modelling and support systems (Gero 1994; Newell and Simon 1976). The aim of computational exploration is not to model specific human phenomena but to build possible systems for experimentation (Simon 1995). These three applications, as most of design research, have a dominant individual focus. In this thesis computational explorations are conducted to understand not so much the inner mechanisms of the individual design process but the linkage between design action and social change.

2.4 Computational Modelling

In this Section prior work on computational modelling is reviewed. The goal of these systems in creativity and innovation can be a) to generate and study possible types of creative behaviour and innovation patterns; b) to model processes observed in human behaviour; or c) to aid human

creativity and innovation. Computational explorations of the first type consist of designing the components of a system and their interactions, and observing response patterns to controlled changes. From these explorations the modeller extracts generalisations or ‘laws of qualitative structure’ (Newell and Simon 1976). As an empirical approach, theorisation proceeds from these qualitative observations supported by experiments and simulations (Nelson 2002; Simon 1995).

Two main approaches in the literature are considered relevant: the exploration of creative behaviour and the modelling of innovation diffusion. Within the former, computer models inherit a focus on generative processes and leave evaluation outside the system, generally by human observers who speculate whether ‘computers can be creative’ according to criteria external to the system itself (Boden 1994; Bringsjord and Ferrucci 2000; Hofstadter 1995). Within the latter approach, computational models aim to reproduce innovation phenomena from case studies.

2.4.1 Models of Creativity and Discovery

2.4.1.1 Generative Models

Early computational explorations aimed at understanding the creative process were developed by Newell et al (1964), Bradshaw et al (1983) and Langley et al (1987). Given all the necessary domain data and appropriate heuristics, these programs replicate the scientific discovery of laws from the history of physics, mathematics, and chemistry. These types of programs use search heuristics to reproduce known scientific rules or to find new and interesting proofs and numeric sequences (Colton 1999). The human developer intervenes in these systems by formulating the problem, representing data, designing the heuristics, and selecting and interpreting the output (Csikszentmihalyi 1988; Langley 2002).

This line of research is now circumscribed to the fields of machine learning and knowledge discovery (Langley 2004). Some lessons from this approach include: insufficient quantity and quality of explicit data is available; explanatory rather than descriptive models are needed; and support systems are preferred over automated systems (Langley 2000).

A similar argument is found in other automated generative processes. Some authors discuss the possible creativity of systems such as the painting program Aaron by Harold Cohen (Holtzman 1994; Kurzweil 1999; McCorduck 1979). Cohen himself acknowledges that this process is not creative inasmuch as all domain knowledge and heuristics remain as determined by the developer, i.e., no self-modification occurs (Cohen 1999). Analogy-making programs such as Copycat (Hofstadter 1995) and Tabletop (French 1995) address the role of reinterpretation or *slippage* as probabilistic categorisation (Mitchell and Hofstadter 1991). The claim that unusual responses from these types of systems ‘can actually make people laugh’ (Hofstadter 1994) could imply that they pass a kind of Turing test of creativity (Bringsjord and Ferrucci 2000). However, the alleged creative process belongs to the developer who defines and implements an unchanging code that supports possible slippages or combinations.

2.4.1.2 Generative-Evaluative Models

Saunders (2002) proposes a model of curiosity as a heuristic in design. This model incorporates evaluation and generation of novel solutions in groups and supports bottom-up emergent structures such as clique formation. Generation and evaluation in this model are implemented at the individual level with no explicit representation of collective structures. As a consequence, no second-order emergence is possible and sociality remains an external notion construed by the observer (Conte et al. 2001; Sawyer 1999).

Macedo and Cardoso (2003) build a model of expectations and surprise as a tool to investigate the role of knowledge in creativity. They include creator and jury agents and define creative agents as those which generate designs that are beyond the expectations of other agents. Creator agents with diverse knowledge sets are said to generate more surprising designs for jury agents with small expectation sets.

Heck and Ghosh (2000) analyse a type of creativity in a simulated ant colony. They consider strategies that optimise foraging as creative because ‘they cannot be deduced from applying logical reasoning to available knowledge’. Notwithstanding the inaccuracy of this definition against current knowledge in creativity research, this modelling approach demonstrates that populations where a few insects have exceptional behaviour perform better as a whole (i.e., find more food sources more rapidly) than populations where all insects share a simple foraging rule, although at the expense of more resources. This is consistent with the high fitness of heterogeneous populations where a few individual learners and a large majority of non-learners or imitators collaborate (Boyd and Richerson 1995).

2.4.2 Models of Innovation

Economic aspects of innovation have been extensively modelled computationally (Nelson and Winter 1982). Models of evolutionary economics seek to investigate the role of innovation as the source of growth and increased productivity (Andersen 1994). Other approaches address sociological (Gilbert et al. 2001) and geographical aspects of innovation (Baptista 2001). The modelling of knowledge diffusion (Haag and Liedl 2001) and contagion (Lynch 1996) have also contributed to a better understanding of the diffusion process.

A common goal in the literature is to reproduce stylised facts from empirical research such as lock-in situations (David 1985; Leydesdorff 2001), innovation networks (Ahrweiler 1999; Camagni 1991), path-dependence (Kenney and von Burg 1999), interdependencies (Frenken et al. 1999), spillovers (Cohen 2002; Giese et al. 1983; Silverberg and Verspagen 1994), knowledge disclosure, emergence of dominant designs (Baum et al. 1995), and increasing returns (Prendergast 1992). The predictive power of this approach is consequently used to formulate national and regional policies of R&D investment, product life cycle (Pajares et al. 2003), and demographics (Axtell and Florida 2001).

The dominant modelling paradigm consists of describing an equilibrium state, dynamic or stationary, and to characterise patterns of perturbations using rational agency. However, a more realistic alternative is under development where agents do not have a perfect understanding of the environment and do not share a common and consistent set of beliefs (Castelfranchi 1998, 2003; Sargent 1993).

Various techniques are used to implement this empirical alternative including genetic algorithms, neural networks, classifier systems, cellular automata, and agent systems. These methods address patterns of innovation in complex environments, i.e., with multi-dimensional and non-linear interactions.

Of particular relevance to this thesis are previous work on cellular automata of innovations (Leydesdorff 2000; Moldovan and Goldenberg 2004) and multi-agent systems of diffusion (Teitelbaum 2000). Whilst no single modelling approach captures all the dimensions and stylised facts, these methods support comprehensive models that deal with innovation as a complex dynamic system.

In static models, adoption preferences, artefact characteristics, and costs do not change over simulated time (Marimon et al. 1990). In contrast, in dynamic models of innovation the central problem is how agents with changing and imperfect information organise (Dosi et al. 1988). The former case is predominant and assumes that changes in the environment are exogenous (Silverberg and Verspagen 1994).

Only more recent co-evolutionary models consider selection as endogenous in order to examine the interaction of actors and environment (Windrum and Birchenhall 1998). Simulation models that explore co-evolutionary dynamics assume that the generation of new products is shaped by consumer choices (Hirooka 2003). In turn, consumer decisions are based on preferences that are not fixed but change and evolve over time in response to new products.

This portrayal of innovation as a coupled, second-order learning system provides alternative explanations to some diffusion phenomena, i.e., dominant designs are a convergent outcome of the

system but different conditions yield a process of market differentiation leading to the emergence of niches (Windrum 1999).

2.4.3 Artificial Societies

One way to study how complex phenomena emerge from interacting individuals is to build exploratory computational models that contribute to our understanding by analogy. Simulation is of particular relevance as a tool to build hypotheses and discern patterns of behaviour in the social sciences (Hegselmann et al. 1996).

Social simulation aids intuition by analogy with artificial societies, i.e., *in silico* laboratories where certain social structures are reproduced in the computer with the aim to discover the interaction of local or micro mechanisms and collective or macro structures of interest (Epstein and Axtell 1996).

Agent societies have been used as an experimental research method *in silico* in recent years (Gilbert and Doran 1994; Suleiman et al. 2000). This approach aims to capture the micro-macro relation between individuals and groups by describing the behaviour of the former and observing the resulting emergent structures in simulated time. The method reveals patterns in the ‘growth’ of the structures of interest (Epstein and Axtell 1996). The origins of this modelling approach are found in *Artificial Life* (Langton 1989) where insect colonies that exhibit a form of collective intelligence have been extensively modelled.

In extending the multi-agent paradigm to the modelling of societies of more complex individuals (such as humans), key assumptions have been kept including individual causation of behaviour and bottom-up emergence (Schelling 1971). However, the need to model behaviour causation in more detail and to account for circular and lateral emergence has been stressed recently (Castelfranchi 1998, 2001; Conte et al. 2001). The main reason to account for explicit group structures is that they are assumed to feed back into individual behaviour in circular or second-order emergence (Gilbert 2002). Thus, individual behaviour is seen as a function of internal representations and emergent social structures.

A set of techniques to represent agent societies are social networks (Wasserman and Faust 1994). Networks represent individuals as nodes and their relations as links (Hanneman 2001; Rogers 1979). Modelling of diffusion in social networks has addressed the effects of phenomena including centrality and link directionality (Buskens 1999), group cohesion (Young 1998), and external influence (Valente 1996).

Computational simulation of artificial societies is considered appropriate when the target system is complex, there are important non-linearities between variables, and there is interest in the dynamics of the system (Bainbridge et al. 1994; Conte et al. 1997; Gilbert and Conte 1995). This approach aims to extract general principles or patterns from observing and manipulating the system (Holland 1995).

The main concepts in the study of complex adaptive systems are: adaptation, the process whereby an organism fits itself to its environment; aggregation, the development of large-scale behaviours from the aggregate interactions of less complex agents; emergence, the formation of properties at one level by the combination of qualitatively different properties at a different level (Gilbert 2002); and nonlinearity, i.e., the end value for the whole is not equal to the weighted sum of its parts.

2.5 Situated Behaviour

In order to approach the study of individual action embedded in a social setting, this Section reviews situated cognition (Clancey 1997) and social situatedness (Ross and Nisbett 1991). Situated cognition has been defined as knowledge that develops ‘as a means of coordinating activity within activity itself’ (Clancey 1997). Situatedness emphasizes the role of interaction and

context, i.e., organisation of behaviour is considered an emergent result of the dynamics of a system (Grosjean et al. 2000). A basic formulation of situatedness describes behaviour (B) as a function of the individual (I) and its situation (S), i.e.: $B = \{I \cdot S\}$ (Lewin 1935). Current debate centres on the relative contributions of individual and situated or situational factors in determining behaviour (Malle et al. 2000).

The assumption underlying situated behaviour is that ‘what really matters is not who you are, but where you are’ (Waller 2002) and similarly ‘where you are when you do what you do matters’ (Suwa et al. 1999). Research evidence consistently illustrates the power of the situation in influencing behaviour (Argyle et al. 1981; Asch 1955; Clancey 1997). However, not all situational factors can be considered as determinant, sometimes their predictive power can be small when compared to individual differences (Ross and Nisbett 1991). As a both-and framework, situatedness implies that to define individual behaviour, one must consider the process by which the individual perceives the situation (Clancey 1997).

The importance of situatedness in the study of creative behaviour can be summarised by the observation that normal reaction to an abnormal or exceptional situation yields exceptional behaviour (Ross and Nisbett 1991; Waller 2002). The Fundamental Attribution Error (FAE) indicates that people tend to overestimate the role of individual traits and underestimate the importance of the situation and context when interpreting other people’s overt behaviour (Fein et al. 2001).

The study of situational factors may indicate details of the immediate and the broader social context within which people that receive the ascription of creativeness operate. Such factors would make seemingly exceptional actions less exceptional, and more congruent with ordinary behaviour (Ross and Nisbett 1991; Simon 2001).

Suwa et al (1999) call for a computational study of situations in design by replacing the prevailing static world view of computational models with behaviour in context so that it occurs as a function of how the situation is individually constructed by agents. Moreover, Gero (2002) define S-invention or S-creativity (situated creativity) as the discovery of ideas during the design process which are not expected before the process commences. This type of creativity is novel within a particular situation. More research is necessary to understand a) what defines a design situation at the immediate and more distant levels, b) what situational factors support S-creativity, and c) how S-creativity works not only in the generation but in the evaluation of objects and ideas.

In design two types of situated behaviour are of relevance. On one hand there is interaction with a physical environment during the process of designing (Gero 2004). The environment consists of knowledge, and design tools such as sketches and models. On the other hand, the designer interacts with a social environment both in immediate settings as part of a design team and at a general level as part of a social system.

The Thomas Theorem is often cited to summarise the significance of situated behaviour: “If people perceive a situation as real, that situation is real in all of its consequences” (Cosser 1977; Thomas 1951).

2.6 Summary

An open research question is how creativity takes place within a system, i.e., what are the mechanisms that determine the role of individuals, fields, and domains. As important as the isolated characteristics of these components is the nature of their interaction.

Creativity studies have contributed insights and hypotheses about the creative process, person, and product. Innovation studies have helped understand phenomena at the field and the domain level, i.e., how diffusion occurs, how knowledge is spread, enlarged and revolutionised. What is missing is an understanding of the micro-macro link.

Computational modelling presents advantages for experimentation. Figure 2.4 summarises the background analysis presented in this chapter. Main references are included for each component of the system: individual, field, and domain.

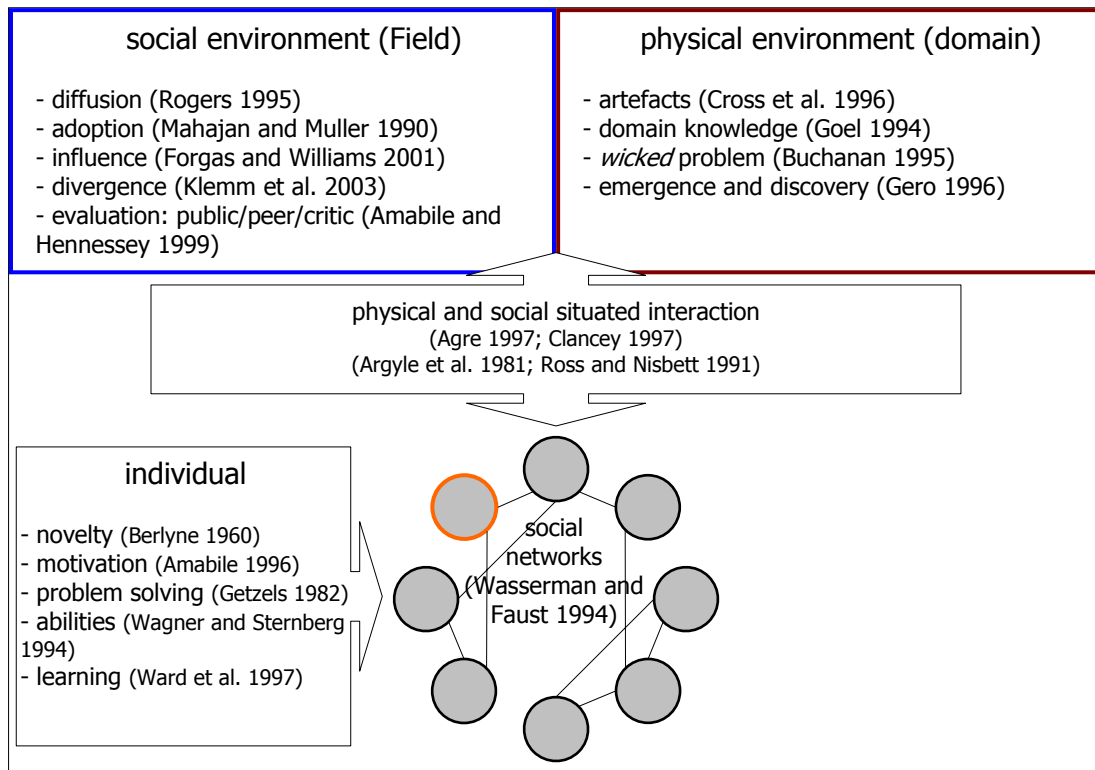


Figure 2.4 Social and physical situatedness in design applied to a systems view of creativity.

Chapter 3

Social Influence and Divergence

This chapter presents an introductory exploration into the principles of innovation diffusion and change agency. The aim is to build and experiment with the simplest possible framework that captures qualitative properties of design as a source of social divergence. The approach is based on cellular automata modelling (CA) of social interaction due to the clarity with which simple rules simulate complex collective phenomena. The models presented in this chapter are simple -all are described in a few instructions- yet they yield interesting patterns of collective change. In following chapters the findings suggested by these results are further explored under a more comprehensive modelling framework of socio-cognitive design agency.

3.1 Social Simulation

The computational simulation of social phenomena has received special emphasis during the last decade (Conte et al. 1997; Gilbert and Doran 1994; Suleiman et al. 2000). A primary modelling framework is cellular automata (Axelrod 1997; Cowan and Jonard 2004; Goldenberg and Efroni 2001; Moldovan and Goldenberg 2004).

3.1.1 Cellular Automata

Cellular automata (CA) is one of the simplest simulation tools for the study of social systems (Nowak and Lewenstein 1996). CA are dynamical systems that provide a formal framework for investigating the behaviour of complex systems (Von Neumann and Burks 1966). CA operate on a uniform regular lattice, i.e., a finite grid structure of two-dimensional points that have the same kind of relationship to other points or neighbourhood. Points or cells in a lattice have one of a finite number of states, typically binary. The state of cells is updated through a number of discrete time steps according to a local uniform and deterministic rule, i.e., based on the states of neighbouring cells. In a typically rectangular lattice neighbourhoods are generally Von Neumann or Moore, formed by the four or eight adjacent cells in the lattice respectively. In CA of social systems the set of cells is called a *population*.

One of the strengths of CA is their flexibility. Lattices can be n -dimensional, cell states may be represented by real numbers, and update rules may contain assumptions about interacting individuals as different as magnets and insects. Cells can contain more than one state or can be empty; they can be stationary or move around other cells in the grid. Finally, cells can also present individual differences. It is not hard to see why CA have been considered a universal computation representation (Wolfram 2002). Whilst CA operate on simple rules, their interaction over time is capable of producing a great variety of unexpected behaviours. Emergent collective structures have been applied to the study of physics, economics, biological and social systems.

CA of social phenomena have been used to understand segregation (Schelling 1971), social impact (Latané 1996), and majority formation (Axelrod 1997) amongst other social phenomena (Kennedy 1998). Theoretical aspects of diffusion of innovations have been implemented in CA (Moldovan and Goldenberg 2004) capturing the sigmoid curve of adoption diffusion and word-of-mouth effects.

The ergodicity of 2-dimensional CA (Liggett 1999) is often presented as an analogy of culture formation (Axelrod 1997; Epstein and Axtell 1996; O'Sullivan and Haklay 2000). Although the sources of ergodicity in CA (i.e., recursive random walks) do not account directly for the tendency of humans to form social clusters, interesting validation arguments exist for CA of social systems (Schelling 1971). In particular (Clark 1991) and (Portugali et al. 1994) address validation of Schelling (1971) of segregation patterns in residential areas whilst Laurie and Jaggi (2003) extend the model.

The formation and development of minorities is of special relevance for design research when designers are considered change agents of their societies (Gero 2000). The role of design as a social activity can be seen as the process by which a new value is introduced by an individual or a small group and then be spread through a society that follows local rules, i.e., without centralised coordination.

Creative design can be seen as a source of social change, in particular as the precursor of innovation. At the stage where a new idea or solution becomes widespread, it is said to become a commodity in economics terms. At such point the triggering of a “creative destruction” cycle occurs (Schumpeter 1939; Stein 1997). CA of social divergence have received limited attention in the literature.

The work presented in this chapter is an introductory exploration of the basic principles of innovation diffusion and change agency. Results from a number of CA are presented that capture qualitative phenomena of design as a social divergent activity.

3.2 Convergence

The study of convergence provides a starting point to address the phenomenon of social change. Different types of Ising or voter models (Liggett 1999) have been proposed to explore the problem of social influence and similarity, i.e., “if people tend to become more similar when they interact, why do not all such differences eventually disappear?” (Axelrod 1997).

Given the assumption that in social settings similarity leads to interaction and interaction leads to still more similarity, a CA framework of social influence is used to address the maintenance of group heterogeneity. This assumption of *homophily* is defined as the degree to which individuals who interact tend to have similar opinions (Lazarsfeld and Merton 1954; Rogers 1995). Findings from such models suggest that under certain assumptions, initial disagreement can be a source of polarisation of opinions (Epstein and Axtell 1996). This principle is consistent with empirical evidence (Sunstein 1999).

From a design viewpoint, models of social convergence capture aspects of the diffusion of ideas or objects in a population of adopters. An important question for design is to understand how this process of diffusion is related to the introduction of new ideas. The question is extended from the maintenance of diversity (Axelrod 1997) to the sources of novelty and diversity. In this Section

a number of principles are extracted from a CA of convergence from which extensions to study divergence are formulated.

3.2.1 Experimental setup

The CA proposed by Axelrod (1997) to study homophily is described as a rectangular grid of cells c_n . At initial time cells are assigned a random set of values v represented by integers. The size of this value set V is given by the number of ‘cultural’ features in the model. Following Axelrod (1997), features represent the set of individual attributes that are subject to social influence, whilst traits are the possible values of such attributes. This describes a culture as a list of features or dimensions. For each feature there is a set of traits or alternative values the feature may have. Under this formulation two individuals have the same culture if they have the same traits for each of their features. The degree of cultural similarity between individuals in a population can be obtained as a percentage of their features with an identical trait. Figure 3.1 illustrates cells with random values with 3 features and 10 traits in a Von Neumann neighbourhood.

The dynamics of the model consist of picking a random cell to be active and pick at random one of its neighbours. With probability equal to their similarity, these two cells interact by selecting at random a feature on which the active cell and its neighbour differ (if one exists) and changing the active cell’s trait on this feature to the neighbour’s trait on this feature. A random cell c_i may update a feature at every discrete time step according to the following rules –notation as used by (Axelrod 1997):

- select a random neighbour c_j of cell c_i
- let $G(c_i, c_j)$ be the set of features g such that $(c_i, g) \neq (c_j, g)$
- given the set of common features $c(c_i, f) == c(c_j, f)$ and $G \neq \emptyset$, set $v(c_i, g)$ to $v(c_j, g)$

Namely, the probability that a cell will copy an unequal feature from a random neighbour is given by the number of features they already have in common. This embodies the idea that similar individuals tend to interact and therefore influence each other. The underlying assumption is compatibility. Compatible cells share at least one feature and form a *compatible zone* on the grid within which they influence each other at random. In Figure 3.1 cells c_i and c_j form a zone since they share a trait on their third feature (underlined). Arrows represent potential contact between adjacent cells.

A CA may contain at any time more than one compatible zone, i.e., groups of cells with a probability of interaction equal to zero since $G = \emptyset$. However, the border between cells from two incompatible zones can be broken by the spread of a third *conciliatory* value, i.e., a value that shares at least one feature with each group of cells. Cells with all common features form a *converged region* on the grid. In Figure 3.1 (c_j, c_k) is an incompatible pair, i.e., cells are unable to interact with each other. However, they may become compatible if another neighbour, c_i , passed the trait on its first feature. This conciliatory process can be called ‘ice-breaking’.

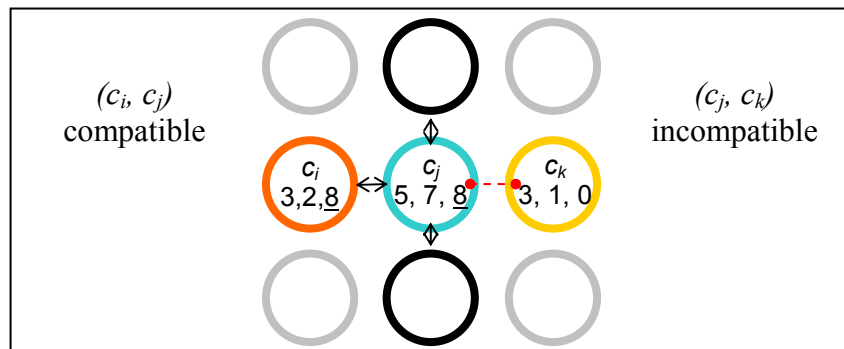


Figure 3.1 Sample CA cells in a Von Neumann neighbourhood with three features and ten possible traits per feature (0-9). The pair (c_i, c_j) is compatible: they share a trait; the pair (c_j, c_k) is incompatible.

CA exhibit Markov properties where the probability matrix expresses the likelihood of every cell to copy a value from its neighbours at every time step. However, an analytical approach to this problem is unfeasible due to the size of the probability matrix (Borovkov 2003). Stochastic modelling is a convenient way to explore the effects of different assumptions in this framework.

The typical grid analysed by Axelrod (1997) is of size 10 x 10 cells. Feature and trait spaces range from 5 to 15, i.e., grids where one hundred cells can have from five to fifteen variables and from five to fifteen possible values on each variable. Cells are typically arranged in Von Neumann neighbourhoods, i.e., they interact with adjacent cells to the north, south, east and west. Moore neighbourhoods are also considered, i.e., a total of eight adjacent cells including those in diagonal directions. Axelrod's model (1997) is implemented in Pascal and Visual Basic; both versions are available on the Internet (Axelrod 2004).

We implement a replication¹ of this CA using Java2 and the RePast library (Collier 2002). Some changes are made in this replication in order to test and explain the observed results. Firstly, the grid map is made a ring torus so that cells on the edges of the lattice interact with the neighbouring cells in the opposite edge. This causes all cells to interact with a constant number of neighbours avoiding potential artefacts along the edges and corners. Secondly, different types of grids are used including square and hexagonal in order to observe potential structural effects. Figure 3.2 shows CA of sizes 10 x 10 and 50 x 50 at initial simulation time. Values are represented by colours to facilitate observation.

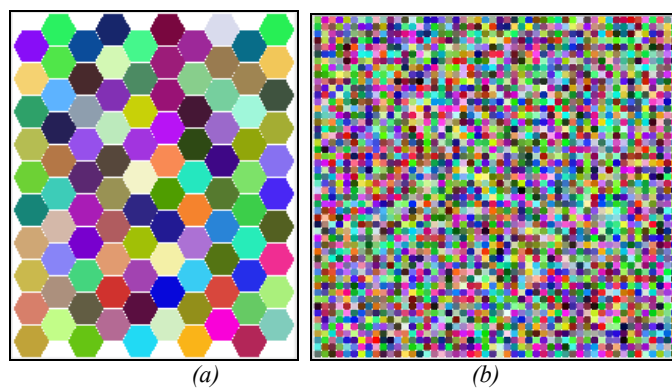


Figure 3.2 Sample CA grids where cell values are mapped into a colour space. Compatible zones are easily perceived by the emergence of clusters with similar colours. Grids are (a) hexagonal 10 x 10 and (b) rectangular 50 x 50

3.2.2 Results

The stopping condition for these simulations is reached when further interaction between cells is not possible. This equilibrium state is reached when all cells share the same value or when incompatible groups of cells can no longer interact. Depending on a number of parameters, the final state of these CA range from total homogeneity to a series of clusters of cells with incompatible values as the end states shown in Figure 3.3. These findings are consistent with similar studies of tag-flipping transmission (Epstein and Axtell 1996).

3.2.2.1 Diversity

Maintenance of diversity occurs when several groups with different values persist at the end of a simulation. Maintenance of diversity is largely affected by initial conditions (Axelrod 1997). When the number of features increases and trait size remains constant (10 traits), homogeneity increases as shown in Figure 3.3a (3 features) and Figure 3.3b (5 features). This can be explained by the

¹ I am grateful to Rob Saunders and Nick Kelly for their valuable feedback and the instructors from the RePast workshop held at the University of Chicago: Nick Collier, Michael North and Tom Howe.

notion that with more features there is a higher probability that the CA consists of one single compatible zone from initial time. However, when the number of possible traits per feature increases (25 traits), heterogeneity also increases as illustrated in Figure 3.3c (5 features) and 3.3d (7 features). The reason is the declining probability that cells have anything in common with their neighbours at initial time. With larger trait spaces, incompatible regions tend to form rapidly given the higher diversity of initial values.

The range of interaction is also determined by local conditions. This is seen by manipulating neighbourhood type from Von Neumann (4 neighbours) to Moore (8 neighbours). Final homogeneity is seen to increase with neighbourhood size. The reason is that when cells are able to interact with more neighbours, more incompatible pairs become compatible through the mediation of common neighbours.

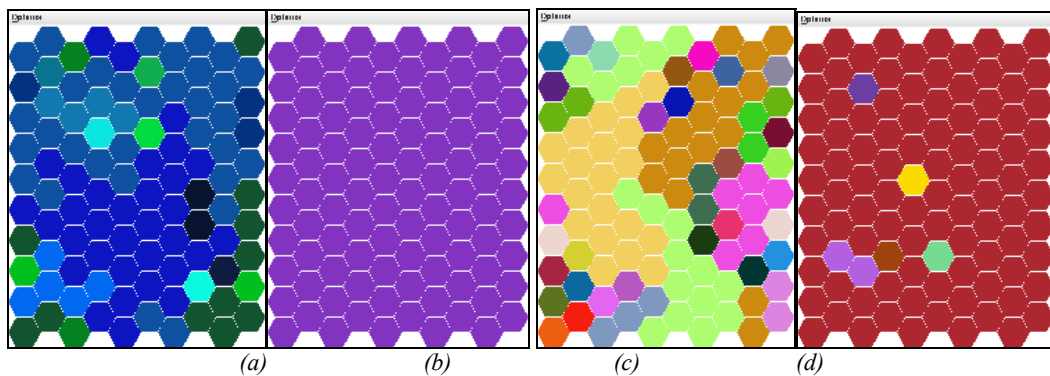


Figure 3.3 End states of typical CA of constant size 10 x 10. In (a) cell values have 3 features and 10 traits. In (b) 5 features and 10 traits typically reaching total homogeneity. In (c) cell values have 5 features and 25 traits, usually ending with high heterogeneity. In (d) cell values consist of 7 features and 25 traits, where only small isolated minorities tend to persist.

The effects of grid size in homogeneity are non-linear. Given a constant value representation, small grids tend to consist of one initial compatible zone, making total homogeneity more likely. In marginally larger grid sizes the probability that incompatible zones form rapidly increases and therefore group heterogeneity tends to increase. However, as grid size continues to increase, extended periods of interaction increase global homogeneity.

The reason for this “counter-intuitive result” (Axelrod 1997) is that in large territories incompatible borders tend to dissolve because conciliatory values have more time to spread across groups. The result is an increase of the process of ice-breaking described in Section 3.2.1 and illustrated in Figure 3.1.

Value structure: how values -such as ideas- are spread through a group - such as a society- is partly determined by their structure. Values or ideas with more elements and variables are expected to take longer time to be spread. However, extended periods of diffusion can facilitate their eventual adoption by a majority. In contrast, values with only a small number of elements are spread more rapidly but tend to be adopted by smaller groups.

To understand this principle consider a new idea that has a binary structure, i.e., expressed as a yes/no choice. Such an idea may be spread easily since it can be perceived and evaluated in a small number of interaction steps between potential adopters. However, such rapid diffusion does not support negotiation, i.e., the creation of common points between initially dissimilar individuals. On the other hand, a new idea that consists of many elements will require further interaction and will take longer to be spread. Extended periods of diffusion support the creation of common points which adopters can gradually share.

If individuals consult more neighbours about adopting an idea, in principle they are bound to consider a wider range of opinions than if they interact with a few neighbours. By combining elements from different views, the likelihood that any two individuals develop similar opinions increases.

Local interaction: the size of local groups within which individuals interact can affect the diffusion of values at the global level. When members of a population tend to interact within larger groups, more global agreement can be expected.

3.2.2.2 Social Structure

To complement these findings, we modify a further parameter of this CA: group structure. One way to do this is to run simulations with a constant number of cells in different grid arrangements. For instance, the following toroid hexagonal spaces are considered: 30 x 30, 90 x 10, and 180 x 5. In these three cases the number of cells is kept constant at 900. At the local level, neighbourhood interaction remains unchanged, i.e., every cell interacts with its four adjacent neighbours. However, as the proportion between width and height of the lattice is changed, so does the degree of separation between distant cell pairs. Degree of separation μ refers to the number of cells between any cell and the furthest cell in the grid. μ is a global condition that can be calculated by the Manhattan or rectilinear distance between grid cells, i.e.,

$$\mu = \sum_{i=1}^n |x_i - y_i|.$$

Where n is the number of grid cells, and x_i and y_i are the values of the i th cell, at points x and y . Whilst the two grids shown on Figure 3.4 have a constant number of 900 cells, degree of separation μ varies significantly. This variation has a significant effect on the CA behaviour.

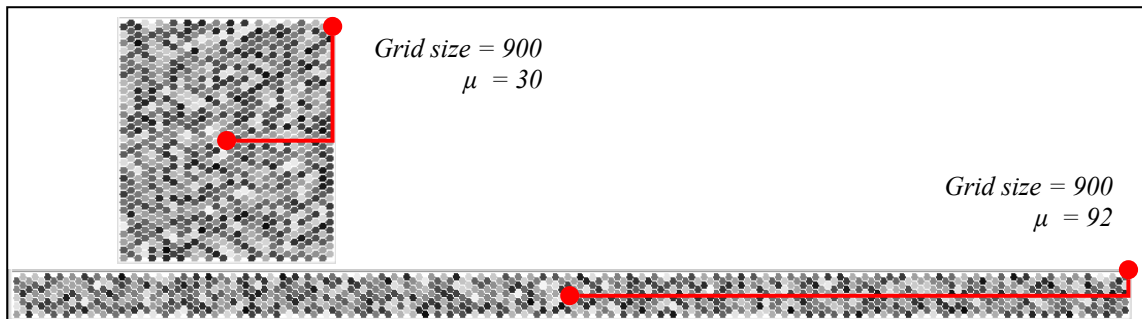


Figure 3.4 CA with constant number of cells (i.e., 900) in different toroid grid arrangements: 30 x 30 and 180 x 5. Degree of separation (Manhattan distance) = 30 and 92, respectively.

Although these CA have the same number of cells, results show that the mean iteration time until convergence and the maintenance of diversity vary significantly, as shown in Figure 3.5. Number of features and trait scope are kept constant at 5. Neighbourhood type is Von Neumann in all cases. Results shown are averages of 100 runs. The results show that simulation time is positively correlated with μ (Pearson = 0.968) as shown in Figure 3.5a. In grids of size 30 x 30, simulations reach the stopping condition at time step 13,500 on average. In grids of size 180 x 5, simulations take a mean of 32,000 steps to reach the end state of convergence. Namely, diffusion in grids of same size but different arrangements may take twice as long to complete.

This result shows that independently of group size, group structure has a significant effect on the maintenance of diversity. In constant grid arrangements, longer interaction periods support an increase of homogeneity as shown in Section 3.2.2.1. However, when μ increases, long interaction periods are positively correlated to diversity. Namely, the higher the degree of separation between

remote cells in a lattice, the higher number of incompatible values form. The key to this apparent contradiction is in the *type* of diversity that degree of separation, μ , promotes, i.e., compatible diversity.

Compatible diversity refers to the continuous generation of similar values by cells that maintain contact but fail to converge to a unique value. Figure 3.5b to Figure 3.5d show that the degree of separation, μ , has such an effect. Whilst a low μ exists in lattices with similar toroid and tunnel ratios, lattices with high μ indicate groups where a ‘bottleneck’ effect occurs. When μ is large, diffusion becomes *aligned* and values advance mostly along one axis. In such conditions cells within compatible zones pass their values and border absorption is unlikely. Alternative values tend to persist, constantly forming new minorities between bordering zones. In contrast, as μ decreases, a dominant value forms that ‘engulfs’ others.

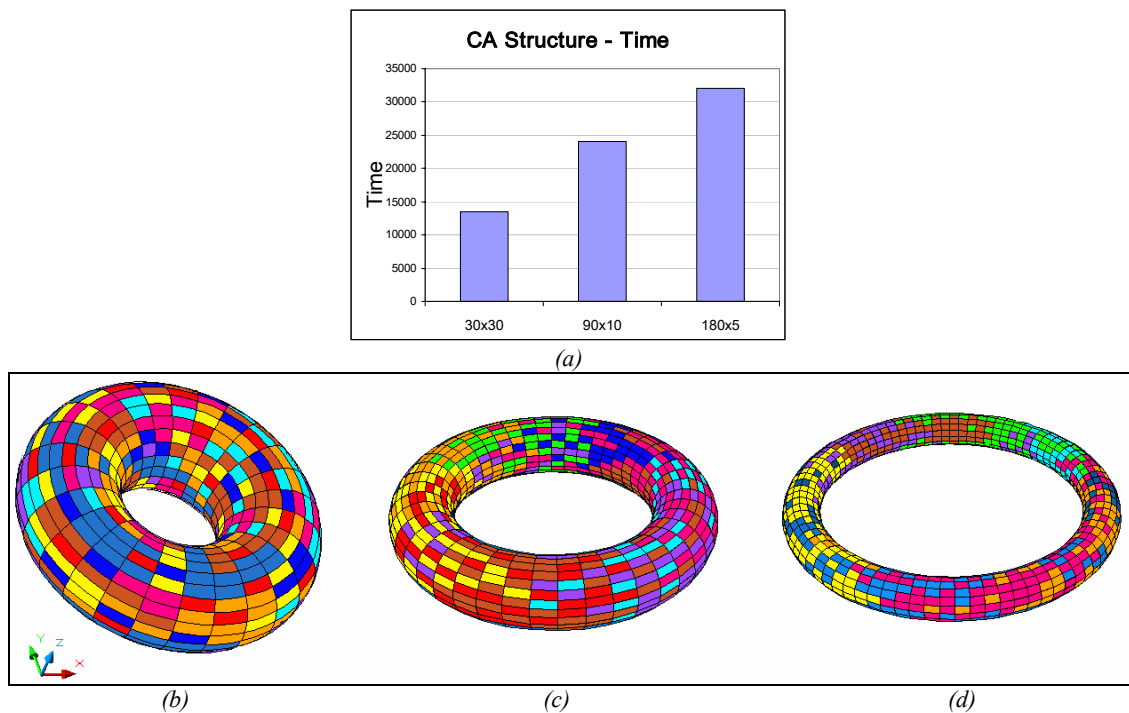


Figure 3.5 Effects of CA structure. Group arrangement affects the patterns of diffusion. Grids with higher degree of separation between cell pairs (a) take longer to converge. Degree of separation is illustrated by ring tori where the radius from the centre of the hole to the centre of the torus tube and the radius of the tube vary: (b) maps the CA grid of size 30 x30, (c) grid size 90 x90, and (d) 180 x 5.

Another way to estimate the structure of this type of CA is by estimating the surface of the ring torus, i.e., $S = \pi^2(R+r)(R-r)$. Where R is the radius from the centre of the hole to the centre of the torus tube or the CA lattice width and r is the radius of the tube or the CA lattice height. But beyond the peculiarities of these representations, these results serve to illustrate the significant effects of the structure of a population on social interaction.

Rather than a particular geometrical representation, social structure can be expressed by the distance between members of a society, i.e., social class, social ties, etc. Social networks are ways of representing such structures (Wasserman and Faust 1994). Diffusion and maintenance of diversity can be expected to be importantly determined by structural conditions at the global level, even if local conditions remain unchanged. The concept of ‘neighbours-of-neighbours’ or degrees of connection in a social network is useful to interpret these results. In a CA where the ‘neighbours-of-neighbours’ are different, diffusion takes place rapidly. In contrast, in CA where more ‘neighbours-of-neighbours’ are the same, diversity is likely to be maintained. This idea of diffusion

and social structure is consistent with the literature (Cowan and Jonard 2004; Reinstaller and Sanditov 2004).

Social structure: Apart from the size of a social group, its structure can importantly determine the diffusion of values. With local conditions constant, increasing the distance between any given pair of individuals (or decreasing the degree of connections) generates an increase of the time needed for the spread of a value.

3.2.2.3 Adoption Curve

During a simulation, the spread of values resembles the sigmoid or S-curve of adoption (Rogers 1995). Cumulative adoption as plotted in Figure 3.6, captures the notion of adopter categories in the literature (Mahajan et al. 1990). In this CA the diffusion process can take different variations of the S-curve of adoption based on the number of features and traits that represent the values. The proportion of early and late adopters and laggards can vary significantly. However, the CA process can be explained in general terms as follows. Initially, cells tend to interact with a few neighbours since only some of them are likely to be compatible. As cells progressively exchange values, compatibility is likely to increase with gradually more cells sharing more values. At a “tipping point” a majority of cells have become fairly similar to each other. Convergence speeds up because at every iteration, cells are likely to exchange values. This process continues until a majority of cells is sufficiently similar, at which point it slows down again since most random contacts tend to generate no value exchange. Most cells have adopted the same or very similar values and only a few remain to adopt. At the final stage, more time per unit of adoption is required until no further interaction is possible either because all cells share their adopted values or because incompatible regions have formed.

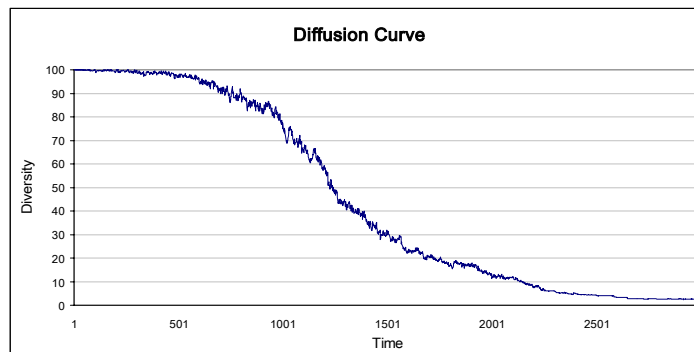


Figure 3.6 Sigmoid curve of adoption. Case with 10 features and 10 traits in a population of 10 x 10 cells. Early adopters slowly converge until step 500, where the process takes off. A majority of adopters rapidly converges until the process slows down around step 2000. Laggards take a further 1000 steps to adopt.

3.2.2.4 Tipping Point

The term *tipping point* is defined by an increase of adoption rate in the sigmoid curve of diffusion (Section 2.2.3). It can be characterised as the time at which a sufficient number of early adopters have created the conditions for the rapid spread of a value through a large majority of the population (Gladwell 2001). Depending on the structural characteristics of the diffusion value, the shape of the curve of cumulative adoption varies. These variations demonstrate that depending on the diffusion value, the proportion of adopter categories and hence the tipping point may vary considerably. Figure 3.7 illustrates how the feature and trait spaces can determine the tipping point. The trends in Figure 3.7 are variations of the general S-curve of diffusion obtained by Monte Carlo simulations traversing the feature and trait spaces in gradual increments. Each trend is averaged over 30 runs of a 10 x 10 population.

In general, in the diffusion of values composed by a larger number of features and traits, the tipping point occurs at a later stage than with less complex values. Upon closer inspection, the tipping point is more sensitive to feature than to trait length, i.e., increasing the number of features holds up the tipping point to a greater degree than increasing the range of possible traits per feature. Namely, with constant number of traits, Figure 3.7a (5 traits) shows that values with more features take a considerably longer mean period to converge. In Figure 3.7b the number of features is kept constant at 5 showing that larger trait lengths cause higher global diversity. Figure 3.7c and Figure 3.7d replicate the two previous cases but increasing the constant to 10 traits and 10 features, respectively. The combination of high number of features and low number of traits promotes rapid and far-reaching diffusion.

Value structure and tipping point: one of the factors that determines the ‘tipping point’ in diffusion can be associated to the structure of the value being spread. In general, the tipping point of values with more elements and variables (i.e., more complex) requires a higher proportion of early adopters. Early tipping points can be associated to values with a small number of variables that are rapidly spread but need not reach a majority.

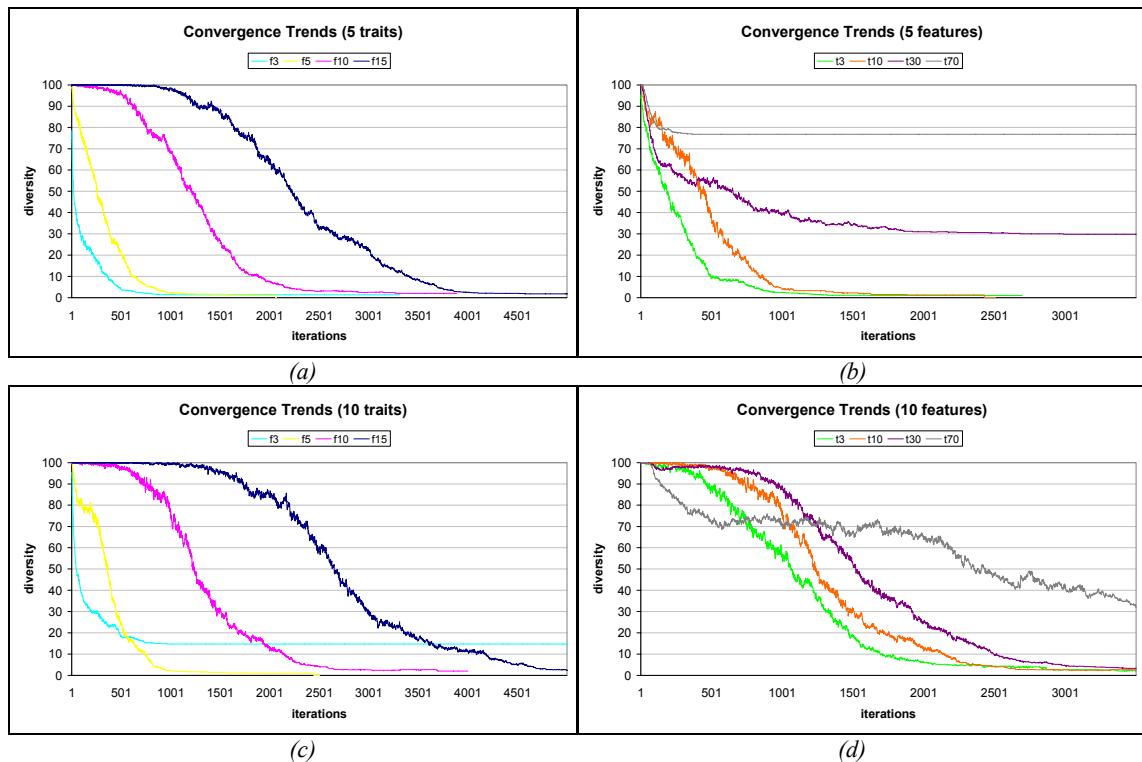


Figure 3.7 Variations of the S-curve of diffusion obtained by traversing the feature-trait space. Changes in the number of features have a large effect of the proportion of adopter categories and the “tipping point”. Changes in the number of traits per feature have a lesser impact. The impact on curve shape can be seen in (a) and (c) where features are manipulated from 3 to 15 with a constant number of traits of 5 and 10, respectively. In contrast, varying traits from 3 to 70 with constant number of features has a lesser impact as seen in (b), 5 features, and (d), 10 features.

3.2.2.5 Intrinsic Divergence

At initial simulation time, the diversity of a population approaches its size, i.e., a grid of 100 cells tends to have about 100 different values or diversity ≈ 1.0 at the outset. All diversity could be assumed to be introduced by the initial random assignment of values. Once the system starts, since

it tends toward global convergence, it may be assumed that diffusion is a process where diversity constantly decreases, at some times steadily, at others rapidly. However, the convergence trend shows a fundamental source of divergence in diffusion. Namely, the curve surface is jagged and consists of small up-down variations that show that cells in fact generate new values by combining some of their features with those from their adjacent compatible neighbours. This is a type of crossover process that shows that the generation of diversity is not limited to initial value assignment but also occurs during a simulation. Under sufficiently large feature spaces, intrinsic divergence can have significant effects.

Figure 3.8 plots three variations of a 10 x 10 population with a varying trait length. Results are normalised over 30 simulations with a constant number of 10 features and 3, 40, and 70 traits respectively. In these cases intrinsic divergence generates a global increase of diversity at the initial stage of diffusion. These protrusions of divergence appear when the value space is sufficiently large to support crossover but sufficiently small to still sustain the formation of large compatible zones.

Intrinsic divergence: when significant individual differences exist within ‘still-compatible’ social groups, the diffusion of a value through a population can be the source of significant variations to the original values. Initial differences encourage interaction (i.e., negotiation) and the production of diversity as common points. But when initial differences are too high, the process of communication breaks down.

In larger value spaces the population tends to global heterogeneity, i.e., converge rapidly to a number of incompatible zones. In smaller value spaces generation of diversity is marginal. But within these extremes, there are potential global-level effects of aggregate crossover as a source of divergence-within-convergence. In particular, given the appropriate value structures, intrinsic divergence can make the final outcome quite unpredictable given the high rate of new values.

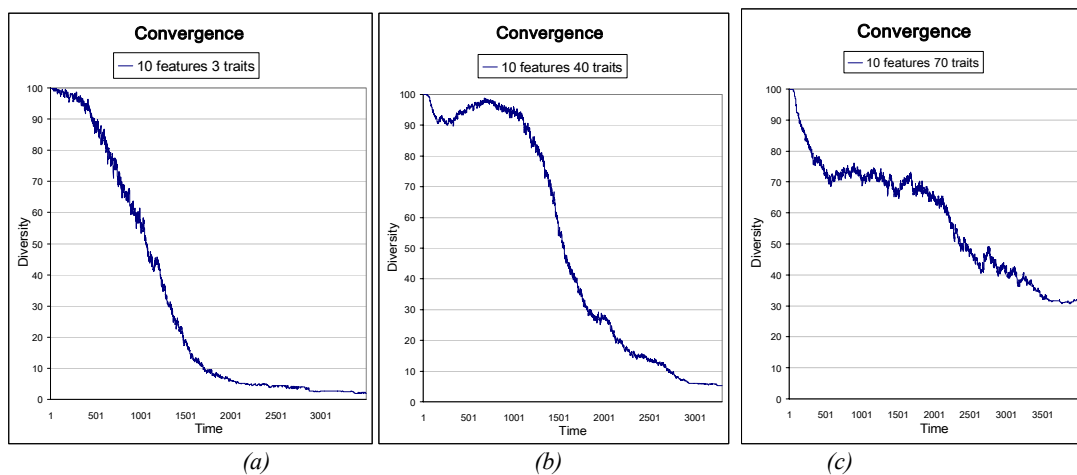


Figure 3.8 Intrinsic generation of diversity during a convergence trend with sufficiently large value spaces. (a) more similar initial values generate marginal diversity; (b) ‘similar but different’ initial values support interaction and the creation of new values; (c) very different initial values prevent interaction. In (a) the tipping point occurs early and a majority rapidly adopts very similar values. In (b) initial values need to change considerably in order to be spread. In (c) cells rapidly form small groups and further interaction is not possible.

3.2.2.6 Minorities

In this CA a minority is defined as a small proportion of the population that holds a different set of values from a dominant group. As noted earlier, the formation of minorities can be determined by

global properties such as population size and structure, by local properties such as neighbourhood type, and by properties of the diffusion values such as feature and trait length. Minorities can be compatible with the mainstream group or can be isolated with virtually no influence over and from the majority. When minorities are compatible, the larger group is more likely to ‘eat’ or convert the smaller group than the other way around (Axelrod 1997). In a CA the demise of minorities can be defined more formally by the differential probabilities of absorption at the boundaries (El-Shehawey 2000). Under most conditions this stage of the diffusion process where laggards eventually convert takes a long time to be completed as seen in Figures 3.6 to 3.8. As shown below, this turns out to be a key factor in the potential of minorities to influence their groups.

Figure 3.9 illustrates the intuition that a majority region tends to absorb the smaller region in a CA conveying the idea that a small group would inevitably be absorbed by a larger cultural group - or remain isolated if incompatible. This principle makes the spread of new values within a formed social group highly improbable. The role of design can be assumed as a minority that triggers social change.

Minority absorption: In the diffusion process, a compatible minority is likely to be absorbed by an adjacent majority. However, the contrary seems to occur in instances where a minority triggers a social change such as in the role of designers as change agents.

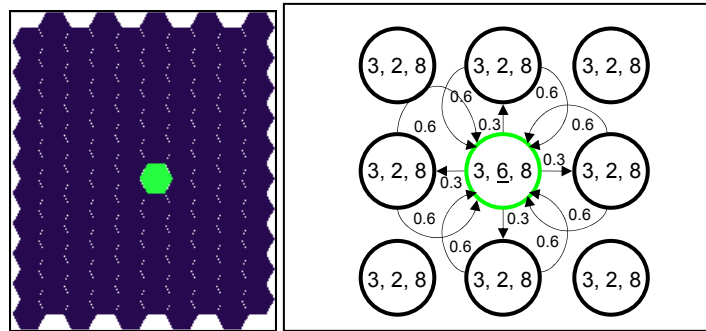


Figure 3.9 The diffusion process creates minorities in a population. When minorities are compatible, they are likely to be absorbed by adjacent majorities as shown in this CA of size 10 x 10 with 5 features and 5 traits.

To assess the role of minorities, a series of experiments are devised where all cells on the CA lattice are initialised converged to the same shared value except for a minority to which a random trait is assigned to a random feature as illustrated in Figure 3.9. Simulations are run on CA of size 10 x 10 with constant feature and trait length and fixed random seed.

From these initial conditions, two experimental settings are set as follows: where the minority at initial time is made by one single cell and where it includes two adjacent cells. The particular location of dissenting cells is not significant due to the toroid structure of the space. These simulations are run 1000 times registering the number of episodes where the entire population changes as a result of the minority value being spread across the grid. Results are normalised over 10 runs for each experiment. The minority of one cell triggers a global change with a mean probability of 0.011. When the minority group consists of two adjacent cells, this probability increases linearly to 0.021. This demonstrates the potential of an individual to trigger a global change.

Next, the effects of value structure are considered. Feature length space is traversed in Monte Carlo simulations in these two cases. Experiments are run with a constant trait value of 10 and features from 2 to 10 in increments of 2 and from 10 to 60 in increments of 10. Interestingly, the number of change episodes shows no significant correlation to the number of features. This may seem counter-intuitive since it may be expected that values with less features would spread easier

than more complex values. However, the reason becomes clear when we plot the number of iteration steps that successful diffusion episodes require.

Figure 3.10 plots the linear increase of time and number of features in cases where minorities consist of one or more cells. The number of features does not affect the number of takeovers or global change episodes. However, feature length does affect the mean time length for every episode of global change. The reason is that as the feature space increases, minorities become more ‘resilient’. Namely, the probability of triggering a global change decreases but the same occurs to the probability of being absorbed by the majority. In principle, the complexity of a new value need not determine its eventual diffusion; however complexity does impact the expected diffusion time. These results suggest that even in large CA grids a minority of one cell is able to spread a value.

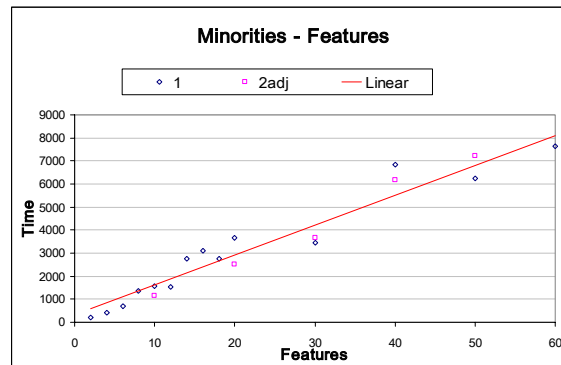


Figure 3.10 Mean time that a minority value takes to be spread through a population plotted against number of features. As value complexity increases, so does the time to convergence which shows their diffusion resilience, i.e., more complex values are as likely to be spread as less complex, but take longer.

Influence of minorities: With a low probability, a minority is able to trigger global change merely by aggregate bottom-up convergence. This occurs independently of group size and value structure. Even new values with many components can be spread since they become more resilient, although they require longer interaction periods.

3.2.3 Discussion

The CA study of social influence and convergence points to factors that affect how social groups form by a decentralised bottom-up process of diffusion. The local interaction of similar neighbours generates different levels of global homogeneity and heterogeneity. However, societies are dynamic systems that cannot be assumed to reach equilibrium states as implied by the stopping conditions of these CA. Whilst principles of convergence illustrate one aspect of social organisation, it is necessary to consider the corresponding force of social divergence. The next obvious question is how to explain the role of diversity in the transformation of social groups or ‘social drift’, a task considered as non-trivial (Axelrod 1997). This is fundamental to understand the role of design as a source of social change.

3.3 Divergence

In this Section the CA framework of social influence is extended to investigate principles of divergence and collective change. The focus is shifted from the bottom-up formation to the bottom-up transformation of groups, i.e., ‘social drift’. In general, these CA are initialised from a converged state where all cells share a common value. Rather than defining a stopping condition, these simulations are run for arbitrary periods within which the effects of different assumptions are

assessed. The objective is to understand the factors that affect the occurrence of social change during a given time length and under control conditions.

From a design point of view, the emphasis is on the conditions under which collective transformations triggered by an individual or a minority are likely to occur.

3.3.1 Experimental setup

These experiments assume that based on certain local conditions, individuals may choose to dissent. One possible local condition that triggers inconformity is defined as routiness, i.e., the recognition that all surrounding neighbours have a uniform value. The CA described in the previous Section is extended with the behaviour described in the following rules –notation used consistently with the original description (Axelrod 1997):

- select a random cell c_i and its neighbours $\varepsilon(c_{j\dots n})$
- let $G(c_i, \varepsilon)$ be the set of features g such that $(c_i, g) \neq (\varepsilon, g)$
- iff $G = \emptyset$, given a probability P set $v(c_i, g)$ to a random number r from ϕ
- else given the set of common features $c(c_i, f) \equiv c(c_j, f)$ and $G \neq \emptyset$, set $v(c_i, g)$ to $v(c_j, g)$.

Namely, when a cell c_i is randomly selected, it samples its neighbourhood for differences, G . If all adjacent neighbours ($c_{j\dots n}$) have the same value then with a uniform probability P the selected cell changes one of its feature to a random trait from a given probability ϕ . This is shown in Figure 3.11. At a given time step neighbours have different values (Figure 3.11a). At a later point, all cells in a neighbourhood may have same values (Figure 3.11b). When a dissenter cell identifies this routiness, it switches one of its features to a random trait (Figure 3.11c).

Intuitively, if P is high and new values are introduced frequently, then dissenters would impede the formation of groups. However, at some point it should be possible for a social group to approach convergence whilst the occasional introduction of a new value may enable the occurrence of change episodes. One way to direct the search for conditions that produce these macro effects is to consider the ratio of dissent activities in a human society. The US Occupational Census of 2000 (United States Census Bureau 2000) and other related analysis (Florida 2002) show that creative occupations such as design range from 1 to 15% of all occupations, depending on the definitions used.

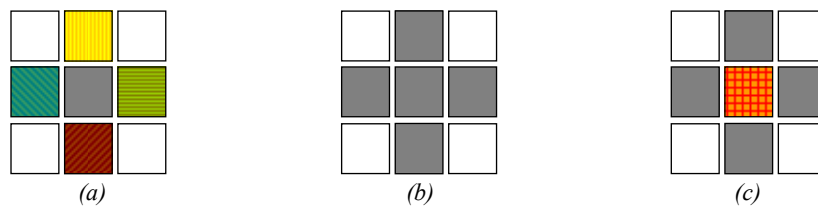


Figure 3.11 The dissenter cell: Local routiness triggers the introduction of a new value by a cell with an independent variable as a function of a uniform “probability of dissent”. In (a) all neighbouring cells have different values (colours), in (b) convergence causes all cells to have a common value, and in (c) the dissenter cell introduces a new value by changing a random feature to a random trait.

3.3.2 Results

3.3.2.1 Creative Destruction

A Monte Carlo exploration of the probability of dissent P from 0.0 to 1.0 is plotted in Figure 3.12. CA of size 10 x 10 with 5 features and 5 traits are run 10,000 steps. At initial time the population is converged to a single dominant value. Results are mean of 10 simulations. In Figure 3.12a diversity is defined as the mean number of values in a population. This measure is averaged by the total simulation length, i.e., a simulation with diversity = n indicates a population which had n different values present on average. The effects of dissent in diversity are non-linear, i.e., with no dissent or

$P = 0.0$, the mean number of different values during a simulation is 1.0, i.e., only one initial value persists during a simulation. As P increases, cells that detect local routiness are more likely to introduce new values into the population. As a result, the mean number of values during a constant simulation time increases significantly. Diversity rapidly reaches high levels even with relatively low dissent, i.e., < 0.1 . However, as P further approaches 1.0 and cells are likely to introduce a new value every time they detect local routiness, the increase of diversity slows down reaching a limit. Such limit is determined by population and neighbourhood sizes, as well as by feature and trait lengths. These factors set the probabilistic limit for the generation of new values based on the number of neighbouring cells necessary to define local routiness.

The number of change episodes are measured as the number of occurrences in which a new value introduced by a dissenter cell is spread through a population and replaces the dominant value. Results shown in Figure 3.12b are normalised over 10 simulations from a CA of size 10×10 with 5 features and 5 traits. A change episode is registered at the time when a new value reaches an adoption of 1.0. Figure 3.12b plots the effect of divergence in change episodes. With $P = 0.0$ no cell is able to introduce new values and thus no global change is possible. As the likelihood of introducing a new value increases, the number of change episodes rapidly increases until it reaches a maximum point after which the noise generated by the frequent introduction of new values gradually impedes total convergence. At $P = 1$ when a high number of different values co-exist at any given time, global agreement is unlikely.

Individual dissent and social change: In these CA the effects of individual divergent actions are non-linear to collective change. A small ratio of dissent generates the highest possible number of group changes whilst agreement is still possible. As dissent increases, more different values exist but diffusion of any single value becomes more unlikely.

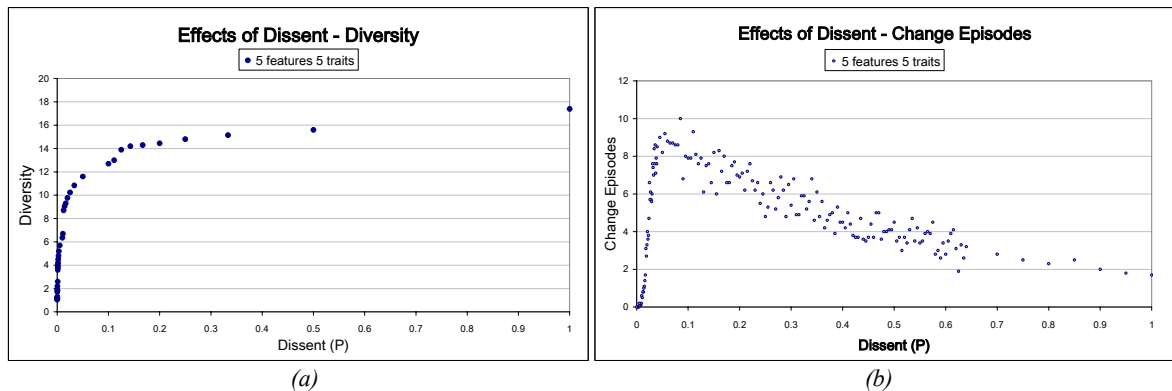


Figure 3.12 (a) Mean diversity over dissent $0 < P < 1$. Diversity increases significantly with small values of dissent but rapidly stabilises. (b) Mean number of change episodes of group convergence over dissent $0 < P < 1$. Marginal dissent reaches the maximum number of change episodes.

Whilst these particular values cannot be generalised outside the conditions of these CA, they suggest a pattern in the relation between individual dissent and social convergence. Societies can be expected to have different rates of dissent (Sunstein 2003). Figure 3.13 replicates the experiment with a CA of 10 features and 5 traits where an equivalent pattern of effects is observed.

These results demonstrate in extremely simple terms the viability of bottom-up decentralised collective change. Not only is social change possible by the differences introduced by minorities, but it seems that change *needs* to have a marginal source if a social structure is to be maintained. At the core level, most of the time and most of the cells follow a uniform tendency to converge. This is complemented by the occasional dissent by an individual which becomes capable of triggering a

change of the entire population. Based on the findings on minorities reported above, these cycles of change can be expected to occur independently of the size of the population.

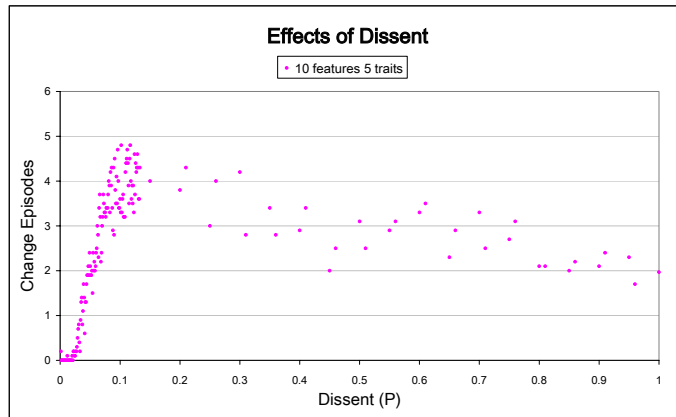


Figure 3.13 Replication of Figure 3.12b with a CA of 10 features and 5 traits

3.3.2.2 Change Episodes

Under closer inspection, the patterns of diffusion of new values vary significantly. Random walks of absorbing boundaries generate erratic patterns (Liggett 1999). Figure 3.14 plots the diffusion of a newly introduced value by a dashed blue line against the dominant value, a continuous red line. In the first three cases (Figure 3.14a, b, c) the new value is adopted by different ratios of the population but is eventually absorbed by the dominant value. In Figure 3.14d the new value introduced by a dissenter cell is rapidly spread through the grid replacing the previously dominant value. Dominance in Y axis plots the number of cells adopting competing values in a 10 x 10 population, i.e., a dominant value = 100.

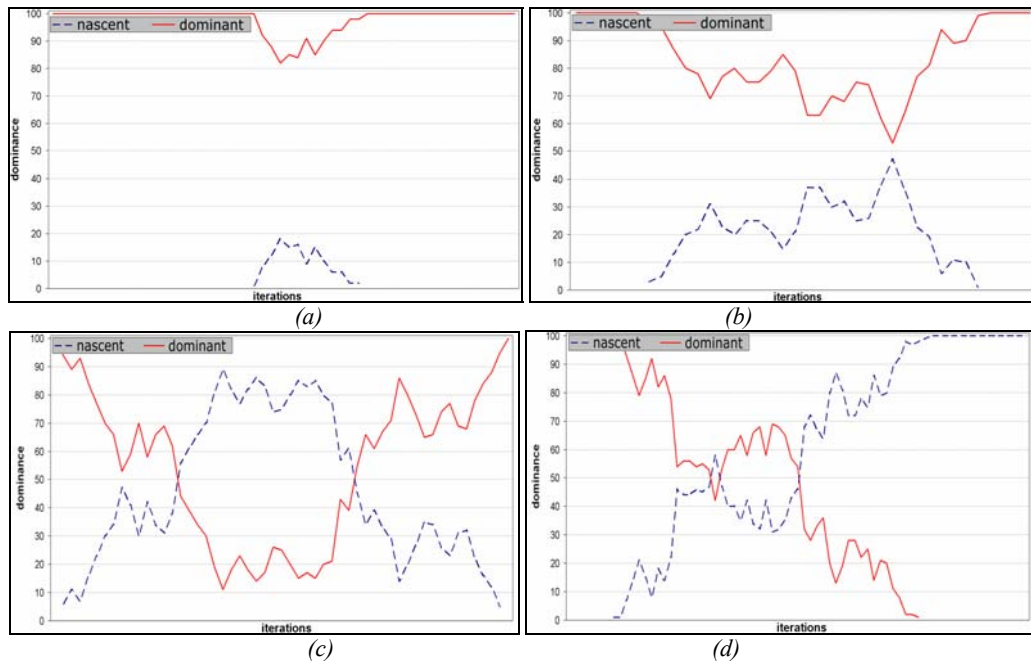


Figure 3.14 Episodes where a dominant culture (continuous red line) is challenged by an alternative value (dotted blue line) with varying consequences. From (a) to (c) the new value is adopted by increasingly large numbers but it is eventually absorbed by the dominant value. In (d) the new value becomes dominant.

Figure 3.14a shows a nascent value that is spread to a maximum of 18 individuals before it decreases and disappears. A mirror effect in the dominant culture is seen as individuals exchange adopted values. Figure 3.14b is an episode where the competing cultures reach around fifty percent of the population, after which the dominant culture returns to total dominance. Figure 3.14c shows the dominant culture decreasing until only eleven sites share the value only to come back to dominance after a number of time steps. Lastly, in Figure 3.14d the dominant culture is replaced by an alternative value that is spread across the population.

As Rogers (1995) suggests, current methods of inquiry tend to focus only on successful innovations, i.e., the pro-innovation bias defined in Section 2.2.5. However, computational simulation supports the study of the principles behind all cases, irrespective of the outcome.

Pro-innovation limits: whilst the research literature has focused on cases of successful diffusion, these may be only a small percentage of the total attempts at triggering collective change.

3.3.2.3 Opportunistic Innovation

Mediating values can overtake new ideas when compatible with more segments of the population. This is illustrated in an episode of population of 10×10 with 3 features and 5 traits shown in Figure 3.15 where a dominant culture is seen to decrease (line A, value $[3,5,0]$) as a competing value is spread (line B, value $[3,2,0]$). Around time step 95,000 a second new value is introduced by a different site (line C, value $[3,5,4]$) and in the boundary between the two alternative values a third new value appears and gains dominance (line D, value $[3,2,4]$). The third value (line D) is not strictly ‘new’ but is a consequence of social influence: a combination of traits introduced by the two competing values (lines B and C).

The ‘novelty’ of the mediating value (line D) is not generated by dissenter cells but is a collective result of diffusion. The reason why this mediated value becomes dominant may not be immediately apparent. Arguably, it capitalizes on the spread of the other values and since the original mechanism of social influence supports the dissemination of different traits (i.e., check for shared trait, copy different trait) the new value reconciles competing alternatives. Moreover, the diffusion of the other new values increases the likelihood of spread of the mediating value. Figure 3.15b depicts this process where the probability that the mediating value $[3,2,4]$ takes over value $[3,5,0]$ is increased as a side-effect by the diffusion of values $[3,2,0]$ and $[3,5,4]$.

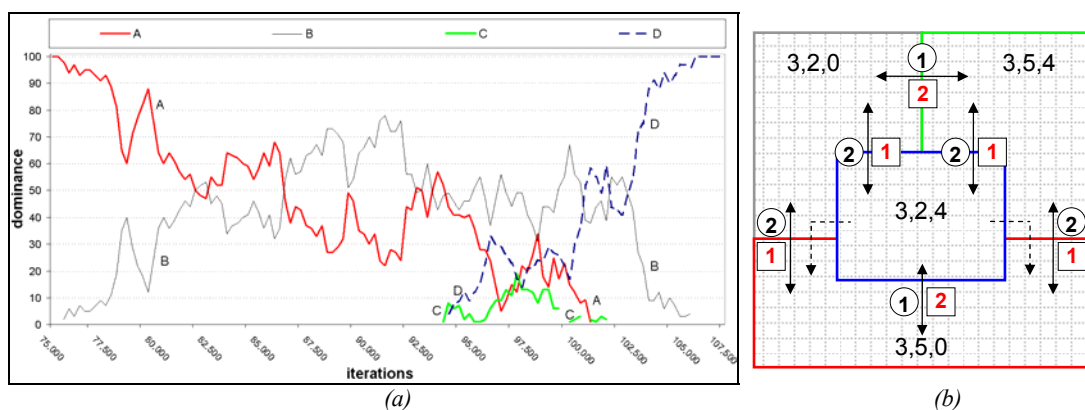


Figure 3.15 A change episode is shown in (a) where a dominant culture is challenged by two competing values; a fourth new value generated by the dissemination mechanisms becomes dominant. (b) Border probabilities of a mediating value $(3,2,4)$ facilitate the spread of compatible values

Opportunistic innovation: Values that become dominant need not be strictly new, they may be a combination of more ‘radical’ competing values. The combination of different new values can be easily spread in a population when it represents a compromise for different groups.

3.3.2.4 Structure of Minorities

The next question concerns the structural effects of minorities or dissenter groups. Given that even a very widespread value can be absorbed by a minority, we turn our attention to the principles that determine the likelihood of diffusion based on initial conditions.

Two experiments are set where a constant number of dissenter cells are initialised. In both cases the population is initialised converged to a shared value except for four cells which are located in ‘adjacent’ and ‘disperse’ arrangements as shown in Figure 3.16. Adjacent cells share neighbourhood whilst disperse cells are not neighbours. Given that the diffusion of a new value may take long times, the objective is to see whether this minor initial difference has an effect in the long run. The experiment is run with constant traits = 5 and varying features from 5 to 10 in a population of size 10 x 10. Each simulation is run 1,000 times with each condition.

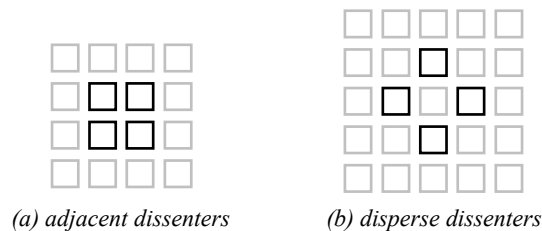


Figure 3.16 Four dissenter cells are defined at initial time in two different arrangements: where they share neighbourhoods (a) and where they do not share neighbours (b).

Results demonstrate that the number of global change episodes is consistently higher with initial disperse dissenters. Minorities of disperse dissenters succeed in spreading a minority value a mean of 20% more often than minorities of same size but in an adjacent arrangement as shown in Figure 3.17a. Adjacent dissenters trigger global change with a mean probability of 0.038 and 0.032 with 5 and 10 features, respectively. Disperse dissenters do it a mean probability of 0.044 and 0.039 respectively.

This demonstrates that diffusion phenomena need not depend on the rate of dissent or on individual attributes of the members of a population. A structural property such as the location of dissenter cells is sufficient to explain an increase of global change.

This finding is confirmed by a further experiment where a constant dissenter arrangement of adjacent cells (Figure 3.16a) is initialised in two types of grids: one with Von Neumann neighbourhoods and another one with Moore neighbours. Simulations are run 1,000 times in a 10 x 10 population with 5 features and 5 traits.

Results consistently indicate that it takes shorter periods for a new value to spread through a population with Moore than with Von Neumann neighbourhoods. Change episodes in populations of small neighbourhoods take a mean of 640 and 1420 steps with 5 and 10 features, respectively. When the population is structured in larger neighbourhoods, a mean of 510 and 1380 steps are necessary for each change episode.

Figure 3.17b compares the time taken by recorded change episodes in 1000 runs. In these cases a constant number of dissenters is initialised, so their individual characteristics and their location are not sufficient to explain why in some cases a new value spreads more often or more rapidly. Instead, global characteristics of adopter cells explain how often and how easily a population undertakes collective change.

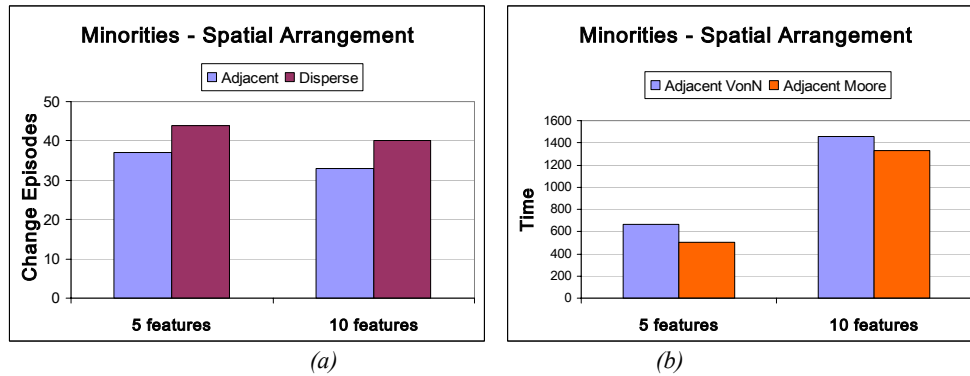


Figure 3.17 The impact of dissenter cells can vary significantly depending on factors such as their arrangement on a population. (a) Disperse dissenter cells tend to spread a new value around 20% more efficiently than adjacent cells. (b) Change requires less time in groups with larger neighbourhoods.

Social structure and change agency: The way members of a population are organised plays a key role in diffusion. The same actions by change agents in differently organised populations can produce significant variations of group impact.

3.4 Displacement

Whilst CA of social influence tend to assume a well-connected population, social structure can have an important effect on the outcome of diffusion as demonstrated in Section 3.2.2. The extension presented in this Section is aimed at understanding further effects of the way in which populations organise. Social networks can be assumed to be non-uniform (Barabasi et al. 2001; Watts and Strogatz 1998).

One basic way to explore this in a CA is by populating the lattice with only a ratio of cells (density < 1.0) that move through empty spaces according to a set of simple displacement rules. Such behaviour is aimed at allowing cells to form groups as an emergent result of actions based on local conditions. The space between cell groups can represent either geographical or temporal divisions between social groups.

3.4.1 Experimental setup

The CA described in Section 3.2.1 is kept unchanged except for a variable called density defined as the ratio of non-empty grid cells. When density = 1.0 all cells in a grid are assigned random values at initial time, when density = 0.5 only half of the grid spaces are occupied by cells. Figure 3.18 shows typical initial and end states for CA sizes 10 x 10 and 300 x 300 with a density of 0.5. Cells move in a CA lattice given the following conditions: a) if an individual has two or less neighbours, it moves one space in random direction; b) otherwise if a random adjacent neighbour is compatible, interact with it; c) else, move one space in random direction. Namely,

- select a random cell c_i and its neighbours $\mathcal{E}(c_{j\dots n})$
- if $\mathcal{E} \leq 2$, move to an empty adjacent cell in random direction
- else, if a random neighbour is compatible, interact with it as in Section 3.2.1
- else, move to an empty adjacent cell in random direction

The assumption is that cells move through a CA looking for compatible neighbours to form groups where they can interact. It is possible to incorporate in this CA the behaviour of divergence as specified in Section 3.3.1 so that dissenter cells introduce a new value when they perceive routiness. This allows the study of the combined effects of displacement and divergence. Further,

displacement rules can also be modified to account for occasional displacement even when a cell has more than two neighbours. This enables the study of group dispersion.

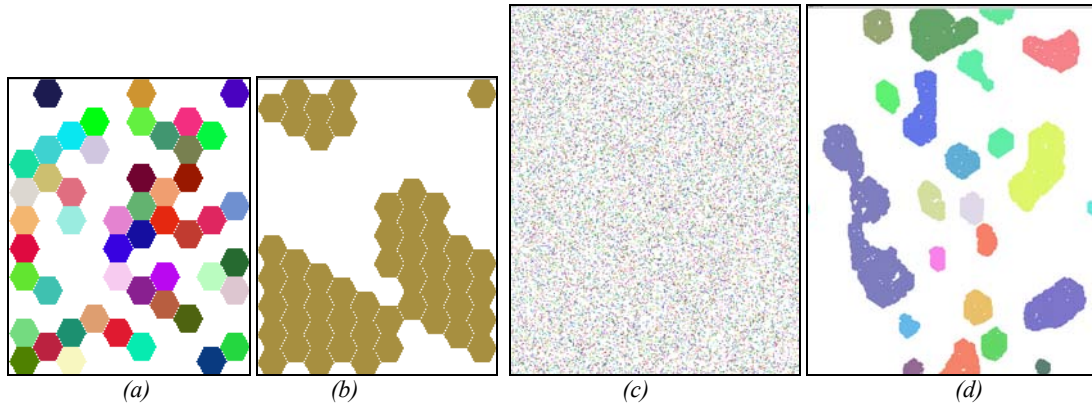


Figure 3.18 (a) CA of size 10×10 at initial and (b) final state;. (c) CA of size 300×300 at initial and (d) final states.

In order to compare convergence trends, Monte Carlo runs are conducted with a constant number of cells = 100 whilst the size of the grid is increased by increments of 0.1 to generate densities from 0.1 to 1.0. When the population of 100 cells is assigned a grid of 10×10 , density = 1.0 and contact between cells is uniform as the cases analysed in previous Sections. As grid increases and population size is kept constant, the density is gradually lowered until a grid of 32×32 yields a density ≈ 0.1 .

3.4.2 Results

Results are normalised over 10 runs with each parameter. In low density cases, different subpopulations form where values evolve independently. Each subpopulation can be seen as a separate CA engaged in separate convergent trends. Given that groups form gradually, during that time other cells join and leave groups creating more diversity than in CA with uniform contact. As a result, the time required for a CA with constant number of cells but decreasing density is increasingly longer. The shape of this relation follows a power-law where very low densities require a long time to converge, but a small increase in density rapidly reduces that time to a level after which equivalent changes in density have no significant impact in time to convergence. This is seen in Figure 3.19 where the mean time to global convergence is plotted against density.

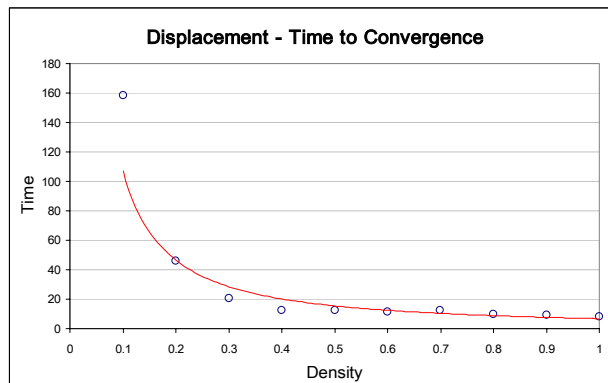


Figure 3.19 Relation between CA density and mean time required to total convergence

Displacement has a similar effect on diversity. Figure 3.20 plots the number of global values to which a population converges after a constant iteration period of 10,000 steps. In this case cell

values have 5 features and 30 traits. As shown in Figure 3.8b, this CA tends to converge rapidly to heterogeneity with a mean of 30 different end values. In this case, as density decreases the CA rapidly tends to homogeneity reaching a mean of 4 final values with a density = 0.9. This can be explained by the fact that when cells are able to move around the grid, they tend to interact with a higher number of neighbours supporting extensive interaction.

Social mobility: when cells are able to change their neighbourhood, this local condition is sufficient to yield global agreement. However, after a point the effects of displacement are marginal.

These findings suggest that the implicit assumption of uniform communication in most CA studies (where density = 1.0) carries effects that do not apply to most density conditions. This important non-stationary behaviour of cells plays a significant role at the macro level. Moreover, the power-law shape of these distributions is consistent with current research on networks (Barabasi et al. 2000).

The effects of displacement are more significant in large populations where a number of different subgroups gradually form. Each group constitutes an independent subpopulation within which the principles of social influence described thus far apply. In sufficiently long periods, each subpopulation converges to different values which would then identify each community (groups having a common or shared value) within the entire grid.

Cell groups need not be isolated. To implement between-group contact, a further probability of displacement is introduced to study group dispersion. As a function of this dispersion probability Dp , any cell can opt to move, potentially leaving a converged group and joining another. With $Dp \approx 1.0$ cells tend to move at all times and group formation is unfeasible. With $Dp \approx 0.0$ groups remain stable for long periods with the occasional cell moving between groups.

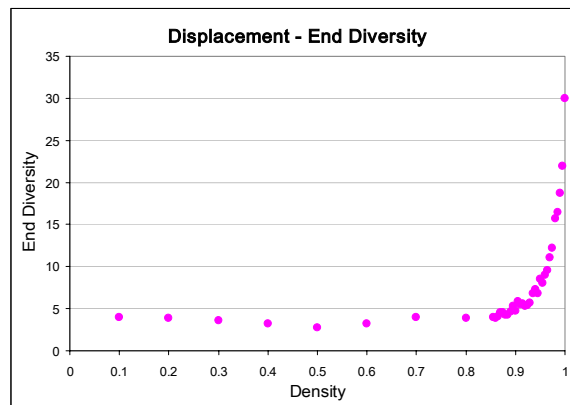


Figure 3.20 Number of values left at the end of a simulation in a CA of size 10 x 10 with 5 features and 30 traits. As soon as small amounts of displacement are possible, global homogeneity is rapidly approached.

An experiment is run with a large CA grid of 300 x 300 and a $Dp = 0.001$, i.e., stationary cells move to an empty adjacent cell once approximately every 1,000 iteration steps. One effect of this behaviour is that given that cells tend to move away from incompatible neighbours, if an incompatible cell gets close to an incompatible group, it can cause a bordering cell to move, which depending on the shape of the boundary can cause other adjacent cells to equally leave the group. This cascade-effect can cause a group to go through major transformations by the action of cells from other groups. Likewise, if the outsider cell is compatible, it may trigger a group change either by the spread of its value or by the creation of a crossover new value with the existing group value.

These effects of displacement between groups have important effects at the global level: in principle, given a large enough feature and trait spaces and a large population, between-group interaction is sufficient to account for continuous generation of diversity.

Between-group interaction: A system within which groups are formed and interaction between them is possible, can support the continuous generation of diversity. This can happen in two fundamental ways: firstly, by the transformation of groups (new groups form, existing groups dissolve) and by the combination between values from different groups. The former is a type of ‘social change’, the latter of ‘cultural change’.

Divergence can be introduced in between-group studies by the behaviour of dissent described in Section 3.3.1. By now it is clear that dissent combined with interaction between groups can support a system where total homogeneity is highly unlikely and continuous cycles of ‘creative destruction’ are possible. Such cycles can be triggered by new values occasionally introduced, or by foreign values brought from a different group, or even by the combination of existing and foreign values.

Figure 3.21 plots a CA of 300 x 300 with $Dp = 0.001$. Since only cells in the boundaries can move, in the long term the effects are not significant at the macro level. 200,000 iteration steps pass between Figure 3.21a and Figure 3.21b in both cases subpopulations maintain their overall shape, although their values change. With higher dispersion probabilities these social groups become indeed less resilient, but also new groups are easier to form.

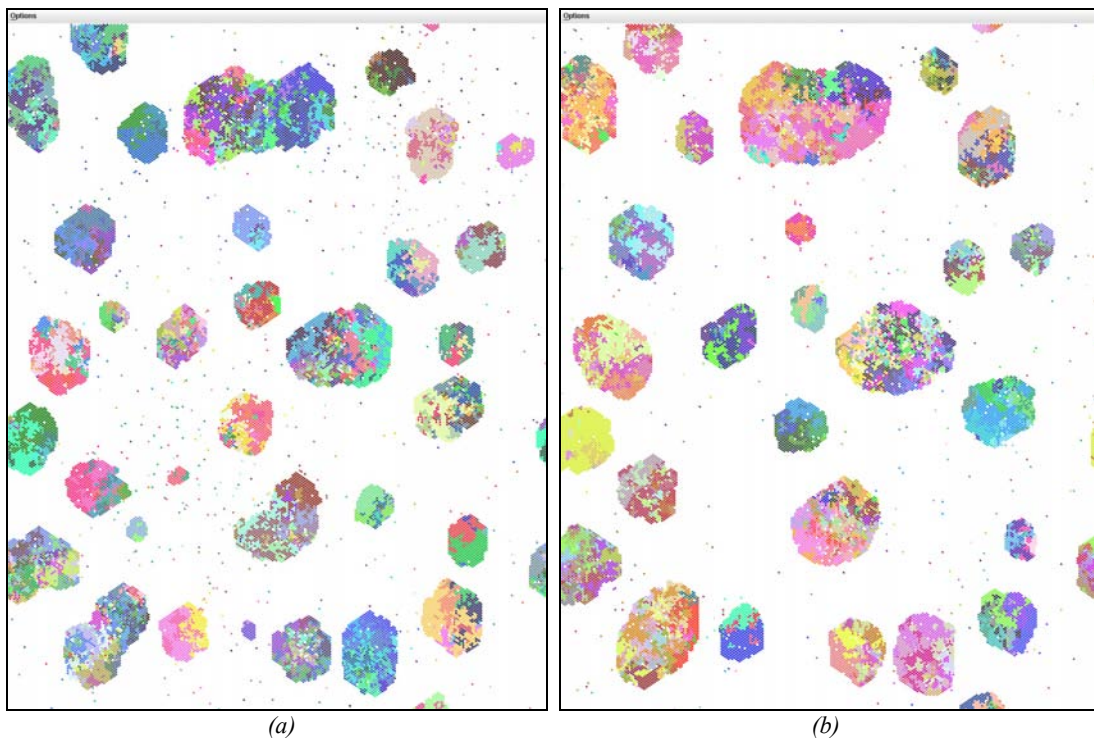


Figure 3.21 Interaction between-groups. 90,000 cells in a 300 x 300 grid, 0.25f density = 22,500 particles, dispersion probability = 0.001. (a) step 50,000 and step 250,000. ‘Social’ or cell groups transcend ‘cultural’ or value changes.

This captures one of the key issues that CA studies invariably conflate: the difference between social and cultural structures. Whilst ‘social’ groups remain constant under these conditions, ‘cultural’ changes occur in the values of each group.

Current computational resources allow systematic experimentation with CA of limited sizes. At higher CA sizes it is unfeasible to conduct Monte Carlo simulations where parameter spaces are traversed. In terms of displacement and divergence combined, at this stage we can only run single cases where convergence is unattainable in reasonable time (days/weeks). Given that our target human societies are measured in the millions, this approach is still far from being able to demonstrate these effects at a realistic scale.

3.5 Heterogeneity

The last extension to this CA of social influence approaches the study of individual differences in relation to group change. This extension assumes that particles are heterogeneous and have an individual threshold that defines their probability of introducing a new value. In essence, their behaviour is exactly the same as the one specified in Section 3.3.1 but the probability is non-uniform. It is drawn from an individual value assigned to each cell.

Whilst previous Sections demonstrated the potential of an individual to trigger group change, in this Section change agency is explored in individual differences. From a design viewpoint the emphasis is on determining whether change agency can be predicted by individual characteristics.

3.5.1 Experimental setup

Individual abilities of cells are a function of their probability to introduce a new value. These are assigned to cells at initial times from a Gaussian distribution. During simulation time a record is generated of values that become dominant in the group. When a value becomes dominant, it is associated to the cell that introduced it. At end time the initial individual values are compared against the number of change episodes.

A variation of this experiment is to increase the individual ability of cells as they trigger group changes. What we are interested in observing is how well the initial distribution of abilities predicts the definition of change agents after a number of iterations. Intuitively, change agents can be predicted by high *abilities*.

3.5.2 Results

First, the number of new values introduced is considered in relation to individual abilities in a CA of 10×10 with 5 features and 5 traits initialised in a converged state and run for 10,000 steps. Figure 3.22 plots a typical control case. Area represents cell abilities sorted in ascending order and bars represent the number of new values introduced per cell during a simulation. Cells with high abilities tend to introduce more values, ($r^2 = 0.506$).

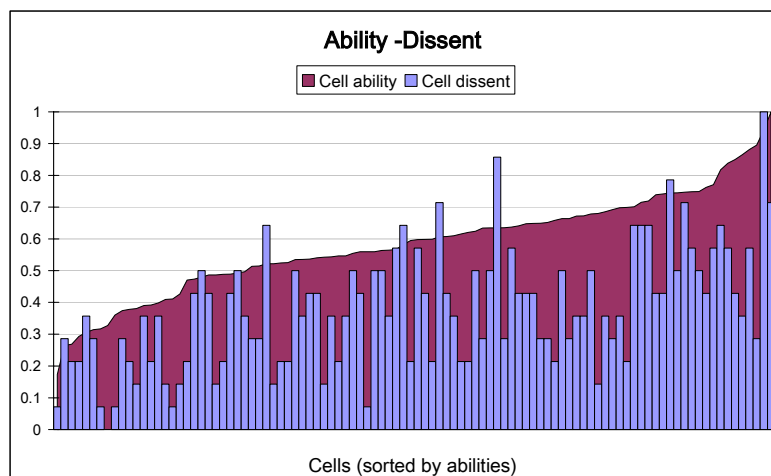


Figure 3.22 Abilities (area) against new values introduced (bars) in 10,000 iteration steps

The reason for this relatively low correlation is the condition of local routiness. Cells with high abilities are bound by local conditions to exert their abilities. This gives opportunity to less able cells that may detect local routiness more often to compensate for their disadvantage.

This principle is confirmed when the experiment is repeated in a CA with same characteristics but with Moore neighbours. In this case, correlation between abilities and dissent consistently decreases ($r^2 = 0.436$) demonstrating that increasing the dependence to local conditions renders individual differences even less important.

Situational and individual factors of change agency: As situational factors increase in determining an outcome, the importance of individual differences decreases.

This relationship between situational and individual factors is confirmed when the number of successful change episodes is considered. As above, a CA of size 10 x 10 with 5 features, 5 traits and individual abilities is initialised in a converged state. The objective is to measure the number and sources of episodes of group change. To this end, every time the population converges to a new value, the cell that introduced that value is given credit. Dominant values generated by the combination of competing values are not considered. In order to consider a sufficient number of change episodes each simulation is run 1 million steps.

Figure 3.23 plots abilities sorted in ascending order against the number of change episodes triggered by every dissenter cell. Area represents cell abilities sorted in ascending order and bars represent the number of change episodes triggered per cell during a simulation. A decrease in the correlation between abilities and the triggering of social change is observed ($r^2 = 0.432$). This can be explained by the notion that the diffusion of new values is a factor outside the control of any individual.

This is a basic premise but is well illustrated in this simple experiment: when dissenter cells depend on the state of other neighbouring cells, their individual differences as abilities to introduce a change become less determinant of their role as change agents.

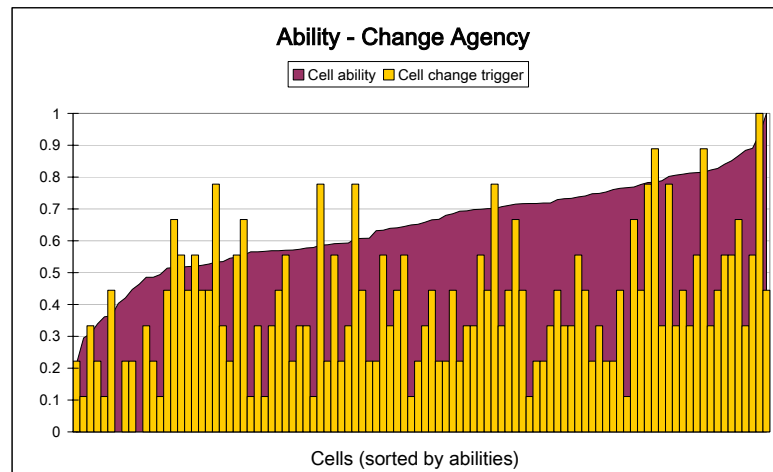


Figure 3.23 Abilities (area) against actual group changes triggered (bars) in 1 million iteration steps.

Abilities and opportunities: individual abilities alone do not explain change agency. Two basic types of situational factors need to be considered: a) the situational conditions that support individual behaviour and b) the situational conditions that determine the impact of such behaviour.

3.6 Discussion

Cycles of convergence and divergence (i.e., ‘creative destruction’) can be described in two ways: firstly, as the continuous effort by a minority to dissent and influence their group to avoid total homogeneity, and secondly as the constant collective sense-making response of social coherence when individuals are faced with uncertainty. These forces complement each other to create dynamic but coherent groups. It is possible that the relation between the diffusion of design ideas and social change is located between these extremes. This chapter has presented explorations with cellular automata (CA) of convergence and divergence that suggest a number of general principles that deserve further consideration.

Intuitively, ideas have been assumed to spread throughout a social group based on their intrinsic merits (Rogers 1995). However, the bottom-up organisation of diffusion suggests that this process can be significantly determined by factors such as the structure of the idea (number and range of variables) as well as the structure of the social group (number and arrangement of individuals). Whilst ideas may be spread based on their content and merit, there are situational factors that can play an important role.

In these CA, ideas are represented by random values in order to analyse these situational factors independently of their content or the individual differences of their creators. However, the advantage of CA simplicity is also its main disadvantage in that the patterns observed are product of random processes. These models are described in a few lines of code, computation is cheap, and results are visually explanatory but no reasoning is implemented. Influence is reduced to direct copy of values, and there is no relation to design processes. In sum, these models hint at some key principles but are too general: they can be equally applied to fluid dynamics, insect colonies and electromagnetic fields. What is necessary is a richer representation of values, of choice, of influence, and ultimately of some kind of design behaviour. In other words, CA cells need to have more *agency*.

The analogy to social phenomena suggested by Axelrod (1997) is based on the ergodic property of two-dimensional CA, i.e., the probability equal to 1 that a system where interaction is determined by recurrent random walks tends to converge (Liggett 1999). However, as dimensionality increases, this probability rapidly approaches zero. In CA of three or more dimensions, transient random walks cause the system to maintain diversity.

The following chapter introduces a more comprehensive framework of agency in design as part of a social system where the findings from these CA studies are made operational at a more elaborate level of behaviour based on existing systems views of creativity (Feldman et al. 1994).

Chapter 4

Framework of Design and Social Agency

This chapter introduces a framework for the exploration of design as a social activity. An agent-based approach is used to formulate a more comprehensive representation of the processes involved in defining designers as social agents of their societies. Simplicity is traded for a more significant representation of behaviour related to design. This framework consists of three main components: individual agents that implement a type of design behaviour; groups of agents that evaluate and adopt the products of design; and a domain of collectively selected products. These three components are based on a systems view of creativity.

A framework of design as a social activity is presented in this chapter. The aim of this framework is to enable experimentation with aspects of the micro-macro link of change agency in a social group where design solutions are generated and evaluated. A number of parameters are defined to enable experimentation with the relation between individual and situational conditions in a type of design activity.

This framework implements the components of the DIFI systems model of creativity, i.e., Domain-Individual-Field Interaction (Feldman et al. 1994) discussed in Section 2.1.6. A computational implementation of this framework that enables experimentation with such components and their interaction is formulated.

Patterns of interest include how the individual can transform the field and contribute to the domain; what field conditions facilitate or hinder change; and how the contents and rules of the domain affect the relation between field and individual. The twofold assumption is that there are causal relations between these components and that simulation is a convenient tool to inspect them.

The focus of this framework is on design as a social activity. A social system is defined with the following components: groups of adopters (i.e., Field), designers (Individuals) and design products or artefacts (Domain). Adopters are organised in social networks where interaction between neighbours determine their decisions to adopt or reject design artefacts. Designers are agents that conduct a simple design task. These framework components support the ‘growth’ of

generative and evaluative phenomena considered as fundamental in the definition of creativity in Section 2.1.1. These phenomena include peer recognition, popularity, influence, productivity, and differentiation. None of these dimensions is sufficient on its own to define ‘creativity’ (Gardner 1993); it is a combination of them what is generally considered (Cropley 1999).

The framework eliminates some limitations of simpler modelling paradigms such as the cellular automata (CA) explored in Chapter 3 (Castelfranchi and Mèuller 1995). The state representation is extended from binary or numerical to a geometrical representation that supports multiple interpretations and more comprehensive mechanisms of group influence. The perception of geometric features is the base for processes of design, adoption and diffusion. A richer state representation further supports adoption decisions based on multi-objective evaluation functions and provides a clearer test bed for causal analysis (Carley 2002). Components of these evaluation functions are exchanged between adopters organised in social groups. In this way adoption decisions are socially determined (Castelfranchi 1998). A domain of selected design artefacts is collectively built by adopters during a simulation. Whilst CA are ‘memoryless’ (Gutowitz 1991; Tomassini et al. 2002), social groups accumulate a type of collective memory. In particular domains consist of artefact repositories whose entries are representative of the design behaviour and adoption decisions of the population.

Furthermore, the design of new artefacts is coupled to the social process. Whilst in previous CA studies of social influence new values are randomly introduced by an exogenous mechanism such as the experimenter (Cowan and Jonard 2004), in this framework design behaviour is based on strategies that result from the interaction of designers with adopter groups. Competition is addressed by initialising a number of designers within a common adopter population.

Figure 4.1 depicts the conceptual structure of this framework. Three levels are defined: at the person level the individual designer engaged in a task that captures some properties of problem finding and solving in design. At the social level, groups of adopters and opinion leaders. At the epistemological level, repositories of selected artefacts and knowledge generated by designers. This framework supports experimentation with the components of the DIFI model and their interaction (Feldman et al. 1994).

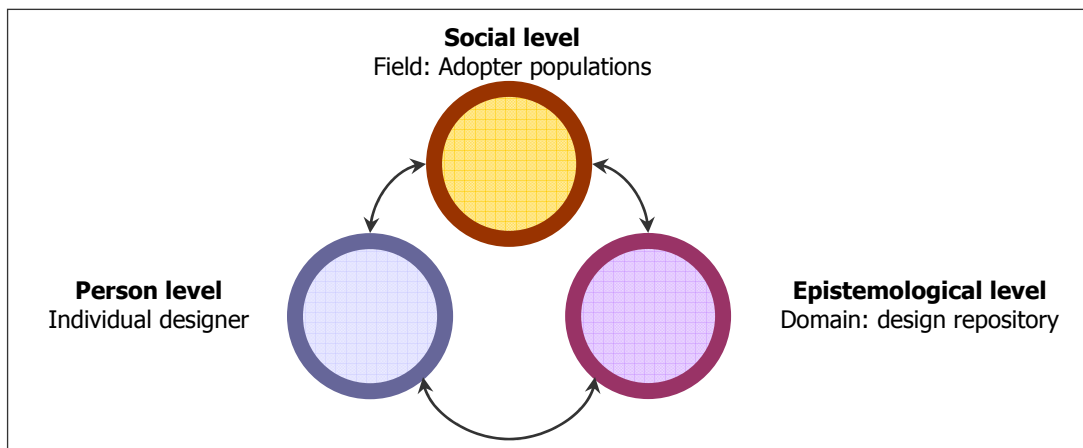


Figure 4.1 Conceptual structure of the framework (Feldman et al. 1994)

At the person level, individual designers are based on the PRSVL model of person-context interaction (Wagner and Sternberg 1994). That model explains the behaviour of individuals on the basis of five elements: individual differences, roles, situations, values, and luck. Individual differences are implemented in this framework through preferences, abilities, and learning mechanisms. Roles are assigned in a top-down direction to designers and adopters and generated bottom-up in the case of opinion leaders and gatekeepers. Situations are defined by factors such as

social interaction, time schedules, and population sizes. Values are given by the task description and adoption functions. Lastly, luck is implemented by computational pseudo-random processes.

Two types of agent roles are defined in this framework. First, the roles of designer and adopter agents are assigned in a top-down direction to agents at initial time, i.e., these agents keep their role during all the simulation. Another type of role is organised in a bottom-up direction as a result of agent interaction. These are the roles of opinion leaders and gatekeepers. Namely, at initial time no agents are given these roles; they are initialised as `null`. These roles are filled by adopter agents that meet certain criteria during a simulation as a result of their interaction with other agents. These can be temporary roles held by different agents at different times. Who executes these roles and when is collectively defined by the population.

4.1.1 Notation

In this chapter standard first-order logic notation is used to define relationships between variables (Wolfram 1999). Namely, \neg is read ‘not true’, \approx ‘approximately equal’, \wedge ‘and’, \vee ‘or’, \Leftrightarrow ‘if and only if’, \Rightarrow ‘such that / then’, ... ‘sequence’, \equiv ‘exactly the same as’, \forall ‘all x has property y ’, and \exists ‘an x with property y ’. Greek characters are used to represent parameters following standard usage such as Σ for ‘summation’, θ for ‘probability density’, ϕ for ‘statement’, σ for ‘standard deviation’, τ for ‘time variable’, Δ for ‘variable change’, and Δ^+ for ‘variable increment’. Other variables are defined in tables before their use. In general, capital letters are used for arrays and small letters for variables.

4.1.2 Chapter Outline

This chapter continues by revisiting the computational method of agent modelling. Some examples are given of socially-situated agents based on classic social-psychology experiments. Then the role of designer agents and the representation of design artefacts are described. Adopter behaviour including social influence and opinion leadership are defined. Lastly, the implementation of the domain is specified. The chapter closes with verification of the main assumptions and a discussion of the type of questions addressed, and the parameters to inspect.

4.2 Agent Framework

Definitions of human agency normally centre on intentional action (Bandura 1989; Vollmer 1999). The term ‘agent’ in computational modelling is ambiguous (Wooldridge 2000), but is generally used to distinguish from automated or reactive type of behaviour (Luck and D’Inverno 2001). At the implementation level, agents are distinguished by the conditional nature of their responses. Whilst objects *must* act in determined ways, agents *may* act, i.e., choice is involved. The choice to act is assumed to be grounded on functions or reasons of which beliefs, desires and intentions are recurrent examples (Jennings and Wooldridge 1998). Agents are seen as the “loci of decision making” (Wooldridge 2000). The dominant paradigm in computational agency is rational agency (Rao and Wooldridge 1999).

In this framework, agent behaviour is defined by processes of perception, interpretation, and social interaction (Gero and Fujii 2000). Agents’ features and other conditions that characterise their interaction are determined by parameters that the experimenter can observe and draw causal inferences from. The experimenter runs simulations, builds hypotheses, and analyses effects of manipulating these variables. This is a way of doing science by ‘growing’ the phenomena of interest and relating them to initial assumptions and conditions (Epstein and Axtell 1996).

4.2.1 Autonomy

The term autonomy is used in the rational agent paradigm as the self-control of an agent’s state and goals, i.e., *auto* (self) and *nomos* (rule or law). The canonical autonomous rational agent is considered to operate independently of any external control. It is defined as one whose actions are

“under its own control and not driven by others” (Russell and Norvig 2003; Wooldridge 2000). However, consistent evidence demonstrates that when humans are situated in a shared space or task, their behaviour can be expected to be different than in isolation (Ross and Nisbett 1991).

Indirect control or influence from physical and from social environments is an important determinant of human behaviour (Agre 1997; Argyle et al. 1981; Bass 1990; Clancey 1997). Individual reasoning and action can be importantly shaped by environmental cues and by other individuals especially in new or complex situations. In such cases it is unfeasible for an individual to reason and learn in isolation. Organisms that exhibit intelligence build and use physical and social structures to enable and facilitate behaviour (Bandura 1986; Clancey 1997).

Being limited to the study of isolated behaviour, the paradigm of rational agency locates causality within the individual (i.e., inside-the-head reductionism) (Rao and Wooldridge 1999). As a result, social ability is literally considered as “trivial and paradoxical” in that it involves “giving up autonomy” (Wooldridge 2000).

The paradox takes place when in order to enable group formation and cooperation, rational agents need to access the mental states of other agents (Luck and D’Inverno 2001). Indeed, teamwork in rational agents is explained “in terms of the individual mental states of team members” (Wooldridge 2000). Therefore, rational agency depicts social interaction as a linear process, i.e., a group as the sum of its members’ mental states as seen in Figure 4.2. In general, the notion of ‘group’ is not made explicit and remains a construct of the observer (Gilbert 2002). However, non-linearity is pervasive in most biological and social phenomena (Holland 1995; Marsili et al. 2004) and complete rationality has been considered as inadequate for sociality to emerge (Verhagen 1998).

Inasmuch as emergence within the system is only possible when emergent results are explicit at a different level than its parts (Conte et al. 2001; Sawyer 1999), it is assumed that “minds are not enough for modelling society” (Castelfranchi 1998).

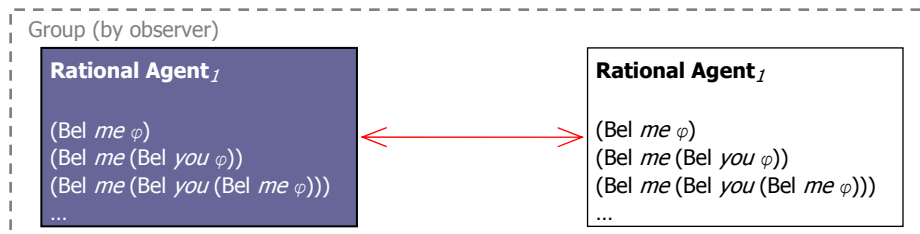


Figure 4.2 Social ability as the nesting of mutual beliefs. Notation reads “Agent believes statement φ ” after (Wooldridge 2000)

In this framework autonomy is interpreted as independence from the experimenter’s control, i.e., once the initial conditions and rules of interaction are given, the experimenter cannot determine the system’s path. However, autonomy is not taken to define agents as self-sufficient in isolation of other agents.

Agent autonomy is interpreted as interdependence, i.e., social mutual dependence. Agent interdependence is defined as reliance on the physical environment and on other agents to determine behaviour.

4.2.2 The Social Agent

The internal state of social agents includes individual and collective components that gradually go from the individual to group structures such as pair, team, group, community, class, to a society. In an agent-social environment causality is located in the *transition* from individual to groups.

Table 4.1 lists the variables of social agency.

Table 4.1 Agent behaviour variables.

SOCIAL AGENT BEHAVIOUR		
LABEL	VARIABLE	TYPE
α	Agent social behaviour	Instruction set
v	Internal state component	Variable set
Π	Situation	Variable
Ω	Environment state	Variable
ω	Perceived environment	Variable

Layers of influence form a type of ‘subsumption’ architecture (Brooks 1991) where agent behaviour is caused by components that range from individual to social. Figure 4.3 shows a schematic definition of the social agent where agent-environment interaction is mediated by layers that range from individual to collective characteristics.

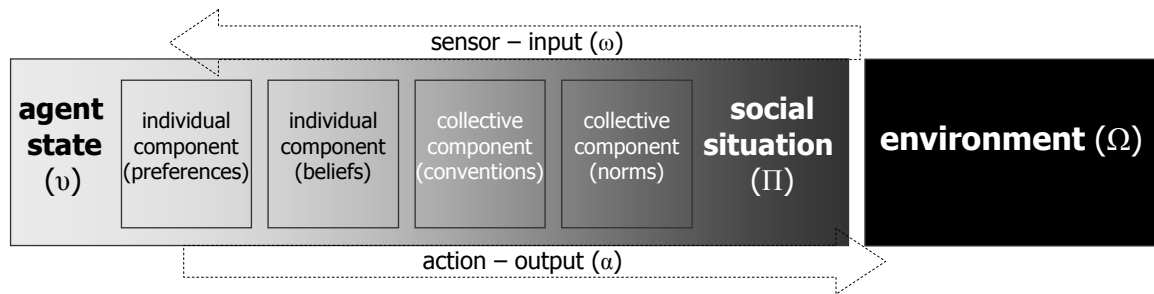


Figure 4.3 Schema of behaviour by a social agent. In isolation, it is a conventional agent-environment divide. As part of a group, behaviour is determined by a combination of individual and emergent structures that mediate interaction with the environment.

Social behaviour α of an agent in an environment Ω is defined in Eq. 4.1.

$$\alpha = \left\{ \frac{[\Pi(v, \omega)]}{\Omega} \right\}. \quad (4.1)$$

where individual behaviour α is determined by a situation Π of internal state components v and perceived external state ω . Internal state components v range from individual to collective and include perceptions, goals, preferences, and knowledge. Environment Ω is perceived by an agent as interpreted external state ω .

For instance, external state could consist of a measure of group unanimity. Unanimity may be perceived as group pressure (*groupP*) and become part of a situation when construed in combination with a relevant internal state. Such a state may consist of disagreement and a low extroversion threshold (*lowExt*) (Eysenck 1991). The result is a situation of influence of opinion that elicits compliant behaviour as illustrated in Eq. 4.2.

$$\text{Compliance} = \left\{ \frac{\text{Influence}(v_i, \text{groupP})}{\text{Unanimity}} \right\}, v_i = (\text{disagree} \wedge \text{lowExt}). \quad (4.2)$$

Equivalent measures of group unanimity perceived by agents that have different levels of extroversion can lead to the construction of two possible situations, i.e., compliance or assertiveness (Argyle et al. 1981; Asch 1951). In this way the same environment Ω can elicit different overt behaviour α_n from agents that construe different situations Π_n . Likewise, different environments Ω_n can generate a similar response α from the same agent within different situations Π_n . When a perceived environment condition ω is a strong determinant, agent behaviour can be expected to be normalised in a group. In contrast, when personal factors v dominate, behaviour is independently defined and more differentiated across a population.

4.2.2.1 Decisions under Group Pressure

An example of social agency is presented in a computational implementation of the Asch compliance paradigm (Asch 1951, 1955). In this widely replicated experiment test subjects comply with erroneous judgements expressed by associates of the experimenter when placed within certain group settings. The task consists of matching the length of a test line with three options as shown in Figure 4.4. Although test subjects provide correct estimations when tested in isolation, they tend to comply when faced with a contradicting unanimous group.



Figure 4.4 Original experimental conditions (Asch 1955)

The variables of this system are presented in Table 4.2. In this multi-agent replication two types of behaviour are defined: social α and covert α' . Covert actions yield the responses given by agents in isolation. Social behaviour consists of expressing that response publicly. An experimental variable is introduced to determine the level of difficulty of the task. Task difficulty ($0.0 < \Omega_d < 1.0$) is a function of the distance between test and control lines. When $\Omega_d \approx 0.0$, lines are close and easy to compare and agents tend to individually produce correct estimations α'_c . When $\Omega_d \approx 1.0$ line lengths are distant and hard to match and agents tend to produce wrong estimations α'_i .

Table 4.2 Asch compliance paradigm variables.

ASCH PARADIGM MODEL		
LABEL	VARIABLE	TYPE
α	Social behaviour	Boolean
α'	Covert behaviour	Boolean
α'_c	Correct estimation	Floating-point
α'_i	Incorrect estimation	Floating-point
v_e	Extroversion threshold	Floating-point ($0 < v_e < 1$)
v_a	Ability	Floating-point ($0 < v_a < 1$)
Ω_d	Task difficulty	Floating-point ($0 < \Omega_d < 1$)
Ω_β	Task threshold	Constant

Task difficulty eliminates the need for fixed responses by confederate subjects as in the original experiment. Instead, each agent estimates an individual response α' as a function of task difficulty Ω_d and individual ability v_a .

Ability ($0.0 < v_a < 1.0$) is implemented as a probability to correctly match line lengths. Agents with $v_a \approx 1.0$ can distinguish line lengths even in difficult tasks $\Omega_d \approx 1.0$. In contrast, agents with low abilities $v_a \approx 0.0$ cannot differentiate line lengths even in the simplest tasks $\Omega_d \approx 0.0$. Abilities are randomly assigned through the group from a Gaussian distribution.

A correct estimation α'_c is reached when the combination of abilities and inverse task difficulty is greater than an arbitrary task threshold Ω_β . An incorrect estimation α'_i is reached when this sum is less than Ω_β .

$$\alpha' = \begin{cases} v_a + (1 - \Omega_d) > \Omega_p \Rightarrow \alpha'_c \\ \text{otherwise} \Rightarrow \alpha'_i \end{cases} \quad (4.3)$$

Where as a function of their abilities v_a and task difficulty Ω_d , some agents reach correct α'_c and others incorrect α'_i estimations. Interesting group dynamics occur when contradicting estimations are publicly expressed as opinions.

The social ability of these agents consists of publicly expressing their estimations following a sequential order within their groups. Agents are assigned an extroversion threshold ($0.0 < v_e < 1.0$) (Eysenck 1991) from a Gaussian distribution. They are also assigned a turn to publicly state their response τ_a . The decision to express an opinion (α, τ_a) is a function of individual extroversion and group pressure. Group pressure Ω_G is a cumulative group-level measure that increases when agents agree on their opinions. When agents consecutively agree on a common response, group pressure increases linearly towards that response. If an agent has a different estimation ($\neg\alpha$), it expresses its opinion as a function of its extroversion v_e . Namely, if at turn τ_a , $v_e < \Omega_G$, the agent complies, otherwise it chooses to differ.

$$(\alpha, \tau_a) = \begin{cases} [(\alpha \neq \alpha_{\tau-1}) \wedge (v_e < \Omega_G)] \Rightarrow \alpha(\text{comply}) \\ \text{otherwise} \Rightarrow \alpha(\text{dissent}) \end{cases} \quad (4.4)$$

The agent that first expresses its opinion is not subject to group pressure since turn $\tau = 1$ and $\Omega_G = \emptyset$. Group pressure builds up with every subsequent opinion. The last agents to express their responses are likely to face high group pressure if previous responses have agreed. Group unanimity forms when all expressed opinions concur. In the original experiment the test subject is indeed instructed to respond only after all other group members have expressed theirs, i.e., $\Omega_G = N - 1$ where N is group size. Asch (1951) found that unanimity is the strongest situational determinant for compliance.

Figure 4.5 shows a typical case of compliance. Individual estimations α are shown for every agent in the table. The graph plots agent group ($N = 8$) by response order in the horizontal axis and extroversion thresholds v_e in the vertical axis. Agent *ag7* is the only agent to reach a correct estimation α_c . However, its turn to provide a response in the group τ_a is at a time where all previous agents have collectively formed an opposing unanimity $\Omega_G = 6$. At such point group pressure Ω_G (slope line in graph) is greater than *ag7*'s v_e and therefore it complies with an incorrect group judgement and contributes to form unanimity.

In our model, unanimity occurs more frequently around the extremes of task difficulty causing most agents to conform to high group pressures. This is consistent with the original experiment where the task is extremely simple. Moreover, it suggests that in tasks of medium difficulty compliance may be less significant than the Asch paradigm could suggest (Leyens and Corneille 1999).

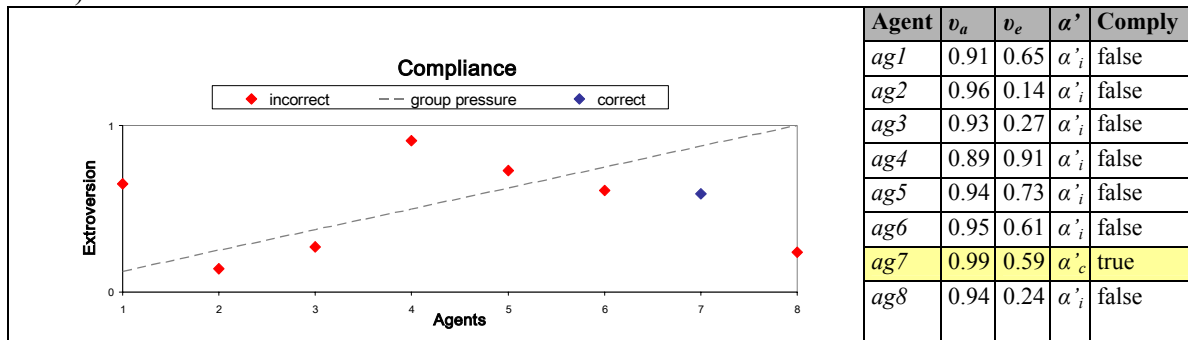


Figure 4.5 Agent implementation of Asch's experiment (1951) where an agent complies with an erroneous majority despite reaching a correct estimation (α'_i).

In this model of compliance personal factors play a role in determining behaviour. If ag_7 in Figure 4.5 had an extroversion value higher than emergent group pressure ($v_e < 6$), it would avoid compliance by providing a right response. Likewise, situational factors matter. If ag_7 was allowed to respond at an earlier time τ_a or if a previous agent had differed, ag_7 would have faced a lower group pressure Ω_G and avoided compliance. Therefore, resulting behaviour can only be explained by a combination of individual and emergent group conditions. In this case, the aggregate effect of group pressure combined with an individual threshold of extroversion.

Different insights extracted from the verbal account of yielding subjects from the original experiment after conditions were revealed provide further details on the sources of compliance (Asch 1951). Influence effects fell into three categories: distorted perception, distorted judgement, and distorted action. The first two are a type of informative influence whilst the third is a type of normative influence (Waller 2002). Informative influence occurs when individuals formulate their own choices based on information provided by others. Normative influence consists of conforming to the choices provided by others.

These sources of behaviour can be mapped onto components v of compliance. Three types of situations can be defined within which sufficient conditions exist for distortion. Firstly, some individuals had their perceptions distorted and their behaviour subsumed by group influence. This corresponds to compliers who did not trust their own perceptions and based their responses on what they assumed were correct group perceptions (Asch 1951). Other compliers had their judgements distorted, i.e., they believed that their perceptions were right but their judgements incorrect. Lastly, a third group trusted their perceptions and their judgements, yet chose to conform their actions to the majority. A social agent may choose to comply or dissent, but in both cases it bases its behaviour on its interaction with others (Sunstein 2002).

$$\text{Compliance} = \left\{ \frac{\text{Distortion}(v_i, \text{groupP})}{\text{Unanimity}} \right\}, v_i = (\text{perception} \vee \text{judgement} \vee \text{action}) . \quad (4.5)$$

4.2.3 Multi-agent Adopter Architecture

Social agents form the basis of an architecture of adoption and social influence. Adoption is defined as the decision process by which an agent accepts an available solution. The analogy refers to social groups which evaluate and buy or adopt design artefacts. The conceptual level of social interaction is shown in Figure 4.6. The assumption is that there is an emergent but explicit entity at an upper level that results from the aggregation of individual actions. Social structure emerges from agent interaction (bottom-up) and feeds back into individuals (top-down). This provides another level of analysis with properties not deducible from its isolated parts, i.e., group pressure, majorities, etc. An agent can model and direct its behaviour in a way in which it believes will direct other agents' behaviour, i.e., they will be influenced. Social structures can consist of a pair of agents, team, group, class, majority, society, or population.

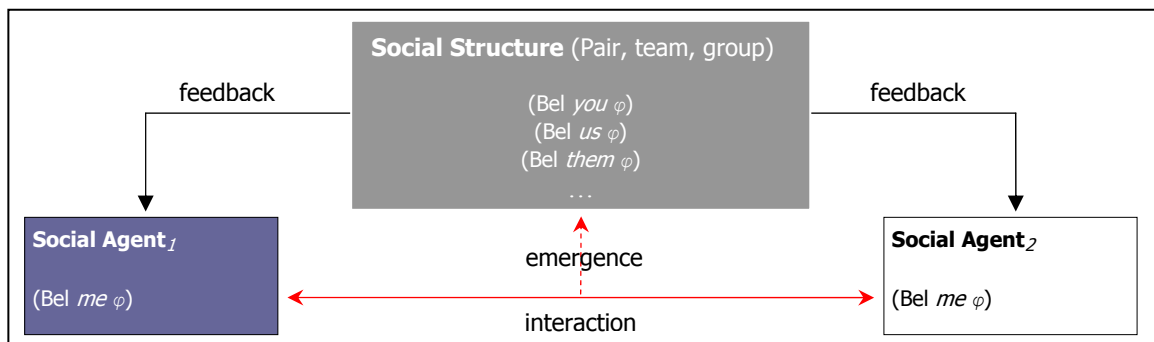


Figure 4.6 Explicit social structure formed by the beliefs (Bel) of two agents. Compare to Figure 4.2

Social agents are influenced and seek to influence the behaviour of others. The defining characteristics of social agents would have no relevance in isolation separate from a social group. At the implementation level, Figure 4.7 shows a diagram of a system of adopter agents where elements of the decision process of adoption become part of the group structure. Such elements may include processes such as perception, preferences, requirements, and choices. Group structures emerge from agent interaction and mediate their interaction with the environment. These structures are shared by agents at different times causing them to exhibit different degrees of normalised behaviour. Perceptions may become collectively biased, preferences may be emphasised by groups at different times, and socially permissible actions may be established. Namely, the perception of a solution by a group of adopter agents may be similar, but not their priorities or requirements.

A decision-making process of interest in design is the adoption of solutions. Design artefacts are assumed to be evaluated by a population in two complementary ways. Individually, adopters form their own perceptions and develop their own preferences. In a group, adopters exchange, compare, and influence each other on their perceptions, preferences, and choices. These shared elements constitute what is *common* to members of a community or a group.

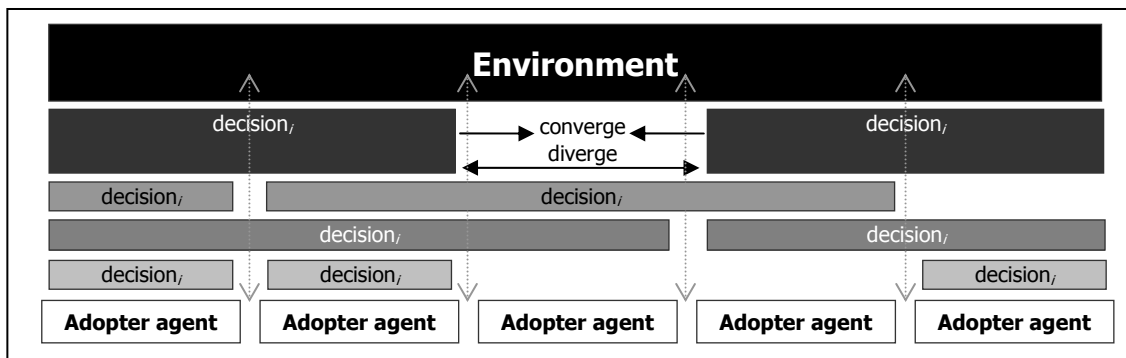


Figure 4.7 Socio-cognitive architecture where behaviour components become part of emergent group structures.

A social space or social network is defined in this framework as an arrangement of neighbouring agents as shown in Figure 4.7 and variables in Table 4.3. However, social interaction is usually assumed to take place in more than one social environment simultaneously (Wasserman and Faust 1994). For this reason, adopter agents in a design model should be organised in a number of social spaces where they have different connections with other agents (neighbours) and different ways of interacting with them. In other words, social agents inhabit several social spaces, i.e., they have different positions within kinship, work, acquaintances, and other types of social environment or space.

Each social space can be modelled with different parameters, i.e., different extroversion thresholds and rules of interaction. Likewise, social spaces can be implemented in various ways including but not limited to n -dimensional grids such as those inspected in Section 3.2.2.2, or social networks of various types (Wasserman and Faust 1994; Watts and Strogatz 1998). In the former type of implementation, social position is defined by the location of a cell within the grid; in the latter type by assigned social ties.

Table 4.3 Social spaces variables.

SOCIAL SPACES		
LABEL	VARIABLE	TYPE
Γ	Social space	Sorted set
γ	Social position	Social net node, index
v_e	Individual extroversion threshold	Floating-point ($0 < v_e < 1$)

A social space Γ in this framework depicts a sorted set of social agents where their locations (represented by nodes in a social graph) and their relations (links connecting nodes) are randomly assigned. Social spaces Γ_i are sets of agent positions γ .

$$\text{Population} = \left\{ \begin{array}{l} \Gamma_1(\gamma_{i..n}) \\ \Gamma_2(\gamma_{i..n}) \\ \Gamma_3(\gamma_{i..n}) \end{array} \right\}. \quad (4.6)$$

Adopter agents are randomly assigned individual positions at initial time on each social space. They receive individual extroversion thresholds v_e from a Gaussian distribution. These extroversion values will regulate agent interaction as described in Section 4.3.3 (Eysenck 1991). Lastly, each social space can be initialised with different conditions including types of neighbourhood.

4.3 Designer Agents

The design task described in this framework captures some of the characteristics of design problems including interpretation; generation of alternatives; negotiable and nomological constraints; no right or wrong answers; and delayed feedback (Buchanan 1995; Goel 1994; Rittel 1984). The task consists of generating artefacts that adopter groups evaluate based on a multi-objective adoption function that maximises geometric relationships and novelty, i.e., artefacts that are more different from the rest.

Designer agents modify their artefacts by learning and applying rules that increase their adoption. If appropriate, they may also imitate more successful competitors. In combination with attracting adopters to their artefacts, designer agents aim to generate artefacts that are selected by experts in the field. Selected artefacts are given a score as they are incorporated into the domain. The performance of designers in this task is estimated along the following dimensions: a) the size of adopter bases and their satisfaction, b) the number and type of design rules generated, c) the influence on other designers' work, and d) the domain entries and scores given by experts. These indicators of performance provide a simple account of phenomena such as popularity, quality, novelty, peer-recognition, and expert juries.

A multi-objective adoption function guarantees that in this task there is no single best artefact configuration. Evolving preferences of adopters causes designers to continually update their artefacts. Whilst there are clear evaluation criteria, the appropriateness of artefacts is given by the existing conditions of the population as well as the actions of other designers. Designers consider artefact changes by modelling the evaluation decision of target groups. Feedback is only obtained after the artefact is made available. Solutions can be gradually modified. There are fixed constraints given by the artefact representation.

Experimental variables of this task can be manipulated by the experimenter to build and test hypotheses. These variables define the characteristics of individual designers, or properties of their interaction with adopter groups, or domain rules. The aim is to vary conditions and run a number of simulations (i.e., cases) a number of times in order to observe patterns that link initial conditions with observed behaviour. Keeping every other condition constant, the experimenter can attribute causal associations. Within a society, a number of competing designer agents are initialised. The number of designers can be varied as well as the frequency and other parameters of their behaviour. First, the artefact representation is described and then details are given on the formation of design strategies and the learning of design rules, design rate and individual differences between designer agents.

4.3.1 Artefacts

Artefacts are defined in this framework as the solutions product of design behaviour. They are an abstract representation that captures some of the properties of design solutions. In this system

artefacts are generated by designers and evaluated by adopters. They support reasoning for adoption decisions. They are implemented as sets of two-dimensional line representations constrained by 12 boundary points as shown in Figure 4.8a, variables in Table 4.4.

This is a simple way of representing features of design artefacts with nomological constraints (Goel 1994). Multiple representation and ambiguity are possible because artefacts are perceived and interpreted by adopters according to a set of randomly distributed perception biases. Figure 4.8b shows sample perceived features of an artefact. The assumption is that people perceive design artefacts in (marginally) different ways and therefore base their evaluations on different features of design products.

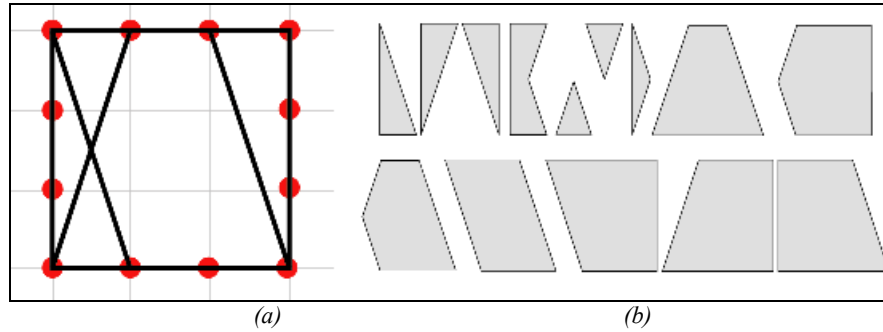


Figure 4.8 (a) A simple design artefact representation and (b) some possible interpretations of an artefact built by adopters based on individual perception biases.

Table 4.4 Notation of artefact variables.

ARTEFACTS		
LABEL	VARIABLE	TYPE
Ω_E	Artefact representation	Line set
v_ϵ	Individual perception threshold	Floating-point
ω_ϵ	Perceived feature	Two-dimensional shape
E	Perceived artefact	Shape set
$\Psi(E)$	Evaluation of perceived artefact	Geometric function set
$\Psi(\omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots})$	Geometric relation between perceived features	Geometric function

At the implementation level, an artefact Ω_E in this framework is given by a set of two-dimensional lines built from pairs of point coordinates. A perceived artefact, E, is an adopter's interpretation of Ω_E . This interpretation is represented in the system by a set of perceived features, ω_ϵ , represented by closed shapes built by each adopter following Hamiltonian cycles in Ω_E . The process of perceiving an artefact is executed individually by each adopter by cycling the line set, Ω_E , in search of closed shapes, i.e., the perceived features of Ω_E . Potentially, any given Ω_E contains a large number of closed shapes as shown in Figure 4.8. However, an adopter does not perceive *all* features of an artefact Ω_E . Depending on an individual perception threshold, v_ϵ , an adopter is enabled to see only *some* of the features of an artefact Ω_E .

A perception threshold, v_ϵ , is individually assigned to adopters from a Gaussian distribution with mean and standard deviation as independent variables. With a tolerance of ± 1 , v_ϵ indicates the number of boundary points in Ω_E that a perceived feature ω_ϵ can include. Therefore, with $v_\epsilon = n$ an adopter will perceive artefact features represented by shapes that include $n-1$ to $n+1$ boundary points. For this reason there are differences between adopters' perceived versions, E, of a common artefact, Ω_E .

In sum, a perceived artefact, E, is represented by a set of perceived features, ω_ϵ , built by an adopter as closed shapes from an artefact description Ω_E using a perception threshold v_ϵ . Closed shapes are built as Hamiltonian cycles from the line graph representing an artefact. The problem of finding singular paths is NP-complete (Garey and Johnson 1979), so perceived features ω_ϵ are built

by exhaustive search with a branch limit $v_\epsilon \pm 1$. Namely, the algorithm traverses the graph taking every point as the initial vertex and building polygons that return to it without intersecting after visiting $v_\epsilon \pm 1$ vertices.

$$E = \left\{ \frac{v_\epsilon \pm 1}{\Omega_E} \right\} = \{ \omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots} \} . \tag{4.7}$$

Where an artefact Ω_E that is represented as a line graph is perceived as a set of features, ω_ϵ , (closed shapes) given a perception threshold v_ϵ . Figure 4.9 shows four different perception processes of a common artefact where v_ϵ determines the number of vertices of perceived features ω_ϵ . In Figure 4.9(a) an adopter requires a perception threshold, $v_\epsilon \approx 10$ in order to perceive the resulting feature, ω_ϵ , of this artefact. In Figure 4.9(b) a perception threshold, $v_\epsilon \approx 9$ is required to perceive the resulting feature, ω_ϵ . In Figure 4.9(c) $v_\epsilon \approx 6$ yields the resulting feature, ω_ϵ . Lastly, in Figure 4.9(d), $v_\epsilon \approx 3$ enables the perception of this artefact feature. Because perception threshold, v_ϵ , has a tolerance of ± 1 , the same adopter could perceive artefact features in Figure 4.9(a-b).

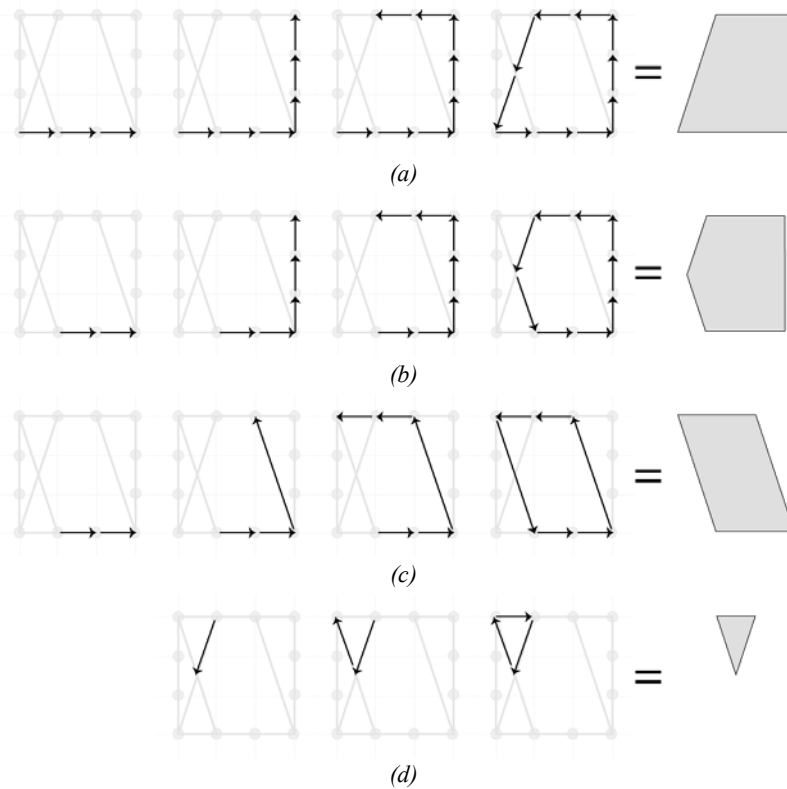


Figure 4.9 Hamiltonian cycles yield artefact features. In (a) an adopter requires a perception threshold, $v_\epsilon \approx 10$ in order to perceive the resulting feature; in (b) adopter's perception, $v_\epsilon \approx 9$; in (c) adopter's perception, $v_\epsilon \approx 6$; in (d) adopter's perception, $v_\epsilon \approx 3$. Because perception threshold, v_ϵ , has a tolerance of ± 1 , the same adopter could perceive artefact features in (a) and (b).

Because artefact features are represented by two-dimensional shapes, it is possible to evaluate artefact geometry $\Psi(E)$. A geometric relation ψ exists between two or more perceived features, i.e., uniform scale, rotation, intersection, etc. These are expressed as $\psi_i(\omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots})$, i.e., the type of relationship and the features involved.

Figure 4.10 shows five artefacts with perceived features, ω_ϵ , that exhibit the geometric functions implemented in this system: (a) uniform scale, (b) alignment and rotation, (c) rotation and intersection, (d) reflection, and (e) uniform scale and reflection. Naturally, geometric relations are

built based on the perception of the corresponding features, i.e., the scale property of Figure 4.10(a) is only perceived if both triangles in Figure 4.10(a) are perceived, and similarly for each case in Figure 4.10. In the case of Figure 4.10(a) the relation is written as $\psi_{scale}(\omega_{t1}, \omega_{t2})$.

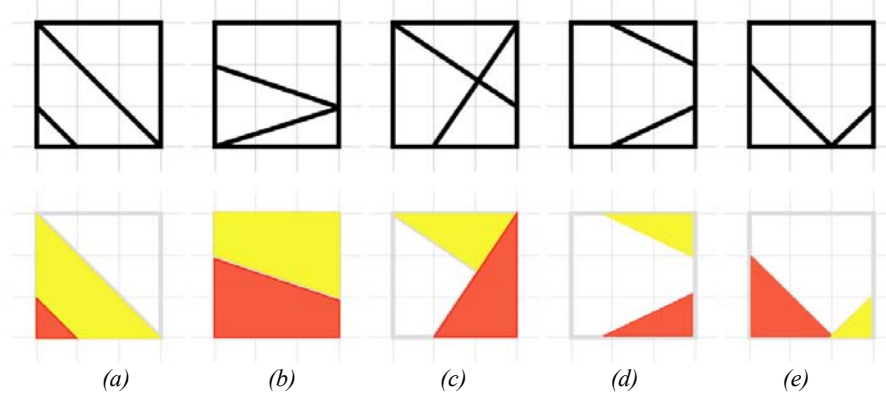


Figure 4.10 Types of geometric properties between artefact shapes or perceived features, ω_ϵ . Potentially perceived features in (a) exhibit a uniform scale relationship; in (b) alignment and rotation; in (c) rotation 90° and intersection; in (d) vertical reflection; and in (e) horizontal reflection and uniform scale.

The evaluation of an artefact $\Psi(E)$ by an adopter is given by the set of geometric relationships between the perceived features ω_ϵ by the adopter.

$$\Psi(E) = \{ \psi_0(\omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots}), \psi_1(\omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots}), \psi_{\dots}(\omega_{\epsilon 0}, \omega_{\epsilon 1}, \omega_{\epsilon \dots}) \}. \quad (4.8)$$

Given that the adoption function maximises multiple geometric relationships, an artefact is a compromise between conflicting evaluation criteria. Namely, a single artefact cannot contain all geometric characteristics (i.e., some aspects of scale and alignment are mutually exclusive). The design task therefore consists in adapting artefacts to adopters' demands. When the system is initialized, artefacts are configured and assigned to each designer. Typically, artefacts are all set to a common configuration from which designers start their task. The first step is to build design strategies.

4.3.2 Strategies

Designer agents evaluate their artefacts to decide what features to change in order to increase adoption. Variables are presented in Table 4.5. This decision determines the strategy to follow. We assume that designers are able to sample their adopter groups. Firstly, designer agents use the mean perception threshold v_ϵ of their adopters to model the set of perceived features, ω_ϵ , of their artefacts. Secondly, designer agents use the most frequent adoption preference of their adopter group as a target preference. Adopter preferences -introduced below in Section 4.4.1- consist of individual biases of geometric relationships. Namely, adopters assign a preference bias to every geometric criterion such as alignment, rotation, etc. A preference $\rho(\psi)$ is implemented as an adopter bias between 0.0 and 1.0 for each geometric relation of a perceived artefact. These two feedback elements from the adoption group provide designer agents with the basis on which adopters choose their artefacts. If the artefact of a designer has no adopters, then random perception threshold and criteria preference are set.

Table 4.5 Strategies variables

STRATEGIES		
LABEL	VARIABLE	TYPE
$\rho(\psi)$	Adoption preference	Floating-point
$P(\Psi)$	Set of adopter group preferences	Floating-point set

$\rho'(\psi)$	Most frequent adopter group preference	Floating-point
μ	Design strategy	Function
μ_{Comp}	Competition strategy	Function
μ_{Diver}	Diversification strategy	Function
μ_{Diff}	Differentiation strategy	Function

Based on the mean perception threshold v_e , designer agents simulate the perception and the adoption evaluation of its adopters to obtain the estimated artefact performance $\Psi(E)$. The result is an approximate perceived performance of the artefact by criterion $\psi_i(\omega_{e0}, \omega_{e1}, \omega_e \dots)$. This is rated against the highest adoption preference $\rho'(\psi)$ of the adopter group. Three types of strategies are defined based on this rating: competition, diversification, and differentiation (Nattermann 2000). In this way the designer agent ‘decides’ what to modify based on how its artefact performs against the preferences of its adopter group.

$$\rho'(\psi) = \text{mode}(P(\Psi)); P(\Psi) = \{\rho(\psi)_0, \rho(\psi)_1, \rho(\psi)_{\dots}\} . \quad (4.9)$$

Where the set of adopter group preferences $P(\Psi)$ is a set of the individual preferences of adopters. $\rho'(\psi)$ is the most frequent preference of the group.

A competition strategy is defined by a designer agent when the performance of the main adoption preference is above the mean of all geometric criteria. In competition mode, designer agents aim to improve the features that provide good performance on the preferred geometric criterion. For instance, if the main preference of adopters is rotation, designers aim to modify their artefacts to increase rotation relationships. Competition indicates that the designer is likely to increase adoption by gradually increasing the performance of the preferred criterion, i.e., it has a chance to improve.

$$\rho'(\psi) > \text{mean}(\Psi(E)) \Rightarrow \mu_{Comp} . \quad (4.10)$$

Diversification strategies are selected by designer agents when the performance of the main adoption preference is the best geometric criterion of the artefact. In diversification, designers set to improve features where their artefacts perform best other than the adopters’ preferred geometric criterion. For instance, if the main preference of adopters is rotation and this criterion receives the highest score (i.e., is the best feature of the artefact), then designers aim to modify other features without decreasing the rotation rating. Diversification indicates that the designer is likely to improve performance in an additional criterion.

$$\rho'(\psi) = \max(\Psi(E)) \Rightarrow \mu_{Diver} . \quad (4.11)$$

A differentiation strategy is chosen when artefact features perform below average on the adopters’ main preferences. In differentiation, designers aim to improve features that perform best on different geometric relationships. This is because an implicit criterion of novelty controls the adoption function, so adopters may prefer an artefact that performs well in a different criterion. For instance, if the main preference of adopters is rotation and the designer’s artefact performs poorly on rotation but performs very well in alignment, it may choose to improve alignment. Differentiation indicates that given its current artefact, a designer is not likely to improve performance on the preferred criterion but is likely to offer good performance on other criteria.

$$\rho'(\psi) < \text{mean}(\Psi(E)) \Rightarrow \mu_{Diff} . \quad (4.12)$$

At initial time, when all artefacts start with the same configuration, all designers engage in differentiation strategies until they start finding out what features perform well in the current population. Then, designers start to modify their strategies. The adopter population does not

converge into one solution: when artefacts get too similar, designers seek to improve other features. Strategies therefore indicate what features of their artefacts designers change (and *why*). The actual change is based on a type of learning process in which designers generate and apply rules.

4.3.3 Learning

Designer agents follow a learning mechanism to generate rules. Variables are presented in Table 4.6. Design rules are ‘condition : action’ pairs obtained from random changes to selected lines. A rule is formed when a designer modifies a feature of its artefact and as a result obtains positive feedback. Feedback consists of an increase of artefact performance in the adoption evaluation function. Therefore, rules improve the geometric characteristics of artefacts.

The lines to be changed are determined from estimating their contribution to perceived features that return high adoption values. Lines rank low if they are used in features that are not valued by adopters or if they are not part of perceived features.

Table 4.6 Learning and imitation variables.

LEARNING		
LABEL	VARIABLE	TYPE
$\delta\Omega_E$	Design rule	Array
$\Delta\varepsilon$	Change of perceived feature	Function
$\Delta^+\Psi(E)$	Increase of perceived artefact evaluation	Function
$\Delta\Omega_E$	Knowledge base	Array
$(\delta\Omega_{Ei})$	Set of design rules for designer agent i	Array
$K(\Delta\Omega_E)$	Type of access to knowledge base	Variable
K_{pub}	Public access to knowledge base	Variable
K_{prv}	Private access to knowledge base	Variable
$\overline{\delta\Omega_E}$	Imitation	Function

Rules are built in an informed trial-and-error process: designers try changes to low-ranking lines at random for a limited number of times. If they find a new rule, they build and apply it; if not designers imitate more successful artefacts. A design rule is defined as a change of perceived feature such that an increase on evaluation occurs.

$$\delta\Omega_E = \left\{ \Delta\varepsilon \Rightarrow \Delta^+\Psi(E) \right\}. \quad (4.13)$$

The knowledge base is the set of design rules generated by all designer agents during a simulation run.

$$\Delta\Omega_E = \left\{ \delta\Omega_{E0}, \delta\Omega_{E1}, \delta\Omega_{E\dots} \right\}. \quad (4.14)$$

Designers need not generate new rules every time. They can store a number of ‘condition : action’ pairs that can be applied at future times when relevant artefact features and performance results exist. This supports different types of knowledge access: designer agents can apply rules that others build, or access can be limited to the rules that each designer generates. This parameter allows the exploration of the effects of public and private access to knowledge.

$$K(\Delta\Omega_E) = \left\{ \begin{array}{l} \Delta\Omega_E \Rightarrow K_{pub} \\ \delta\Omega_{Ei} \Rightarrow K_{prv} \end{array} \right\}. \quad (4.15)$$

Lastly, when designer agents cannot build or apply rules, they resort to imitative behaviour. Designers replace their low-ranking feature with a random line from the best adopted artefact at that time. When this occurs, designers give credit to the designer of the source artefact. This allows

exploration of peer-recognition processes. Imitation is defined as the change of perceived features by the transfer of a feature from an artefact Ω_E with the highest evaluation $\Psi(E)$.

$$\overline{\delta\Omega_E} = \{ \Delta\varepsilon \Rightarrow \Omega_E, \max(\Psi(E)) \} . \quad (4.16)$$

4.3.4 Design Rate

Designers are assigned equivalent artefacts at initial time of a simulation run. At regular intervals they evaluate and modify their artefacts. This rate of design Ω_D is an independent variable measured as a multiple of adoption iterations, i.e., design behaviour can be scheduled as a function of how often adopter agents evaluate artefacts. After a design update of artefacts, adopters perceive the modified artefacts and continue their adoption evaluation based on the changes introduced by designers. In different fields, the rate of design activity can be assumed to be different. This parameter allows the exploration of the effects of design frequency. Design rate is defined as a ratio of adoption iteration steps τ_D .

$$\Omega_D = \frac{1}{\tau_D} . \quad (4.17)$$

4.3.5 Individual Differences

Designer agents have different individual attributes as defined in Table 4.7, i.e., processing and synthetic abilities. Processing abilities refer to the capacity of a designer agent to manipulate design rules. Synthetic abilities refer to the capacity to generate different alternatives during the design process. At initial time designers are assigned individual abilities from a Gaussian distribution.

Table 4.7 Individual Differences and development variables.

INDIVIDUAL DIFFERENCES		
LABEL	VARIABLE	TYPE
v_t	Individual synthetic ability	Floating-point
v_m	Individual memory-analytic ability	Floating-point

Synthetic abilities v_t refer to the number of alternative solutions that designer agents generate during the design process. At the implementation level this is given by an individual limit to the number of trials that a designer has to generate a new design rule. A designer with higher v_t has higher probability of generating new rules than a designer with lower v_t .

$$v_t = \{ \Delta\varepsilon_0, \Delta\varepsilon_1, \Delta\varepsilon_{\dots} \} . \quad (4.18)$$

Processing differences v_m refer to the ability to apply existing design rules. They are implemented by the individual number of maximum rules that a designer can keep during a simulation. With low v_m , designers tend to replace their rules constantly and have access only to the rules most recently generated. With high v_m , designers have access to a large number of rules.

$$v_m = \{ \delta\Omega_{E0}, \delta\Omega_{E1}, \delta\Omega_{E\dots} \} . \quad (4.19)$$

Individual differences are dynamic, they do not remain fixed during a simulation run. Designers can modify their initial v_t and v_m values over time. This occurs when a designer agent receives recognition from other designers that imitate their behaviour. When they receive credit from imitating designers, they increase their v_m and v_t values by one unit. These individual parameters allow exploration of the impact of individual differences in the system.

4.3.6 Industry

An industry is defined as the collection of designers competing within a society. The Strategic Differentiation Index SDI is used to measure competition as introduced in Table 4.8 (Nattermann 2000; Smith 1996). In this framework SDI is estimated by the sum of score of adopters measuring the perceived differences between designers. SDI is a measure of the performance of designers. $SDI \approx 1.0$ indicates that features of available artefacts are perceived as different by adopters. When $SDI \approx 0.0$ a ‘herding effect’ takes place showing that adopters perceive no differences between artefacts.

Table 4.8 SDI variables

STRATEGIC DIFFERENTIATION INDEX		
LABEL	VARIABLE	TYPE
Ω_{SDI}	Strategic Differentiation Index	Floating-point

SDI is implemented by the sum of variances given by adopters’ evaluations of perceived artefacts. As adopters evaluate every artefact, they provide an individual variance of artefacts’ evaluations. The sum of variances is the index of differentiation, Ω_{SDI} .

$$SDI = \sum_{i..n} \{ \sigma [\Psi(E)] \} . \quad (4.20)$$

SDI is useful to verify the implementation of the system when compared to design strategies, peer recognition, and adoption satisfaction. At initial time SDI is low as all artefacts are similar. SDI increases as the number of design strategies of differentiation and diversification increase. In contrast, SDI is expected to decrease when designers imitate others, i.e., peer recognition is high. Lastly, inasmuch as adopters maximise artefact novelty, a positive correlation between SDI and adopters’ satisfaction can be expected.

4.4 Adopter Groups

This framework defines a generic adoption schema that can be adapted to address different types of adoption (Pesendorfer 1995). Adopter agents evaluate available artefacts and decide to adopt or reject them. This process is influenced by the interaction with other adopters. A product of this interaction is the organisation of adopters in social groups from which opinion leaders emerge. Opinion leaders gain the role of gatekeepers of the domain.

4.4.1 Adoption Function

The definitions of artefacts and design strategies introduced earlier made reference to the adoption function. This Section describes this process in detail using the variables in Table 4.9. In general, the decisions of social adopters are determined by individual factors such as preferences and by social factors such as influence of opinions. In different design fields more specific assumptions can be incorporated into the adoption functions. For explanatory purposes, in this case adopters evaluate artefacts based on a multi-objective adoption function where six geometric criteria are evaluated, i.e., horizontal and vertical alignment, intersection, rotation, similar bounds, and number of sides.

Table 4.9 Adoption Decision variables.

ADOPTION DECISION		
LABEL	VARIABLE	TYPE
ω_{ϵ}	Perceived feature	Two-dimensional shape

E	Perceived artefact	Shape set
$\Psi(\omega_{e0}, \omega_{e1}, \omega_{e...})$	Geometric relation of perceived features	Floating-point
$\Psi(E)$	Evaluation of perceived artefact	Floating-point set
$\rho(\Psi)$	Adoption preference	Floating-point
α_A	Adoption decision	Floating-point

Firstly, the adoption process implemented in this system maximises geometric relations between perceived features, ω_e . Evaluation of these relations between artefact features yields independent scores per criterion. Namely, an artefact can be perceived by an adopter as having different performance indices for alignment, rotation, and the other geometric criteria. Depending on their individual perception of the same artefact, other adopters may agree or disagree with that evaluation. The adoption function can be explained by the following definition.

$$\Psi = \sum_{i=1}^n \left(\frac{\omega_e}{N_{\omega}^2 - N_{\omega}} \right). \quad (4.21)$$

Where the geometric relation, ψ , between perceived features, ω_e , is estimated by the ratio of perceived feature pairs against all possible pairs ($N_{\omega}^2 - N_{\omega}$). A separate ψ is built for each geometric criterion (i). This objective evaluation yields similar results for adopters that perceive an equivalent set of features from an artefact. For adopters that perceive different features of an artefact, this evaluation yields different results.

In addition, individual adoption preferences $\rho(\psi)$ are implemented in the form of biases for every geometric criterion. These biases are assigned at initial time from a random Gaussian distribution with control mean and standard deviation. This individual bias is a further source of evaluation disagreements. Namely, adopters that perceive an equivalent set of features of an artefact may disagree on their evaluation if their individual preferences are different. This is a way to implement the assumption that even if all adopters can agree on performance measures, the relevance of features is individualised. For instance, we all may agree that a sports car is fast, but speed is an important purchase factor only for some.

$$\psi + = \rho(\psi). \quad (4.22)$$

Where individual preference $\rho(\psi)$ biases the evaluation of a geometric relation, ψ , by adding a weight determined by a random value from a distribution with independent mean and standard deviation. The evaluation of an artefact is given by the geometric relations of its perceived features which include the bias of individual preferences.

$$\Psi(E) = \{ \psi_0, \psi_1, \psi_{...} \}. \quad (4.23)$$

The adoption function of an artefact is translated into the adoption decision as a function of the perceived novelty of the artefact. Perceived novelty is given by the difference per criterion between perceived artefacts. This mechanism promotes artefacts with the most distinctive attributes. Given that geometric functions are mutually exclusive, perceived artefacts are expected to receive a high evaluation in some geometric functions and low in others. As shown above, adopters compare artefacts on every geometric criterion. The artefact with the criterion with the highest difference from the mean performance in that criterion is chosen. This choice is called the adoption decision, α_A .

$$\alpha_A = \max(\psi_i). \quad (4.24)$$

Where the adoption choice α_A is based on the most distinctive geometric criterion between artefacts. Therefore, an artefact with a high index ψ in a criterion where all other artefacts have a

low evaluation is more likely to be adopted than an artefact with a higher mean evaluation Ψ if other artefacts also rank high on the same criteria. Since evaluations are based on different perceived features and different individual biases are applied, the population need not converge to a single artefact. If adoption decisions converge at the population level, they need not be based on the same criteria.

Individual preferences are dynamic. One way in which adoption preferences change is by a mechanism of habituation. Adopters update their preferences $\rho(\psi_i)$ at every adoption decision by marginally increasing their preference for the criterion with the highest score if other artefacts do not perform well in that criterion. This mechanism generates a gradual trend by which adopters ‘get used’ to good artefacts as long as they maintain a degree of novelty.

4.4.2 Adoption Satisfaction

In this framework adopter satisfaction is used as a complimentary post-adoption measure of quality. Variables are introduced in Table 4.10.

Table 4.10 Adoption Satisfaction variables.

ADOPTION SATISFACTION		
LABEL	VARIABLE	TYPE
$\rho(\psi)$	Adoption preference	Floating-point
$P(\Psi)$	Set of adopter group preferences	Floating-point set
v_s	Adoption satisfaction	Discrete variable

Satisfaction v_s is a discrete value given by the comparison of adoption decision α_A and individual preference $\rho(\psi)$. It is represented as $v_s = \{-1, 0, 1\}$. These values correspond to three levels of satisfaction: not satisfied, satisfied, and very satisfied, respectively.

Satisfaction does not determine adoption, it is a measure of how satisfied is an adopter after it formulates its adoption decision α_A , based on perceived performance, individual biases, and novelty. An adopter may choose an artefact that performs very well in unique criteria and still be dissatisfied.

$$\left. \begin{array}{l} \rho(\psi) = \max(\Psi(E)) \Rightarrow v_s = 1 \\ \rho(\psi) > \text{mean}(\Psi(E)) \Rightarrow v_s = 0 \\ \text{otherwise} \Rightarrow v_s = -1 \end{array} \right\} . \quad (4.25)$$

If the preferred geometric criterion $\rho(\psi)$ receives the highest evaluation score of $\Psi(E)$, then adopter satisfaction $v_s = 1$, i.e., the best features of the artefact match the adopter’s preference. However, if the preferred criterion $\rho(\psi)$ is not the highest of $\Psi(E)$ but is above the mean, $v_s = 0$ or adopter is just satisfied. Lastly, if $\rho(\psi)$ is below the mean evaluation component, $v_s = -1$ or the adopter is not satisfied. An adopter may be not satisfied even when the artefact performs well if it is differentiated from other artefacts in criteria other than the adopter’s preferences. If the artefact does not perform well or is not different from other competing artefacts, then the adopter abstains and its satisfaction level $v_s = -1$ by default.

As defined in Section 4.2.2, designers formulate competition strategies when adopters are satisfied and differentiation strategies when adopters are dissatisfied.

4.4.3 Social Interaction

Social interaction complements the adoption decision process. It consists of contact with neighbouring adopters where the aim is to influence their adoption decisions. Variables are introduced in Table 4.11. Adopters are assigned random positions in different social spaces where their positions are represented by nodes and their adjacency by links or social ties.

Table 4.11 Social Ties variables: strength, neighbourhood size.

SOCIAL INTERACTION		
LABEL	VARIABLE	TYPE
Γ	Social space	Sorted set
γ	Social position	Social net node, index
v_e	Individual extroversion threshold	Floating-point ($0 < v_e < 1$)
γ_T	Social tie strength	Floating-point ($0 < \gamma_T < 1$)
γ_H	Neighbourhood size	Integer
v_f	Influence measure	Integer

Social ties are represented by linkages between nodes in a social network. These links determine what adopters (nodes) have contact with each other. The strength of social ties refers to the likelihood that nodes in the social network are maintained over time (Granovetter 1973). Strong ties are characteristic of resilient social relationships such as kinship or friendship, whilst weak ties characterise temporary social networks such as school peers or travel acquaintances.

In this system social tie strength, γ_T , is determined by the probability of interaction between nodes over a period of time. In networks with strong social ties adopter agents maintain contact with each other over longer time periods, whilst in networks with weak ties adopter agents constantly change contact with different neighbours.

In this framework we implement a basic notion of social tie strength as a probability ($0.0 < \gamma_T < 1.0$) that any possible social relation will remain in adjacent positions at the next time step. In social spaces where $\gamma_T \approx 0.0$ there is higher mobility, i.e., adopter agents are shuffled more often and get to interact with different adopters over any given period. In contrast, $\gamma_T \approx 1.0$ bonds adopter together causing a decrease in social mobility, i.e., adopter agents remain in their same neighbourhoods interacting with the same agents for longer periods of time.

$$\gamma_T = P\left(\frac{\Delta\gamma_{i-j}}{\tau +}\right). \quad (4.26)$$

Where γ_T is given by the probability, P , that adopters remain in contact as time, τ , progresses.

Neighbourhood size, γ_H , is given by the number of links from a node -also called ego-centred networks (Wasserman and Faust 1994). γ_H and γ_T are positively related according to the theory that the number of social ties increases with the impact of influence (Granovetter 1978).

A social space or social network is defined in this framework as an arrangement of neighbouring agents as described in Section 4.2.3. Social interaction is usually assumed to take place in more than one social environment simultaneously.

Three social spaces Γ are defined in this framework by the content of interaction. In the first, Γ_1 , adopters exchange adoption preferences $\rho(\psi)$. Within a second social space Γ_2 adopters spread percepts, ω_e . A third space Γ_3 is set where agents exchange adoption decisions, α_A . An extroversion threshold, v_e , is assigned to adopters to control the spread these decision components to other adopters. At initial time $0.0 < v_e < 1.0$ is randomly assigned to adopters from a Gaussian distribution. Different v_e values are given to an adopter in every social space (Marsden and Campbell 1984).

After a period of interaction, a group of adopters may emerge that shares similar preferences, similar perceived features of artefacts, or similar adoption decisions. Random walks in one and two dimensional spaces are recurrent, i.e., have a probability of 1 of visiting the same point given sufficient time. However, it has been proven that this probability in ≥ 3 -dimensional random walks approaches zero (Liggett 1999).

As a result, adopter populations based on three or more social spaces need not converge on these decision components even during long system runs. Influence, v_f , occurs from neighbouring agents $\gamma(i,j)$ in a social space Γ when extroversion $v_e(i) > v_e(j)$.

$$v_f = \left\{ \frac{v_e(i) > v_e(j)}{\gamma(i, j)} \right\} . \tag{4.27}$$

The cumulative influence, v_f , of adopter i represents the cumulative number of neighbours that an agent influences. Figure 4.11 shows a sample influence structure where an adopter with highest dominance v_f (in red) has a large neighbourhood $\gamma_H = 6$.

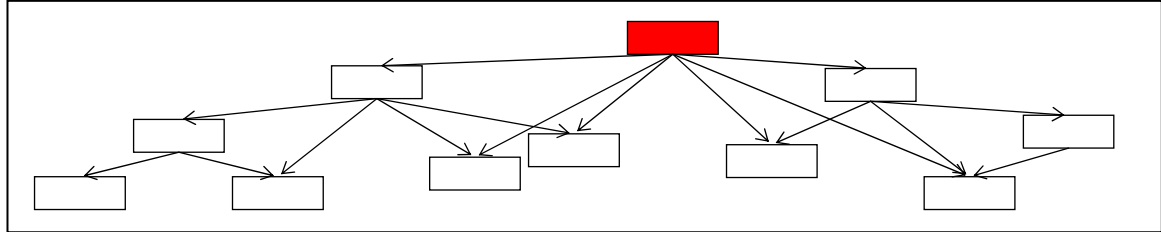


Figure 4.11 Influence structure in a sample space. Adopters are represented by rectangles, influence dominance by arrows. Vertical axis plots influence v_f . Neighbourhood size γ_H increases with v_f , therefore a more influential adopter has larger neighbourhoods as shown.

The distribution of influence dominance v_f in an adopter population is measured by the Gini coefficient, Γ_{gini} , a summary statistic of inequality. The Gini coefficient Γ_{gini} is used in studies of wealth distribution where group resources are limited and exchanged among members of a population. Influence can be seen as analogous to wealth in that it is generated by the interaction between two agents where one may increase its share at the expense of another.

When $\Gamma_{gini} \approx 1.0$ influence is concentrated by a few adopters and more stable dominance hierarchies exist. In contrast, when $\Gamma_{gini} \approx 0.0$, influence is more distributed among adopters. The nearer the Gini coefficient is to a value of 1, the more unequal the distribution. In theory, if the influence in a group of adopters was distributed with a Gini coefficient of 1, it would mean that one adopter has all the influence and everyone else would have none. In contrast, if all adopter agents receive an equal share of influence, then the Gini index has a value of 0.

$$\Gamma_{gini} = \sum_{i,j} \left\{ \frac{[v_f(i) - v_f(j)]}{\text{mean}[v_f(\Gamma)]^2} \right\} . \tag{4.28}$$

Where the difference of every possible pair of influence (i, j) values v_f is divided by square of the mean of the entire dominance set of the population Γ (Dorfman 1979). The diversity of influence in a social space measures how concentrated or distributed is dominance between its members.

4.4.4 Opinion Leadership

Influential adopters gain the role of opinion leaders. These agents are representative of their groups because they have spread components of their adoption decisions. Since there are three social spaces, there are different opinion leaders on every space. This means that there are expert adopters on different topics: some adopters may be influential on perceived features, others on preferences, others on adoption choices. Variables of opinion leadership are introduced in Table 4.12.

Table 4.12 Opinion leadership and gatekeeper role.

OPINION LEADERSHIP AND GATEKEEPING		
LABEL	VARIABLE	TYPE
α_{lead}	Opinion leader	Integer
$\rho_{lead}(\Psi)$	Role-model bias	Floating point
$\Psi(D)$	Domain function	Function

Opinion leaders are defined as adopter agents with influence measures v_f above one standard deviation from the mean of their population.

$$(v_f > v_f(\Gamma)) \Rightarrow \alpha_{\text{lead}} \quad (4.29)$$

Opinion leaders bias the adoption decisions of the rest of the adopter population. This is implemented similarly to individual preferences in Section 4.3.1 but is applied to the adoption function of all adopters. It is a type of role-model mechanism.

The second role of opinion leaders is the potential to become gatekeepers of their societies. Gatekeepers are influential individuals that evaluate and select new artefacts for their inclusion in the domain (Csikszentmihalyi 1988; Feldman et al. 1994). Examples of gatekeepers in design are critics, curators, magazine editors, patent examiners, venture capital companies, competition juries, etc. Gatekeeping varies between disciplines and over time (Subotnik et al. 2003). In some cases gatekeepers are experienced practitioners.

In this framework gatekeeping is executed by influential adopters at a rate called “gatekeeper rate”. Not all opinion leaders are gatekeepers. This depends on the rate of gatekeeping and their actual nomination of entries.

Gatekeepers gain access to further evaluation criteria of geometric relations. This forms the domain function, i.e., the selection process by which a gatekeeper nominates an artefact for entry to the repository.

$$\Psi(D) = \sum_{i=1}^n \left(\frac{\omega_\varepsilon}{N_\omega^2 - N_\omega} \right) \quad (4.30)$$

The domain function $\Psi(D)$ provides the score assigned by gatekeepers to entries. It is equivalent to the adoption function but geom criteria include uniform scale, and vertical and horizontal flip.

4.4.5 Verification

This subsection addresses the verification of the adoption mechanisms. Figure 4.12 shows a system run where a set of artefacts is randomly generated and made available to a population of 100 adopters. The group’s preference for shapes aligned in the horizontal axis is externally increased by assigning extra weight to the corresponding evaluation criterion. As a result of this bias, after a few adoption iterations adopters tend to choose artefact (b) which yields a high value in this criterion, i.e., all perceived shapes are horizontally aligned. However, not all adopters’ decisions converge since perceptions are not homogeneous, i.e., a few adopters perceive features of artefacts (a) and (c) that yield higher scores.

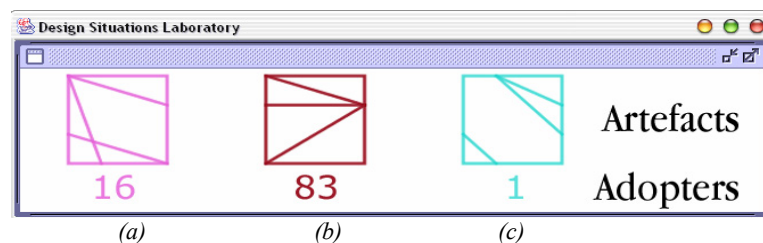


Figure 4.12 Verification run where the weight of a criterion is externally increased. As a result, a majority (0.83) chooses the artefact with perceived features that perform best in that criterion.

4.5 Domain

In this framework a domain is defined as the collection or repository of design artefacts of a population. Variables are introduced in Table 4.13. Entries to the repository are selected by gatekeepers which emerge from the organisation of adopter groups. A repository characterises a population of adopters in time: it can contain a varying quantity and quality of entries as a result of the interaction between designers and adopters. The mechanism by which gatekeepers add new artefacts to the repository can be described as a selection of ‘better or different’ entries. A threshold of entry is set (initialised to zero), which is raised by selected entries. If future artefacts are selected for the same geometric relationships, then they have to receive a higher score. Otherwise, new artefacts can be selected as entries if they receive high values on other geometric relationships.

Table 4.13 Domain variables.

DOMAIN		
LABEL	VARIABLE	TYPE
T	Repository	Pattern set
Ω_T	Gatekeeping rate	Floating-point
E_T	Selected artefact	Integer
Ψ_T	Entry threshold	Floating-point
ψ_T	Domain criterion of choice	Integer
$\Delta \Psi_T$	Decay	Constant
E_{T-M}	Temperature	Floating-point
E_{T-H}	Harmony	Floating-point
E_{T-C}	Complexity	Floating-point

4.5.1 Repository Entry

A repository is defined as a collection of artefacts selected by gatekeepers. At initial time the repository of a population is empty.

$$T = \{E_{T0}, E_{T1}, E_{T\dots}\}. \quad (4.31)$$

Gatekeepers select entries E_T when their evaluations $\Psi(D)$ render an artefact with a score above the entry threshold Ψ_T . The entry threshold of a repository is initialised at $T_\Psi = 0$. With every entry, Ψ_T is increased to match the value $\Psi(D)$ of the last entry.

$$(\Psi(D) > \Psi_T) \Rightarrow E_T, (\Psi_T = \Psi(D)). \quad (4.32)$$

The domain criterion of choice (ψ_T) is given by the geometric criterion with the highest value, $\max(\psi)$, of the latest repository entry E_T .

$$\psi_T = \max(\psi(E_T)) \quad (4.33)$$

A second mode of entry is for artefacts that do not receive an evaluation higher than the entry threshold but which geometric criterion of choice ($\max(\psi)$) is different to the criterion of choice of the last entry. In such case the entry threshold is updated to reflect this change.

$$(\psi \neq \psi(E_T)) \Rightarrow E_T, (\Psi_T = \Psi(D)). \quad (4.34)$$

A decay mechanism of the entry threshold is implemented so that when no entries are selected by gatekeepers, the entry bar is gradually lowered. The ratio of decay is another parameter for experimentation. In different fields, the rules of selection can be assumed to vary.

$$(E_T = \emptyset) \Rightarrow \Delta^- \Psi_T \quad (4.35)$$

4.5.2 Gatekeeping Rate

The rate of gatekeeping determines the schedule of this selection process. Similar to the design rate described in Section 4.3.4, gatekeeping rate is defined as a multiple of adoption iteration steps τ_T . In this way the frequency with which gatekeepers select entries to the domain is made an experimental parameter for experimentation. In different fields, the rate of gatekeeping activity can be assumed to vary.

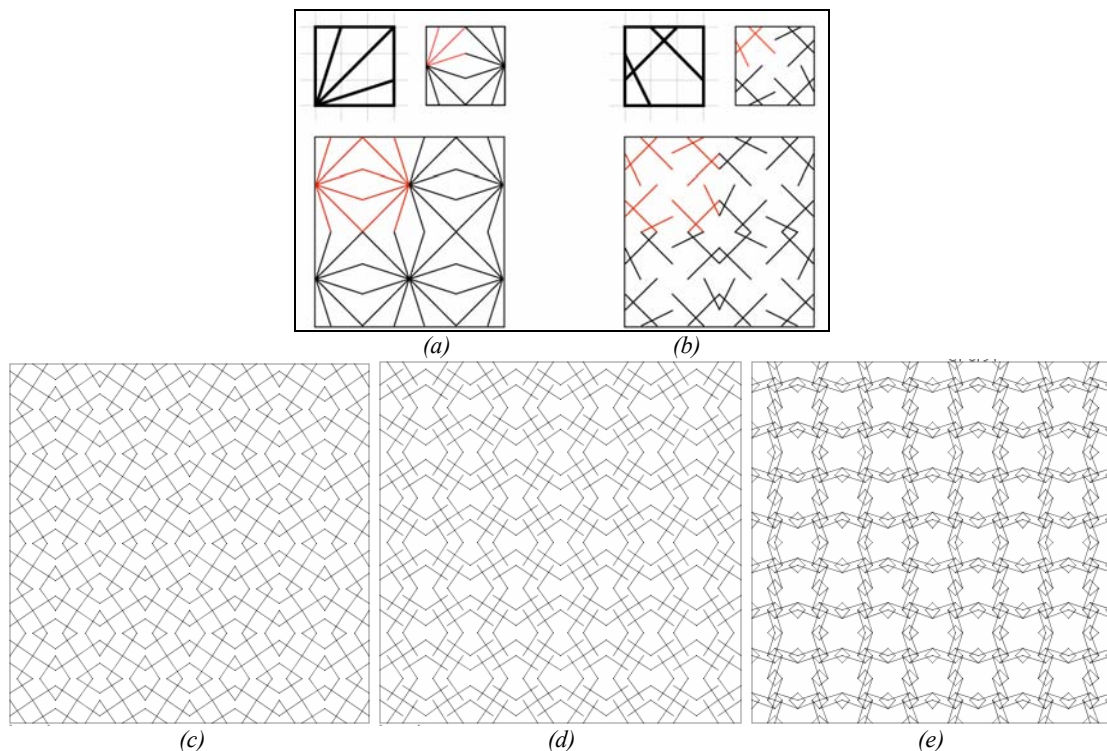
$$\Omega_T = \frac{1}{\tau_T} . \quad (4.36)$$

4.5.3 Patterns

Artefacts that are selected as domain entries have a value associated to them which is given by the gatekeeper's evaluation. However, this evaluation is an *ad-hoc* value based on the individual perception and preference of the gatekeeper. For this reason, we have chosen an alternative way to represent domain entries based on patterns. This representation is chosen to embody the geometric relationships, ψ_T , by which artefacts are chosen as entries to the repository or domain.

Patterns are construed based on the artefact structure defined by designers and on the geometric relationships of their features as perceived by gatekeepers. A selected entry, E_T , is stored as a pattern built by applying its perceived geometric properties, ψ_T , to the artefact line representation Ω_E . This representation supports an alternative way to measure domain entries using an information theory approach. Figure 4.13 shows how an artefact is combined with its geometric evaluation to generate a pattern, and some sample patterns.

$$E_T = (\Omega_E \rightarrow \Psi_T) \quad (4.37)$$



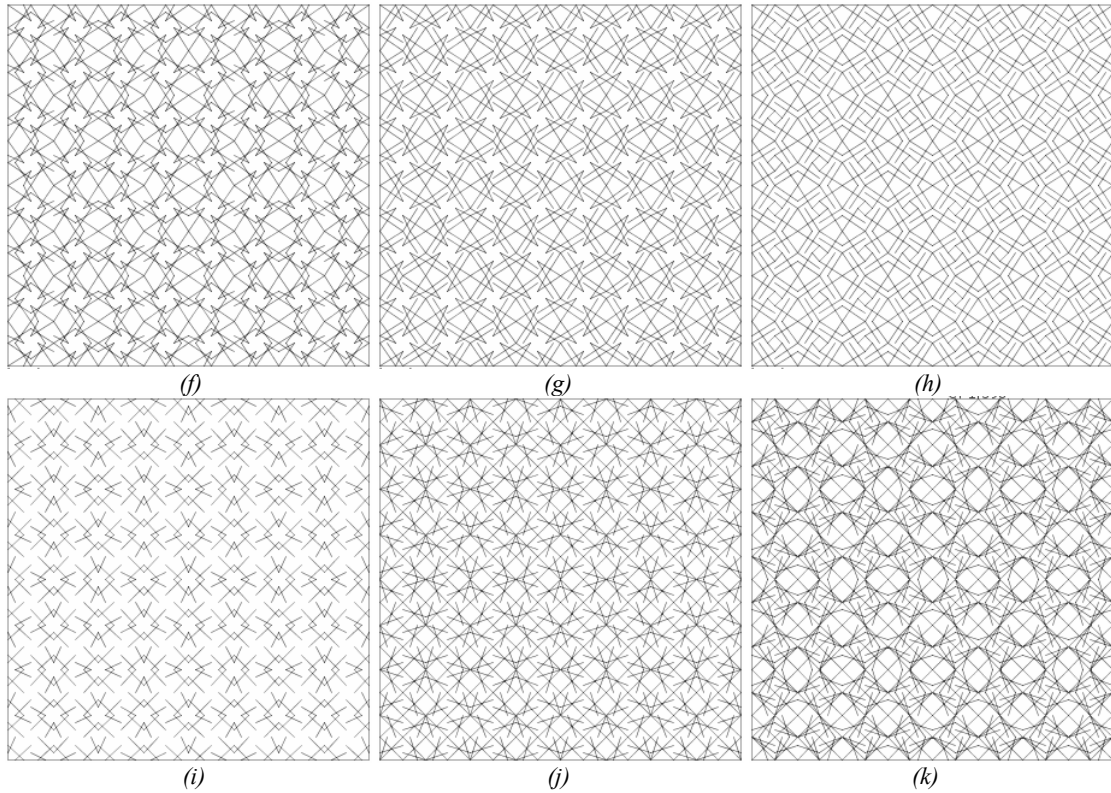


Figure 4.13 Patterns. (a) artefact with flip.V and rot.180 relations, (b) artefact with rot.90 relation, (c) to (n) sample patterns.

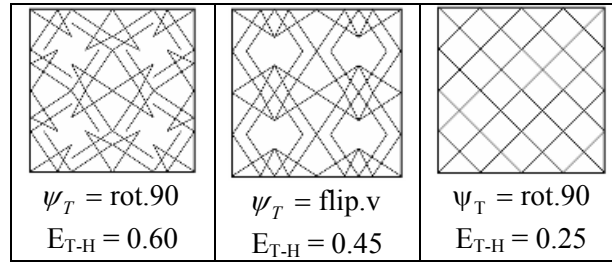
4.5.4 Complexity

A measure of repository patterns is implemented for comparison with the gatekeeping scores. This approach enables comparison across experimental scenarios where adoption, design, and gatekeeping variables are manipulated, i.e., the experimenter is able to observe changes between relative as well as more independent evaluations of domain artefacts across cases.

Pattern complexity, E_{T-C} , is an exogenous characterisation of a domain. It is based on two pattern levels: temperature and harmony (Klinger and Salingaros 2000; Salingaros 1997). Following these authors, the notion of harmony is used as an overall characterisation of a design, and the notion of temperature as a measure of its details. In this system, the concept of temperature, E_{T-M} , describes symbol variation in patterns, whilst harmony, E_{T-H} , is a representation of global symmetry that targets correlations of subunits. In other words, E_{T-M} characterises the unit of a pattern whilst E_{T-H} focuses on the composition of the whole structure. Table 4.14 illustrates three artefacts and their respective patterns. Whilst the temperatures of Table 4.14a and Table 4.14b are equal, the variation of perceived features and geometric relations generate patterns with different harmonies.

Table 4.14 Temperature and Harmony of Repository Patterns.

Temperature and Harmony		
(a) $E_{T-M} = 1.25$	(b) $E_{T-M} = 1.25$	(c) $E_{T-M} = 0.5$



Temperature E_{T-M} takes the artefact representation Ω_E as input and is estimated directly by the ratio of intersections by total number of lines. Harmony E_{T-H} takes the entire pattern as input and is estimated by a combination of measures that include ratio of connection vertices, ratio of closed shapes, length of connection, and the repeatability. The connection vertex is given by the pattern boundary points that connect in a toroid, i.e., when opposing sides of the pattern meet. The ratio of closed shapes is given by the number of lines that produce closed shapes against total number of lines. Connection length is given by end points inside the pattern boundaries. Lastly, repeatability is given by the ratio of shapes that are not repeated in a pattern.

Complexity E_{T-C} is estimated as the product of temperature and the distance from maximum to real harmony. E_{T-C} ranges from dull ($E_{T-H} = 0$) to intelligible ($E_{T-H} = 0.5$) to incoherent ($E_{T-H} = 1$) (Klinger and Salingeros 2000).

$$E_{T-C} = E_{T-M}(\max(E_{T-H}) - E_{T-H}) \quad (4.38)$$

4.6 Discussion

In this chapter a framework of design as a social activity has been formulated based on an architecture of social agency. The main components of this framework are designers, adopter groups, and domains. The design task, adoption functions, and the rules of the domain were described in detail. These mechanisms are an initial approach to implement a system where phenomena associated to creativity and innovation in the literature can be analysed. Designers can be considered successful as a function of multiple dimensions: the size of their adopter groups; the number of their artefacts entered into the domain; the number of other designers that imitate their artefacts; the number of design rules they generate; and the satisfaction levels of their adopters. Nonetheless, the concept of creativity is not reduced to any single of these dimensions, i.e., a creative designer may be characterised as productive but not popular, or vice-versa. The experimenter is to decide what dimensions to evaluate in particular cases.

Cumulative adoption of artefacts addresses a notion of popularity (Simonton 2000). Adopter satisfaction refers to a notion of quality (Babin and Griffin 1998). Selection by experts addresses the idea that creativity is judged by relevant arbiters (Amabile and Hennessey 1999; Gardner 1993). Peer-recognition is considered a necessary element in the creativity literature (Runco and Pritzker 1999). The contribution of each designer to domain knowledge is interpreted as transformation of the design space (Gero 1996) and expertise (Runco and Pritzker 1999). Extension and exhaustion of the design space (i.e., rule generation and application) refer to exploratory-transformational creativity (Boden 1999). The number of hypotheses generated resembles idea productivity. The limit on hypothesis generation and constraints on representation addresses the relationship between constraints and creativity (Amabile 1983).

Parameters for experimentation include: individual differences between designers on the generation of rules and their use. Temporal parameters include the rates at which designers modify their artefacts and the frequency at which gatekeepers evaluate artefacts. A type of normative parameter is the type of access that designers have to existing design rules: in public mode

designers can use the rules generated by all others, whereas in private mode they can only use the rules they generate. Another available parameter for exploration is the weight of individual adoption preferences in the adoption decision process. Lastly, rules of social interaction and the size of adopter populations are available for experimentation.

Whilst these parameters represent only a small part of the large number of issues of creative design, they support experimentation with the following types of questions: How well do individual differences of designers predict performance? What are the effects of having a higher rate of design activity in a population? Or more frequent gatekeeping? How do different types of access to knowledge affect adoption and domain contributions? Under what circumstances are adopters likely to be more satisfied? When will a designer concentrate large adopter groups? Or receive more peer recognition? When will domains be larger or contain entries with higher scores?

These questions are relevant for the understanding of creativity and innovation and have been investigated to different extents in the literature. This framework provides mechanisms that make them suitable for experimentation. This is the topic of Chapter 5 where results from a number of experiments are presented.

Chapter 5

Exploration of Determinant Factors

This chapter presents results from experiments using the framework introduced in the previous chapter. Experiments are designed to assess the effects of two types of independent variables in the system that represent individual and situational factors respectively. Inasmuch as the existing literature focuses predominantly on individual properties, emphasis is given here to situational effects on the link between creativity and innovation. A general class of experimental design is described at the outset with relevant details presented for each experimental setting. The aim of these experiments is to reveal patterns of micro-macro relationships in the system. In this chapter findings from these experiments are limited to the framework and are presented and analysed in relation to other effects within the system. Validation of these findings is addressed in the next chapter in view of evidence from the literature. The results discussed are exploratory and point to the relevance of the method of inquiry. Extensions and applications of these types of frameworks and their results are discussed.

5.1 Experimental Design

The experimental variables under inspection in this chapter were chosen through an iterative process of running and analysing the system's behaviour. A strength of simulation methods is to provide answers to 'what if' questions. Thus the experimenter is able to observe the effects of the assumptions and mechanisms programmed and then return to the drawing board to correct or add further elements to the system (Epstein and Axtell 1996). The specification of the framework as described in the previous chapter is not the product of a linear process where the experimental variables are set *a priori*. Experimentation with the system is necessary to determine the range of parameters, number of cases, number of simulation iterations, and other experimental conditions.

The variables reported in this chapter were chosen based on their appropriateness to illustrate different aspects in micro-macro interactions between individuals and societies that seem relevant in the study of design creativity.

Two classes of experiments are presented. The first series of experiments addresses individual factors defined as those parameters in the framework that determine the behaviour of agents independently from their interaction with others.

A sample of individual factors are selected to acknowledge the role of individual differences in creativity, i.e., the predominant research focus in the literature (Runco and Pritzker 1999; Sternberg 1999). The objective of addressing these types of variables is to explore their role within a complex social system. These experiments also address the verification of the system by generating consistent outcomes coherent with some of the modelling assumptions. Designer agents have individual attributes such as the number of design rules they can generate and the number of alternative solutions that they can build per unit of time.

According to trait theories, individual differences are sufficient to explain who is regarded as creative and when, i.e., creative people are those with the highest relevant individual attributes. In these experiments we explore that apparent truism when individuals are considered as part of a social system. In addition, a less obvious individual factor is analysed: differences in the members of the evaluating groups. In this framework this is addressed by individualised adoption preferences amongst adopter agents.

A second series of experiments is designed to address situational factors, which are defined as parameters that determine time, interaction rules and other environmental aspects of the system. These variables do not affect the agents' internal apparatus but may indirectly affect their overt behaviour, i.e., their design process or their adoption choices. In social psychology experiments situational factors are often manipulated to determine their effects on otherwise equivalent individuals (Argyle et al. 1981). For instance, in the study of compliance to group pressure, a situational variable can be defined as the turn to publicly express a response in a peer group, i.e., a temporal variable. The internal process of perceiving and reasoning about the task remains unchanged for the test subjects, but their turn to respond can yield entirely different behaviour (Asch 1951).

In this framework situational variables include the scheduling of behaviour (who acts when), the type of possible relations with neighbours (who interacts with whom), the ratio and size of groups, and the access to the domain. To an extent, individual and situational factors can be transformed into the other category by making variable attributes of individuals into uniform conditions for all. For instance, the rate of design can be a general condition imposed on all designers or it can be assigned as individual differences of behaviour.

Table 5.1 presents the independent variables explored in these experiments. These illustrative factors for experimentation are representative of the type of questions that can be addressed with this framework. Alternative extensions are described in each Section.

Table 5.1 Experimental Variables

VARIABLE	INDIVIDUAL FACTORS	RANGE
m	Processing Abilities	Number of rules that each designer can access in their process of designing, from 0 to 10 in this experiment. Designers with higher m values can apply rules from a larger knowledge base to modify an artefact.
t	Synthetic Abilities	Number of trials that each designer has to generate changes to their artefacts, from 1 to 10 in this experiment. Designer with higher t values generate more alternative artefacts during their process of designing.

	SITUATIONAL FACTORS	
w	Adoption Biases	Weight of individual adoption preferences for every adopter in a population, from 1 to 10 here. When $w = 10$ the weight of individual biases is tenfold, i.e., adoption decisions are more individualised.
T	Strength of Social Ties	Probability from 0 to 1.0 that links between nodes in a social network are replaced over time.
D	Design Rate	Activity of designers as a function of adoption. D value is the number of adoption steps between instances of design activity. Design rate varies from frequent (10) to sporadic (100) in this experiment. Gatekeeping rate is constant at 10.
G	Gatekeeping Rate	Activity of gatekeepers as a function of adoption steps. G value is the number of adoption steps between instances of gatekeeping activity. Rate varies from frequent (10) to sporadic (100) in this experiment. Design rate is constant at 10.
A	Adoption Rate	Rate of activity of adopters as a function of design and gatekeeping rates combined. A value is the number of adoption steps between instances of design and gatekeeping activity. Rate varies from 10 to 100.
P	Population Size	Number of members of an adopter population. P is varied in discrete values 10, 50 and 100.
K	Access to Knowledge	Binary variable controlling the protection / disclosure of information or knowledge generated by designers during the process of designing. In public mode all knowledge is available to all designers. In private mode access is limited to self-generated knowledge.

When individual differences are explored, all situational factors are kept constant and only the independent variable of interest is manipulated. When a situational factor is under inspection, all individual and all other situational conditions remain unchanged throughout cases. The variable space under inspection is then traversed by small increments, observing the pattern changes generated.

Whilst causality in complex systems is hard to determine (Simon 1990; Wagner 1999), statistical analysis is used to correlate variables and draw inferences from these relations. Pearson correlation between data sets is used to evaluate the extent to which observed values from two variables are 'proportional' to each other (Argyrous 2000; Sirkin 1999). When variables are linearly related this proportion fits a least squares line, i.e., the sum of the squared distances of all the data points from the line is the lowest possible.

The coefficient of correlation (r^2) represents the proportion of common variation or the magnitude of this relationship. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative or inverse correlation while a value of +1.00 represents a perfect positive correlation. A value of 0.00 represents a lack of correlation.

The significance of the correlation coefficient (p-value) depends on the size of the sample from which it is computed, i.e., the number of cases run. Specifically, the p-value represents the probability of error that the coefficient is representative of the population. It represents the probability that a similar outcome would be obtained if we tested increasingly large population samples. A p-value of 0.05 (i.e., 1/20) indicates that there is a 5% probability that the relation between variables is due to randomness. This is customarily treated as a "border-line" acceptable

error level. Most of the experiments presented in this chapter have a correlation significance below the $p < 0.01$ level with the number of cases ranging from 30 to 100.

Outliers are atypical infrequent data points that can have a profound influence on the value of the correlation coefficient. In order to assess the value of the correlation coefficient the respective scatterplots are examined and outliers are excluded from the data set. As a general quantitative approach outliers are defined as observations that are outside the range of ± 2 standard deviations from the group mean. When a correlation is observed between the output of different experiments, bar graphs are used to plot the pattern changes.

As a principle, all variables characterising design behaviour, adoption choices and the domain are treated as dependent variables in these experiments. However, only those where clear patterns emerge are discussed here. In some experiments it is the unchanging nature of a variable rather than a varying pattern which may represent an insight.

Monte Carlo simulation is conducted in these experiments to automate the sampling of the value spaces for each variable (Robert and Casella 1999). This sampling method repeatedly generates random numbers to initialise conditions of a system. Dependent variables are initialised from the relevant type of distribution. Independent variables are initialised from an interval in increments specified at initial time. The random seed of a Monte Carlo simulation can be an experimental parameter for replication or it can be assigned based on the system's clock. The experiments presented in this chapter use the robust MersenneTwister (MT19937) pseudo-random number generator (Matsumoto and Nishimura 1998).

At initial time the random seed is used to assign values from uniform and Gaussian distributions as specified for each variable of the framework. Adopters' preferences and extroversion thresholds and the abilities of designers are set and artefacts are initialised with equivalent characteristics. Once the simulation starts, a variable watcher is scheduled to record the value of each aspect regarding designers, adopters and the domain. In the end the output data set is processed obtaining means and standard deviations after excluding outliers.

In these experiments equivalent artefacts are configured at initial time for all designers. This is to avoid the effect of a designer having an initial artefact with a random advantage. The number of iterations to which experiments are run is 2,500 steps, a time length after which trends tend to stabilise.

Typically, the size of the adopter population is set to 100 and the design rate is set to 10 steps. This is considered a satisfactory compromise between the effects observed in the system and a feasible running time, a mean of 5 minutes per case (Pentium 4M 1Gb RAM). Thus, an entire experiment where an independent variable is explored in ten increments in thirty cases takes around 25 hours to generate the output.

The resulting dataset is automatically recorded in a spreadsheet format and run through a program that takes all mean values and estimates correlations for plotting and analysis. In simple models such as cellular automata it is unproblematic to run populations of thousands of individuals for a large number of iterations. However, in a framework where agents perform perception, geometric evaluation, and social interaction, current computational power only allows to run a few hundred agents for simulation periods measured in a few thousand iteration steps.

As this limitation is overcome, these types of experiments will be suitable for more realistic analysis of larger populations and more cases over longer periods.

5.2 Individual Factors

The objective of these experiments is to assess the role that individual differences play in the interaction between designer agents and adopter groups. The variables under inspection include the individual abilities of designers to generate knowledge and to consider alternative solutions, and the individual evaluation biases or preferences of adopters.

The exploration of designers' abilities is conducted with a constant number of three designers. In each experiment a higher ability is assigned to one designer at initial time whilst the rest are given all constant (lower) abilities. The objective is to observe the effects of such differences in the development of artefacts, their adoption, and their contribution to the domain.

In addition, the relationship between individual differences and the degree of their effects is considered. To this end the range of differences is explored from small to large differences between designers. The objective is to explore how determinant are individual differences in both contexts.

Individual differences of adopters is arguably a more interesting (i.e., less well understood) exploration. The idea in these experiments is to inspect the role that variance of adopters' characteristics have in the system. Namely, what are the consequences of manipulating individual determinants in the adopter population? Would a society of adopter agents where choices are more independent have a different effect on designers' prominence and domain characteristics than a society where adoption choices are more normalised and socially influenced? And, can differences in the composition of evaluation groups account for pattern changes of design behaviour?

5.2.1 Processing Abilities (m)

Processing abilities (m) refer to the capacity to manipulate knowledge (Wagner and Sternberg 1994). In our framework this individual characteristic is implemented by the number of rules that designer agents can access to modify their artefacts (Section 4.3.5). A designer agent with high processing abilities can apply rules from a large knowledge base to modify an artefact.

The assumption is that designer agents with higher processing abilities at initial time will generate and accumulate knowledge that allows them to produce artefacts that yield a larger number of adopters and are selected by gatekeepers.

The main effect of interest is the integration of individual differences within a social system. From a trait theory viewpoint, designer agents with higher processing abilities would tend to perform better than designers with lower abilities where *performance* is defined by one or more dimensions including productivity, peer influence, prominence, contributions to the domain, etc.

In these experiments all simulations are run with constant number of designers, population size, social spaces, and initial artefacts. Three designers are initialised, one of which is given higher individual processing abilities (m) than the others.

Monte Carlo simulations are run in 90 settings traversing the abilities parameter from $m = \{1,10\}$ in increments of 1 (i.e., thirty cases per designer). Pearson's correlation coefficient (r^2) is used to compare initial and end abilities to a number of dependent variables including the size of their adoption groups, domain contributions, and learning.

5.2.1.1 Results

The first result shown in Figure 5.1 illustrates the correlation between initial and end abilities. As Figure 5.1a shows, when the difference between designers is significant ($m = 10$) designers that start with high ability are likely to maintain higher abilities than the rest at the end of a simulation ($r^2 = 0.92$). However, when the handicap is marginal ($m = 1$), this correlation drops to $r^2 = 0.56$.

This effect can be explained by the learning mechanism that allows other designers to increase their processing abilities (Section 4.3.3). Due to the mechanism by which designer agents can generate rules and increase their abilities, it is possible (but not common) for those that start with low abilities to end with higher abilities than the rest.

Secondly, processing abilities are analysed in relation to adopter group size. Here the results show the capacity of individual differences to predict the total number of adopters of their artefacts. As Figure 5.1b shows, when the difference of abilities is low ($m = 1$), initial processing abilities and aggregate adoption yields a correlation $r^2 = 0.26$ that increases to $r^2 = 0.46$ when initial differences are significant ($m = 10$). The correlation of end abilities and adoption in Figure 5.1c yield $r = 0.37$ and $r = 0.40$, respectively. These results suggest that the role of small differences in

determining an outcome is relatively low but increases when individual differences are large. This effect is consistent in other dimensions to different extents. The correlation between end abilities and contributions to the repository in Figure 5.1d ranges from $r = 0.33$ ($m = 1$) to $r = 0.37$ ($m = 10$).

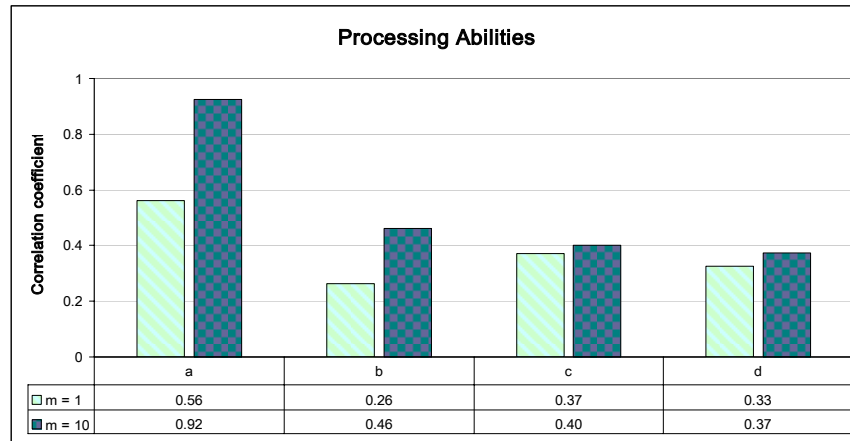


Figure 5.1 Bar graph of the effects of individual processing abilities. Correlations of (a) initial and end abilities, (b) initial abilities and adoption per designer, (c) end abilities and adoption, (d) end abilities and domain contributions.

The medium to low correlations between processing abilities and these variables can be attributed to the notion that design knowledge contributes but is not sufficient to determine performance. This hypothesis is supported by the correlation observed between knowledge base size and adoption satisfaction, a mean $r^2 = 0.1215$ confirming that there is an important factor which the current framework does not account for, i.e., the quality of knowledge. A designer may have a higher capacity to apply more rules and yet do worse than other designers with access to fewer rules. The reason is that the latter are able to find rules that improve relevant artefact features. In other words, the knowledge of the former may become 'obsolete', i.e., irrelevant to the evolving adoption conditions.

When the actual number of adopters is plotted against initial abilities in the extremes $m = 1$ and $m = 10$ compared to the other designer agents with $m = 0$ on each group, the graph in Figure 5.2 shows two interesting effects.

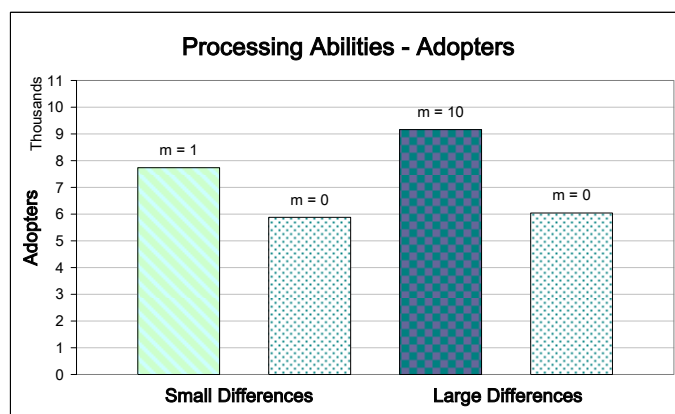


Figure 5.2 Small differences in processing abilities have an expected effect on mean aggregate adoption. However, increasing these differences has only a marginal effect: a tenfold increase of processing abilities yields a competitive advantage of 0.10.

On one hand, the expected role of processing abilities is confirmed by higher processing abilities generating larger adopter bases. On the other hand, the variation of this effect between slight and substantial differences between designers is not as significant as could be expected. When the difference is tenfold, the size of the adopter group of the able designer with $m = 10$ is a mean of 9,160 adopters and the mean number of adopters of the other designer agents is 6,040. In contrast, when the difference is of only one unit, the size of the adopter group of the able designer with $m = 1$ is a mean of 7,740 and the mean number of adopters of the other designers is 5,880. Namely, when a designer agent is extremely more able than the rest, the mean increase of adoption is 0.34 whilst a mean advantage of 0.24 exists when the difference of abilities is only marginal. In addition, these results show that the mean number of adopters of designers with lower ability at initial time also increases when they are placed within a system where a very able designer operates. In other words, the performance of otherwise equivalent designer agents improves as a side effect of having more able competition.

These results can be stated in a principle of individual processing abilities: To consider individual traits as sufficient predictors of performance, designer agents would need to be significantly different. Otherwise, opportunistic factors may account for low correlations. Furthermore, if some learning mechanism is assumed, abilities are poor predictors over time.

5.2.1.2 Analysis

An insight from these results is that individual processing abilities alone are insufficient to predict task performance in this framework. When individual traits are considered not in isolation but within a social system of interactions between generators and evaluators, the correlation between abilities and performance is expected to get ‘messy’. Other contingent factors limit the causal role of individual characteristics suggesting that adaptability of behaviour in a dynamic environment requires the combination of skills with opportunities.

In this framework, processing abilities can be seen as the accumulation of previous knowledge or a type of ‘expertise’ of designer agents. This experiment captures the idea that expertise can have negative effects on performance due to the obsolescence of knowledge. In the experiment where designers are given very high processing abilities, it is possible that they spend most of the time searching through a large corpus of rules without finding more relevant rules than other designers with much smaller (and recent) knowledge bases.

The study of processing abilities could be extended to account for quality and obsolescence of knowledge. One way to do this is to make designer agents assign a score to every rule they generate based on the immediate gain of adoption or expert opinion. This would support knowledge update as a function of rule score.

5.2.2 Synthetic Abilities (t)

In this experiment a second type of individual ability of designer agents is explored. Synthetic abilities, t , refer to the number of trials that a designer has to generate changes to their artefacts (Section 4.3.3). This type of behaviour has been considered as a key determinant of creativity and can be summarised by the phrase “to come up with a good idea, one must have many ideas” (Fischer 1993). This experiment explores the appropriateness of this probabilistic notion by assigning one designer agent a higher synthetic ability than the rest and observing the effects of this advantage. The experiment is replicated in two scenarios: where the difference of synthetic abilities is high (one designer has $t = 10$ and the rest $t = 1$) and when this difference is small (one designer is assigned $t = 2$ and the rest $t = 1$). All experiments are run 30 cases for 2,500 iterations with three designer agents and 100 adopters.

The main aspect to inspect in this experiment refers to the effects of synthetic abilities between cases of low and high differentiation. To this end we record the performance of designer agents along variables that include the number of adopters, peer recognition, knowledge generated, and entries to the domain. To compare designers’ performance these values are normalised, i.e., the

highest value for each variable is equal to 1 and the mean value of other designers in the system is compared as a ratio. In general the expectation is that designers with higher synthetic abilities will perform better than those with low synthetic abilities, i.e., attract more adopters and receive more recognition from peers and from experts.

5.2.2.1 Results

The effects observed in this experiment provide support to the notion that individual differences only partially account for variations of performance. When a designer is assigned a synthetic ability larger than the rest at initial time, on average it can be expected not only to end the simulation also with higher abilities but to have larger adopter groups, receive more peer recognition, generate more rules, and contribute more to the domain as shown in Figure 5.3. As expected, the maximum values on each category correspond to the designers with higher abilities. Further, the larger the difference between the leading designer agent and the rest, the wider the gap of their performances along these criteria. However, the impact of these differences in ability appears as nonlinear.

Figure 5.3a compares the mean value of six variables of designers with slightly higher abilities, $t = 2$, to the mean of the rest of designers with $t = 1$. Firstly, the initial assignment of synthetic abilities is shown: the leading designer has twice as many abilities as the average group (i.e., an ability of $t = 2$ compared to a mean group ability of $t = 1$). Secondly, the ability level at the end of the simulation indicates that the difference decreases arguably due to the mechanism in the framework that supports ability increment (Section 4.3.3). Determined by randomness on the learning process and the fitness of artefact to adopters' choices, initial advantage tends to 'balance out' over long periods. Thirdly, designer agents with higher synthetic abilities accrue more adopters to their artefacts, albeit the difference is marginal. Fourthly, designer agents with leading abilities at initial time are imitated more often and therefore receive more peer recognition. Similarly, they generate more rules than the average, and contribute with more artefacts to the repository than the average designer.

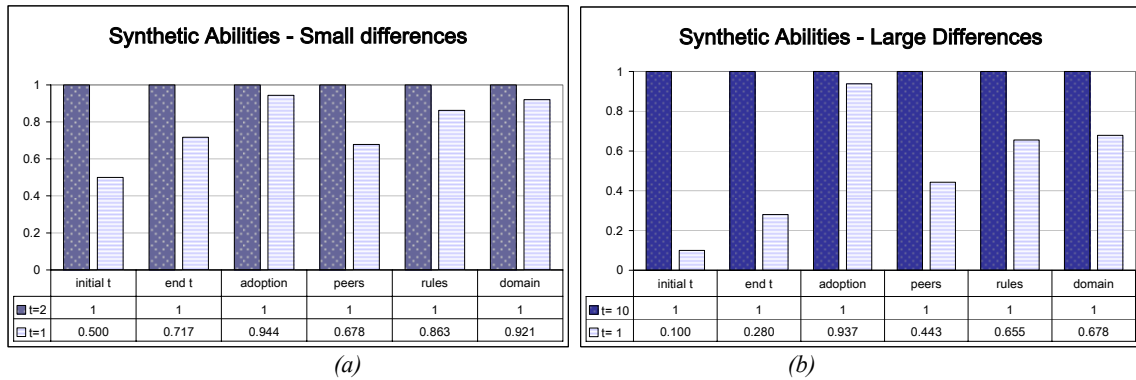


Figure 5.3 Performance ratios of skilled designers. (a) shows the effects of a designer being slightly more able than the rest, whilst (b) plots mean values of designers with significantly higher synthetic abilities.

Figure 5.3b, on the other hand, plots the same effects but in this case the leading designer agent has a much higher synthetic ability than the rest. Namely, one designer is initialised with $t = 10$, whilst all other designer agents are assigned a constant $t = 1$. The effects are similar to the previous case, however the magnitude of such effects is larger along most criteria. Initial ability is seen to be tenfold when compared to the competing designer agents. This is also observed in abilities at stopping time. Unexpectedly, the adoption gap between designers decreases only marginally, showing that in this framework the ability to generate various alternatives whilst designing has only a minor impact on adoption choices. On the other hand, differences in peer recognition, knowledge and domain contributions significantly increase.

Figure 5.4 plots the increase of differences between the two cases shown in Figure 5.3. The argument that individual traits partially account for performance is supported firstly by the marginal variation observed along dimensions such as adoption. Moreover, as Figure 5.4 shows, whilst the synthetic ability of the leading designer increases by a ratio of 4 (from $t = 2$ to $t = 10$), the differences of abilities at final iteration decrease significantly to a ratio of 1.6. As pointed out above, the effect on total adoption is minimal (0.01). Peer recognition, knowledge generation and domain contributions all increase below 0.5.

The effects that one designer with higher synthetic ability at the group level of designers (or an industry) vary. Table 5.2 shows the sum of values for all designers in the two scenarios: when individual differences are small and large. The main impact is observed on peer recognition and knowledge generation. When the more able designer is assigned $t = 10$ there is a group increase of over 20% in these variables compared to cases where the more able designer has $t = 2$. The group increase of domain entries, adopters satisfaction and adoption choices are around or below 5%.

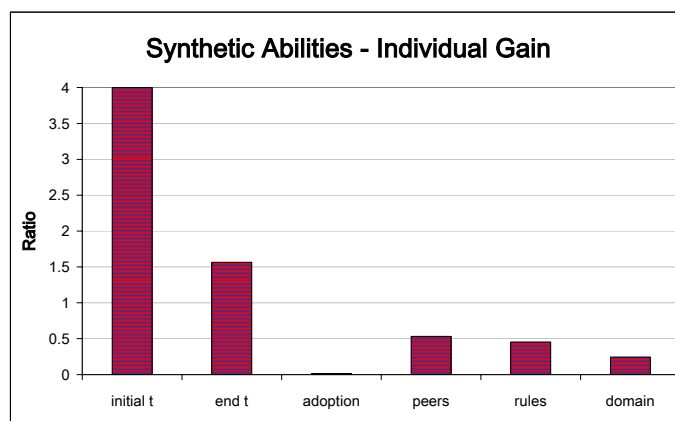


Figure 5.4 Gain ratio between having a synthetic ability $t = 2$ and $t = 10$. Initial differences balance out during a simulation run.

Table 5.2 Effects on Groups with Small Differences and Large Differences

	$\Sigma(\text{adoption})$	$\Sigma(\text{peers})$	$\Sigma(\text{rules})$	$\Sigma(\text{domain})$	$\Sigma(\text{satisfaction})$
Small Diff.	6215	5.6	22.1	21.05	2167
Large Diff.	6281	6.9	27.3	21.73	2294
Total Gain	0.01	0.2	0.2	0.03	0.05

5.2.2.2 Analysis

The effects of individual differences of synthetic abilities in this system of generation and evaluation of design solutions are consistent in tendency but present important differences in degree. As expected, increasing the ability of an individual increases its probability of improving its performance along various criteria. A designer agent with more ability to generate alternative solutions tends to receive more adopters, tends to be more imitated by other designers, tends to generate more design knowledge, and tends to contribute more to the domain. However, this experiment captures the notion that in a complex system of interactions, causality cannot be conceived as linear (Wagner 1999).

These results point to other important factors that determine individual performance beyond individual differences. In a simplistic framework of this kind, a small number of the possible contingencies that a complex system could present are sufficient to demonstrate that the interactions between designers and adopters combine to 'balance out' individual differences.

Further variations of this experiment can be devised in a relatively straightforward way. For instance, one question worth exploring is the point at which individual differences no longer make

any significant difference. The hypothesis to explore here would be that at certain point synthetic ability would give the maximum advantage to a designer agent after which higher abilities do not affect the outcome.

Another possible way to further explore these results is to test some of the assumptions in the framework in order to isolate the mechanisms that would make individual differences of design abilities have a more determinant role. This would require a process of replicating the experiment repeatedly by manipulating parameters or entirely ‘turning off’ some of the mechanisms of the framework such as imitation, learning, adopters’ preferences, and social interaction. Arguably this could yield the ‘necessary conditions’ under which individual traits are sufficient to determine performance. This could lead to a more comprehensive framework that captures the possibility that in different design fields or at different stages within a field, the role and impact of individual factors vary.

Other individual traits of designers that can be explored in this framework include differences of imitation and motivation. The former can be parameterised by assigning individual thresholds of imitation and observing the effects of differences between designers. Would designers that prefer to imitate be able to trade recognition from peers for more adopters or domain entries? Extensions to explore motivation could address the relation between internal and external motivation of designer agents (Amabile 1996).

5.2.3 Adoption Bias (w)

In a framework where generation and evaluation of design artefacts are considered, it is convenient to explore the effects of individual differences not only of generators but also of evaluators. In this experiment the independent variable is the distribution of adoption preferences, defined as the adoption bias (w). The objective of this experiment is to explore how an equivalent set of solutions can be evaluated by adopter groups where their members have different characteristics. On one extreme, individual preferences play a strong part in the adoption decision process. On the other, adopters give less emphasis to their preferences so the adoption decisions of the group become more unified, the perceived features of artefacts have a stronger impact on these decisions, and social influence is stronger.

The adoption bias is analogous to a varying degree of subjectivity across different design fields. With certain types of design artefacts the adoption evaluation can be expected to be normalised leaving only marginal room for individual biases. This is the case when artefacts are evaluated by speed, performance, resource savings, or any other quantitative criteria. In contrast, other types of design artefacts leave more room for interpretation and subjective independent biases can be expected to have a larger impact. This experiment seeks to understand the effects of this assumption in our framework.

With all designers having equal abilities and all other parameters kept constant, the independent variable is the variance of the distribution of individual adoption preferences (Section 4.4.1). A scale is defined as the adoption bias (w) ranging from $w = 1$ to $w = 10$. When an adopter agent has a bias of $w = 1$, its individual preference has one unit of bias in the evaluation of the available artefacts. In contrast, for an adopter with $w = 10$, this bias is tenfold. As a result, when members of an adopter population have a low adoption bias or $w \approx 1$, adoption choices are strongly determined by the artefacts’ characteristics whereas the adoption choice is more individualised when $w \approx 10$. Monte Carlo simulations are run where $1 < w < 10$ in increments of 1. Results are obtained by comparing the mean values of thirty cases for every experiment run for 2,500 iterations with three designers and 100 adopters.

5.2.3.1 Results

Figure 5.5 plots the effects of the adoption bias $w = 1$ and $w = 10$ along adoption satisfaction levels and aggregate adoption. Satisfaction is a post-adoption measure in discrete categories

determined by the fitness between adoption choice and preferences (Section 4.4.2). Adoption refers to the aggregate number of adoption choices during a simulation.

The first result in Figure 5.5a is somewhat expected: adoption satisfaction increases significantly with adoption bias. This can be explained by the adoption decision being biased by individual preference, so adopters tend to adopt artefacts with features that they prefer. An additional result is that satisfaction variance also increases with adoption bias. Namely, in more independent adoption decisions satisfaction is likely to be higher but it is also less stable and less predictable.

Somewhat unexpectedly, Figure 5.5b shows that total adoption is negatively related to adoption bias. When adopters have low adoption preference biases ($w = 1$) aggregate adoption is higher than with high adoption biases ($w = 10$). In other words, abstention increases as adopters fail to see differences between artefacts. This seems paradoxical: adopters are more ‘free’ to make their choices and they are more satisfied with these choices, yet they adopt less than when they are constrained by artefact features and social influence. A key to this apparent contradiction is in adoption variance, defined as the distribution of adoption decisions between designer agents. When adoption variance is high, adopters tend to concentrate their choices in artefacts from a few designers, whereas a low adoption variance refers to a more competitive environment where adopters distribute their choices across all designers. When $w = 1$, mean adoption variance is 0.43 whilst for $w = 10$, mean adoption variance falls to 0.33. This shows that when individual adoption biases are stronger, adopter agents select artefacts from a smaller number of designers, presumably those that satisfy their preferences. Therefore, when adopters have more independence on their adoption choices, they adopt less but are more satisfied with their choices.

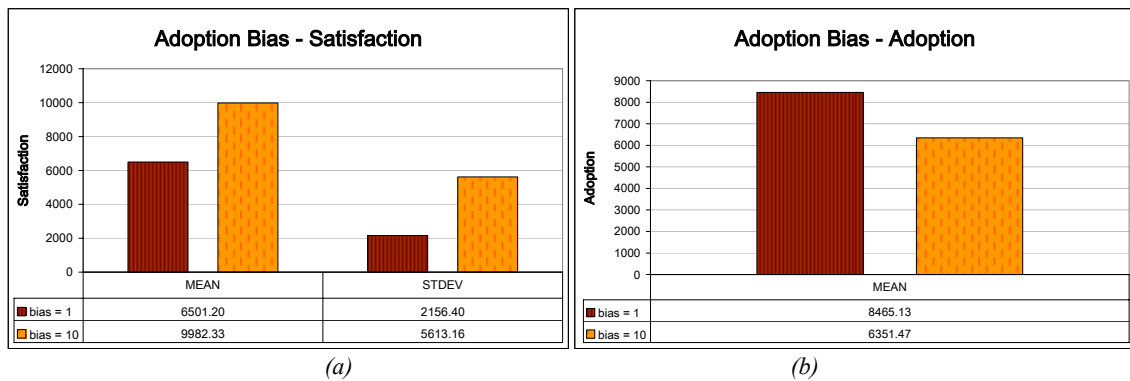


Figure 5.5 Effects of adoption preference bias in satisfaction levels and aggregate adoption. When adopters have more independent choices, $w = 10$, they tend to (b) adopt less artefacts or abstain more and (a) their choices yield more unpredictable but higher satisfaction.

Effects of adoption bias (w) on two aspects of design behaviour are plotted in Figure 5.6. The strategic differentiation index (SDI) measures the difference of artefacts as perceived by adopters (Section 4.3.6). The mean SDI of a simulation run is recorded for every case. The graph in Figure 5.6a indicates the mean and the standard deviation of all cases for $w = 1$ and $w = 10$. Design strategies indicate the direction of artefact change selected by designers (Section 4.3.2). The number of strategies chosen during every simulation run is recorded for every designer. Figure 5.6b shows the aggregate for each strategy of all designer agents.

SDI is negatively correlated with adoption bias showing that perceived differentiation decreases when adoption bias is high, $w = 10$. This is not only a change in adopters’ perception but an actual variation of strategies by designers as observed in Figure 5.6b. When adopters are assigned high adoption biases ($w = 10$), designers adapt their behaviour towards strategies of competition and differentiation. However, their strategies of diversification actually decrease. An explanation for this clear effect may be that when adopters take more independent decisions

($w = 10$) designer agents are less likely to perceive that their artefacts address the population's preferences and therefore they seldom choose to diversify. This could be due to the reduced impact of the social influence mechanism, i.e., less group agreement emerges.

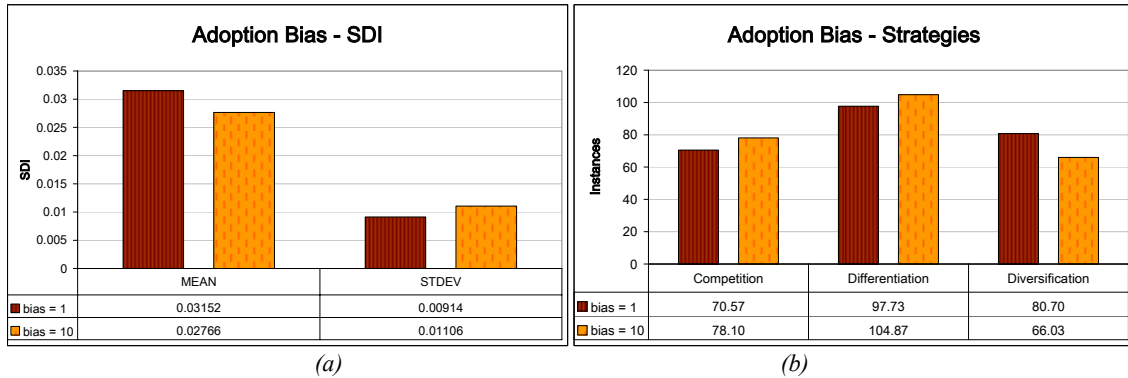


Figure 5.6 Effects of adoption preference bias in SDI and design strategies. In societies where adopters take more independent decisions ($w = 10$), (a) design artefacts are perceived by adopters as more similar and (b) designer agents engage in competition and differentiation but cut back diversification.

The last variable where significant effects of the adoption bias (w) can be observed is the score assigned by gatekeepers to artefacts selected as entries to the domain (Section 4.5.1). Domain entries are recorded during a simulation run with their respective score and time of entry. Figure 5.7 plots the mean score and standard deviation of all cases for $w = 1$ and $w = 10$. Adoption bias is positively correlated with mean domain score, i.e., in cases where adopters take more individualised decisions or $w = 10$, the mean score assigned to domain entries is higher. No associated effects are registered for other domain variables such as the number of entries.

Since the independent measure of artefact complexity (Section 4.5.4) does not mirror these effects, this effect can be attributed to the individual skew produced by the impact of the adoption bias in the selection of artefacts by gatekeepers (Section 4.5.1). When gatekeepers have higher preference thresholds, the merit of selected artefacts can be expected to be perceived as higher.

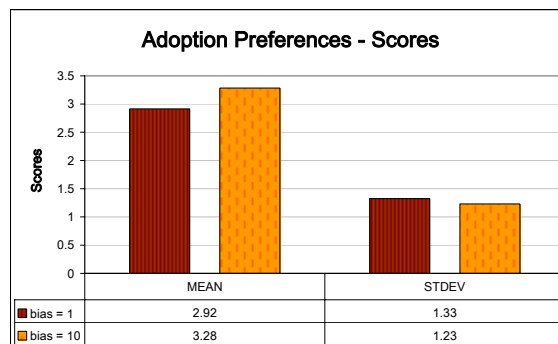


Figure 5.7 Effects of adoption bias in domain score. In cases where adopters take more independent decisions ($w = 10$) gatekeepers tend to assign higher scores to selected artefacts.

5.2.3.2 Analysis

This experiment addresses the effect of individual differences in the evaluators of creative solutions. Results show that increasing the strength of individual biases has a number of effects. Adopters become more selective in their adoption choices and tend to adopt less often but are more satisfied with their choices. This affects the way designer agents choose their strategies causing the generation of more similar artefacts. The selection of artefacts by gatekeepers only seems to vary in assigning higher scores to domain entries.

A consequence of stronger adoption preferences is that the artefacts of a designer agent are more likely to become ‘popular’ in a society where adoption choices are less independent and social influence is stronger, where *popularity* is measured by the total number of adoptions. However, under such conditions the actual adopters of these artefacts may be less satisfied with their choices and experts may assign lower values to artefacts.

These effects represent important ways in which the individual characteristics of the evaluators may determine who becomes creative in a society and when independently of the individual attributes of creators.

5.3 Situational Factors

In this framework the behaviour of agents can be importantly determined by conditions that sit outside their individual state. Where, when, and with whom an agent interacts with is likely to shape a) the way designer agents design, b) the way adopter agents adopt, and c) the way gatekeepers select entries to the domain. In this Section six of these aspects are explored in our framework of design as a social activity. The type of social interaction between adopters is explored. In these experiments individual attributes are not modified, only the type of links that they can develop with other adopters. Then three different rates are explored: the frequency of design behaviour, the frequency of gatekeeping decision-making, and the frequency of adoption of artefacts. In these cases the individual characteristics of each type of agent are not manipulated, only the rate at which they execute their behaviour. Then the effects of population sizes are inspected. The last factor of interest is the type of access to design knowledge.

These are not the only situated factors of the framework. They have been chosen for two important reasons: a) they are simple aspects of contingent conditions that are easy to implement, to keep record of, and to reason about; and b) they often have significant and unexpected effects. Possible extensions and applications are discussed for each experiment.

5.3.1 The Strength of Social Ties (T)

Social ties are defined as interaction links between nodes in a social network where nodes represent the location of adopter agents in that particular social space (Section 4.4.3). The strength of social ties, T , is determined by the probability that the link between a pair of nodes is maintained over a period of time (Marsden and Campbell 1984). Strong social ties exist between nodes in a kinship network, where relationships are often maintained during a lifetime whilst weak ties exist in networks where casual and temporary encounters occur between strangers or acquaintances. In our framework we implement a basic notion of tie strength as a probability $0.0 \leq T \leq 1.0$ that the link between a possible pair of adopter agents will remain at the next time step (Section 4.4.3). In social networks with weak ties, $T \approx 0.0$, there is higher social mobility, i.e., connections between adopters are reconfigured more often and they get to interact with different adopters over a period of time. In contrast, in social groups where agents have strong ties, $T \approx 1.0$, adopters are bound causing a decrease in social mobility, i.e., adopter agents interact within the same groups for longer periods.

The distribution of influence exchanges between adopters can be expected to be associated to the strength of social ties T . Adopter influence is measured by the Gini coefficient, a summary statistic of inequality (Dorfman 1979). The Gini coefficient γ measures the distribution of limited resources that are exchanged among members of a population. Influence can be seen as a limited resource in that it is generated by the interaction between an agent pair where one increases its share at the expense of another. An adopter influences others when it transmits an adoption decision such as a percept, a preference, or a choice (Section 4.4.3). Figure 5.8a depicts a social group with high inequalities, $\gamma \approx 1.0$, where high influence is concentrated by one adopter. In

contrast, Figure 5.8b shows a social group with a more egalitarian distribution of influence, $\gamma \approx 0.0$, where influence is distributed among three adopters.

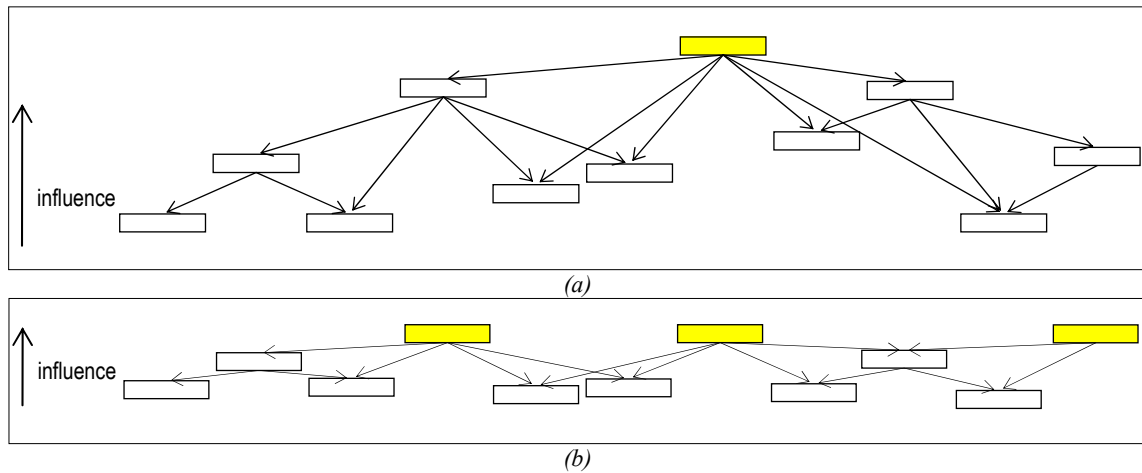


Figure 5.8 Influence structures with different distributions. In (a) Gini coefficient $\gamma \approx 1.0$, in (b) $\gamma \approx 0.0$

The objective of this experiment is to explore the effects that a situational factor such as the strength of social ties, T , may have in the behaviour of adopters and designers and in domain characteristics. To this end the space of $0.0 \leq T \leq 1.0$ is traversed in increments of 0.1 whilst maintaining all individual and other situational variables constant across experiments. Results presented are means of thirty cases per increment with three designers and 100 adopters.

5.3.1.1 Results

The result of varying T from 0.0 to 1.0 shows that influence concentration increases with social tie strength, i.e., in societies with strong ties $T \approx 1.0$, a few opinion leaders become dominant ($\gamma \approx 1.0$). In contrast, as social ties become weaker $T \approx 0.0$, social mobility increases and agents have contact within a varying neighbourhood causing influence structures of dominance to be more distributed ($\gamma \approx 0.0$). Figure 5.9 shows a scatter plot of the relation of tie strength T and Gini coefficient γ with fitness $r^2 = 0.927$. Whilst cases with very strong social ties yield a high Gini coefficient, in most cases it is comparatively low. Figure 5.9a plots the full range on the axes of a non-linear distribution of data points. Figure 5.9b shows the same plot on a logarithmic scale. The same distribution now shows itself to be linear. It is particularly interesting to obtain a non-linear distribution by linear increments of an independent variable (Bak 1990; Frigg 2003). These types of patterns are prevalent in biological and social phenomena and have been found to characterise relations such as the frequency of words in natural language, the growth of cities, metabolism, and the topology of the World Wide Web (Barabasi et al. 2001; Strogatz 2003).

Such distribution relates influence distribution to social tie strength raised to a constant power. The general form takes $y = x^a$, where y and x are variables, and a is a constant exponent. In this experiment the coefficient is -0.37 . Social groups with strong ties $T \approx 1.0$ reach a mean Gini coefficient $\gamma = 0.44$. As T decreases marginally, there is a sudden drop of influence hierarchies rapidly going below $\gamma = 0.39$. However, once this threshold is crossed, even a significant decrease in T does not pull $\gamma < 0.38$. This pattern of the relationship between tie strength and influence hierarchies is a typical result of complex, dynamical systems consisting of many constituents where a critical state can be reached without any exogenous control at which point a system changes radically its behaviour or structure (Bak 1990). In the critical state, a small local perturbation may spread to the whole system and form an avalanche. In this case such point is given by a minimum of social mobility.

Further work can be conducted to find better fitness curves for the relation between social tie strength, T , and influence distribution. However, at this stage the aim is to explore the effects on other variables of interest to better understand the role of this situational factor.

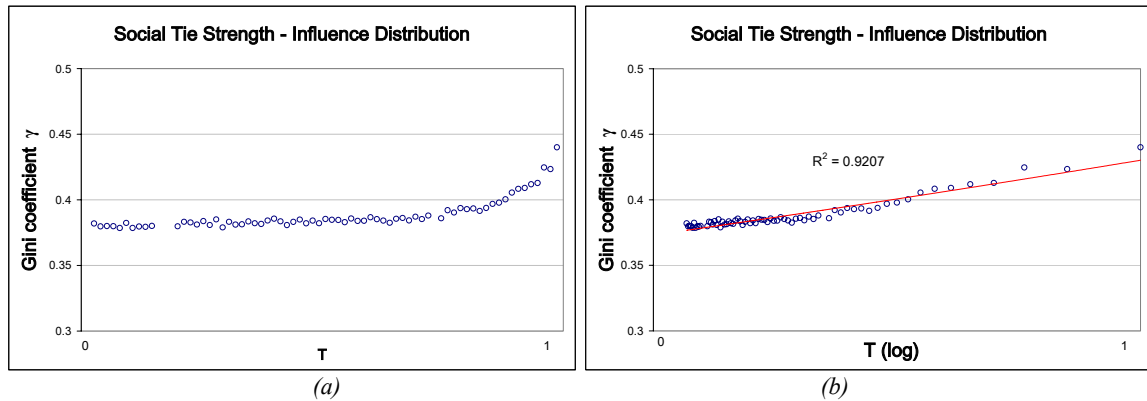


Figure 5.9 Relation between tie strength T and influence distribution γ plotted in (a) full range and (b) log scale. Strong social ties generate hierarchical structures of influence where a few adopters become very influential. Weak social ties generate more spread influence structures with narrow dominance gaps.

This result suggests that in most cases influence hierarchies can be expected to be rather flat or egalitarian, the exception being only when adopter agents tend to remain in stable social positions over long periods. In social groups with strong ties there is lower mobility and hierarchical structures of influence exist between adopters. As a result, in groups with strong links influence hierarchies guarantee that a few individuals become dominant in the spread of adoption opinions. In contrast, in weaker social settings adopters can be expected to influence their peers to a lesser degree.

Influence is more diffused in groups with weak social ties. Small amounts of social mobility in societies of strong ties rapidly reduce disparities. As tie strength decreases further, influence becomes more egalitarian up to a point at which even large changes in social tie strength and mobility do not have a significant impact.

The following figures plot the extreme values of tie strength, T , for clarity purposes. According to the type of distribution shown in Figure 5.9, under most T values results are very similar until $T \approx 1.0$, at which point data points change significantly. In subsequent figures of this experiment only the two ends $T \approx 0.0$ and $T \approx 1.0$ are shown.

At the domain level, the formation of dominance structures shows unexpected effects. On the one hand an inverse correlation is shown between tie strength T and number of entries to the repository. Lower values of T are correlated with larger repositories as shown in Figure 5.10, (Pearson = 0.6706 $N = 30$ $p = 0.001$).

In societies with weak social ties, $T \approx 0.0$, a mean of 97 artefacts with a standard deviation of 43.4 are selected by gatekeepers, whereas in societies with strong social ties, $T \approx 1.0$, a mean of 16 artefacts with a standard deviation of 11.7 are selected.

From the result discussed previously it can be seen that in societies with strong ties, a constant set of adopter agents tends to remain in the role of gatekeepers. Namely, gatekeeping is more stable and controlled by a small unchanging group of influential experts. Therefore, interpretations in which the evaluation of artefacts is based, remain constant over time. As a consequence repositories tend to be smaller. In contrast, in societies with lower tie strength T and therefore where influence is distributed rather than concentrated there is a higher change rate of gatekeepers. The gatekeeper group is constantly composed of different adopters. Consequently, more diverse evaluations mean a larger number of artefacts are included in the repository.

A principle of tie strength and repositories can be stated in this framework as follows: In fields where social ties are strong and influence is concentrated, an unvarying group of gatekeepers generates smaller artefact repositories. In fields where social ties are weak and influence is more distributed, there is a high rotation of gatekeepers that generates a larger and less predictable domain size. Social groups where individuals have stronger links produce more stable gatekeeping, i.e., the process of selecting artefacts for a collective repository remains in the same hands for long periods of time.

One direct result is that such repositories are of smaller size than in equivalent societies where social ties are weaker. The artefacts of designers that operate within weaker social spaces are more likely to be recognized by experts of the field.

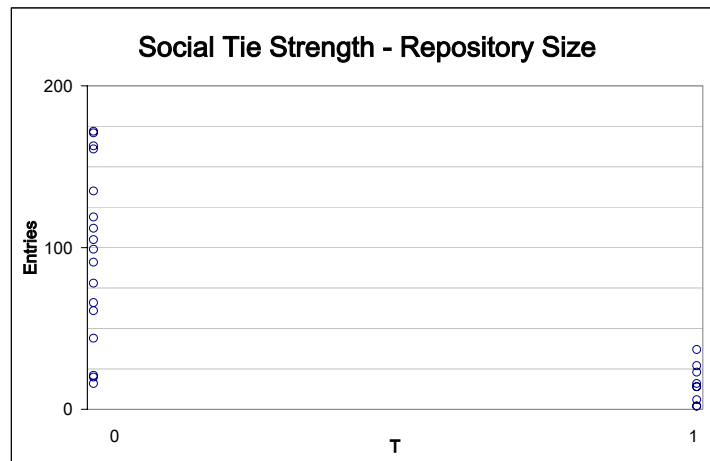


Figure 5.10 Effects of social tie strength T in the number of domain entries selected by gatekeepers. In societies with weak links ($T \approx 0.0$) the size of domains tends to be larger but very unpredictable. In social groups with strong ties ($T \approx 1.0$) domains are consistently smaller.

The differentiation of design artefacts is measured by the strategic differentiation index (SDI) (Section 4.3.6). SDI is an aggregate measure of artefacts' differences as perceived by adopters. These experiments show that SDI is inversely correlated with the strength of social ties T as seen in Figure 5.11a. Designer agents operating on strong social spaces where influence structures are stable tend to generate more similar artefacts whilst the same designers operating on wider distributed influence social spaces have a tendency towards higher differentiation (Pearson = 0.5755 $N = 30$ $p = 0.004$).

Consistent to this pattern are the effects of social tie strength in the satisfaction levels of adopters: adopters in social networks with strong ties reach higher satisfaction levels than equivalent agents related by weaker links as shown in Figure 5.11b.

This effect on design behaviour can be explained by the normative nature of strong social ties. In societies where a few influential opinion leaders exist, adoption choices can be expected to be more similar. As a result, designers repeatedly engage in competition to improve their artefacts. In contrast, in societies with weaker links, adoption opinions are expected to diverge and provide designers with a wider range of preferences. In such cases, different artefacts are adopted.

This result is consistent with the effects obtained in the experiment of individual adoption bias, w , (Section 5.2.3) where a decrease of SDI is observed when more independent adoption choices are taken.

Lastly, effects on the size and nature of adopter groups are addressed. Results show that T is positively correlated with adopter group size as shown in Figure 5.12a (Pearson = 0.608 $N = 26$ $p = 0.001$). The standard deviation of adoption in weak ties (1718) is also significantly higher than in strong ties (726). This illustrates that weak social ties $T \approx 0.0$ increase abstention and make

adoption less predictable. This is a consistent result with the notion that in more rigid societies there is a higher agreement of adoption opinions.

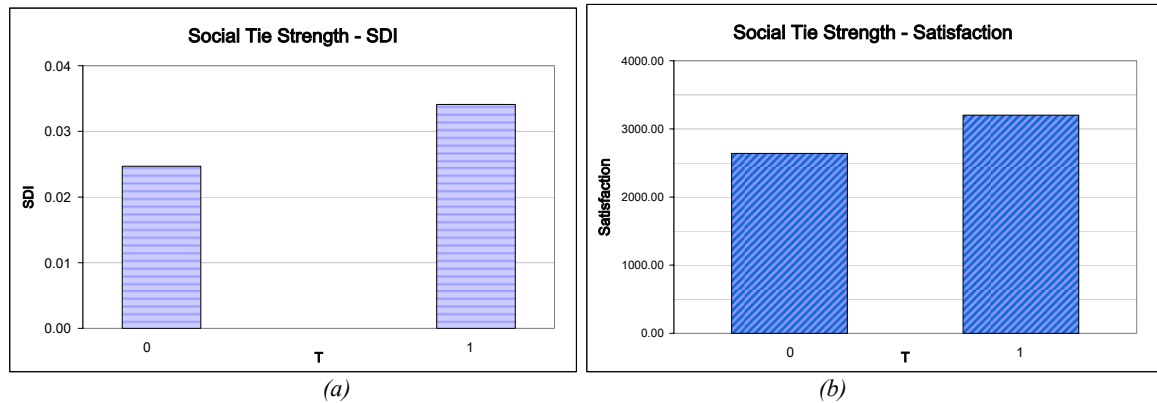


Figure 5.11 Effects of social tie strength T in (a) SDI and (b) satisfaction. In societies with strong links ($T \approx 1.0$) artefacts tend to be perceived as less similar and yield higher post-adoption satisfaction levels than in social groups with weak ties ($T \approx 0.0$).

Adoption variance, on the other hand, is given by the distribution of adopters by designer agent. When adoption variance is high most adopters choose the artefacts of one designer whereas a low adoption variance indicates that adopters distribute their choices amongst all designers. The strength of social ties T is correlated with adoption variance as shown in Figure 5.12b (Pearson = 0.6796 $N = 26$ $p = 0.001$). Namely, in social spaces with weak ties adoption choices tend to be more distributed across designers. In contrast, $T \approx 1.0$ increases total adoption and concentration of choices around a few designers.

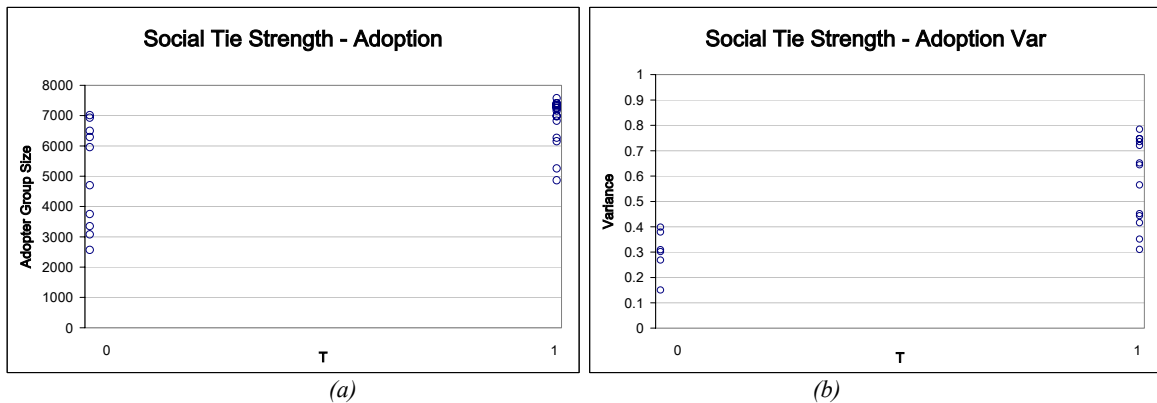


Figure 5.12 Effects of social tie strength T in adoption. In societies with weak links ($T \approx 0.0$) (a) adopters tend to abstain more and their adoption behaviour is more erratic and (b) adoption choices tend to be more concentrated in artefacts from a few designers.

This result has an interesting implication from the designers' point of view. Designer agents with the same individual characteristics but operating in two extremes of social tie strength can expect different outcomes. On one hand, when within a society with weak links $T \approx 0.0$ popularity is lower and more unstable, whilst prominence is harder to obtain. In this framework the popularity of designers is given by the size of their adopter groups and prominence by the distribution of adoption choices. On the other hand, when the same designers operate within a society with strong ties $T \approx 1.0$, one should expect higher and more consistent popularity levels and a higher concentration of prominence, i.e., a few designers concentrating most adoption choices.

Since the shape of the relationship between tie strength T and influence distribution γ is non-linear, lower popularity and lower concentration of prominence can be expected to be the norm in this framework. Under exceptional social conditions, the effects of otherwise equivalent designer agents have a sudden change as the critical point at which influence concentrates is reached. Within such rare situational condition, one designer agent is likely to concentrate the choices of a majority of adopters.

5.3.1.2 Analysis

Many natural and social phenomena including city sizes, income distributions, word frequencies, and hyperlink structures are distributed according to a power-law distribution (Huberman and Adamic 1999). Such a distribution implies that most occurrences are extremely common, whereas some instances are extremely rare. The relation between social tie strength and influence hierarchies in this framework suggests that the system can be expected to generate similar results under most variations of social tie strengths, except when a point of criticality is reached by very low or inexistent social mobility.

Within a society with strong ties, significant effects occur throughout the system. Adopters converge in their decisions, artefacts are perceived as more different, and domain sizes are smaller and more predictable.

Extensions to the study of social tie strength can be directed to explore its relationship to neighbourhood size. In this framework neighbourhood size is assumed to increase with social tie strength (Section 4.4.3) based on the Theory of Social Impact (Granovetter and Swedberg 1992). However, an alternative interpretation worth investigating is that neighbourhoods become smaller as the strength of social ties increase, i.e., with limited time resources, individuals have to distribute their time between their relationships (Florida 2002). The issue then is to observe how a negative or inverse relationship between social tie strength and neighbourhood size affects the observed outcomes.

5.3.2 Design Rate (D)

This experiment addresses the rate at which designers are scheduled to revise and make changes to their artefacts. The design rate (D) is determined as a multiple of adoption iterations. When $D = 100$, designer agents execute their behaviour every 100 adoption steps. When $D = 10$, designing takes place more often at every 10 adoption steps. In all cases, the gatekeeping role is kept constant at 10, i.e., gatekeepers keep evaluating artefacts as entries to the repository at a constant interval independently of them being updated by designers. The assumption is that different artefact life cycles require varying design rates when compared to the rate of adoption and gatekeeping. In other fields, the rate of design may vary over time. In this experiment design rate is kept constant during a simulation.

With all other variables unchanged, Monte Carlo simulations are run from $D = 10$ to $D = 100$ in increments of ten. Results reported are mean values of thirty cases run per increment with three designers and 100 adopters.

5.3.2.1 Results

The main effects of design rate are observed in dependent variables of domain and design behaviour, including rule generation and peer recognition. A power-law function is observed in the relation between design rate D and the size of knowledge bases. The number of rules generated by designers is recorded on every simulation run and the mean values for each experiment from $D = 10$ to $D = 100$ plotted in

Figure 5.13. Whilst the direction of this relationship is expected, its shape is not necessarily intuitive. When designing takes place frequently, $D = 10$, designer agents generate a large number of rules (a mean of 162). The interesting effect is that only a small decrease in frequency of design

behaviour is sufficient to reach a critical point where a sudden drop in rule generation is observed. When design activity takes place slightly less frequently, i.e., $D = 20$, the mean number of rules generated drops to 60 and when $D \geq 40$ a low level is reached around 20 rules after which even significant changes on the rate of design have only marginal effects on knowledge production.

Figure 5.13a plots design rate D against number of rules in the full range on the axes, whilst Figure 5.13b plots this relationship in a log-log scale where the distribution appears as linear.

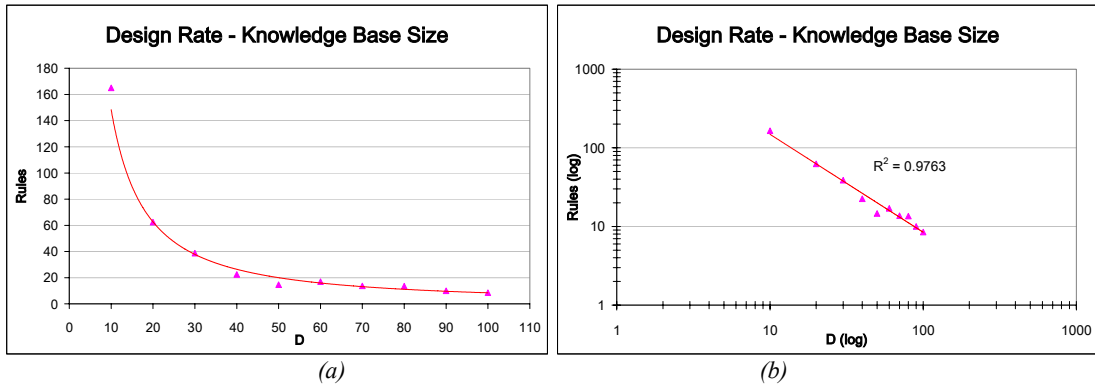


Figure 5.13 Effects of design rate D in knowledge base size show a critical point at which infrequent design behaviour rapidly decreases the generation of design rules: (a) plots this relationship in full scale axes, whilst (b) shows the linear relation in a log-log plot.

This effect can be explained by analysing the mechanism by which the abilities of designers can increase during a simulation run. This mechanism is tied to the recognition by peers (Section 4.3.2), i.e., when a feature of an artefact is imitated, its designer receives an increase of processing and synthetic abilities. This has a ‘cascade-effect’ inasmuch as frequent design activity not only translates into more rule discovery, but with constant imitation, designers are increasingly able to search for further rules. What is perhaps surprising is that once this combination of imitation and knowledge construction is interrupted, the generation of rules stabilises at a low level.

Inasmuch as the generation of design rules is tied to the recognition by peers, the focus is on the non-linear relationship between design rate D and peer recognition shown in Figure 5.14. When design rate is frequent, $D = 10$, mean peer recognition amongst designer agents is 42. With less frequent design activity, i.e., $D \geq 30$, recognition between peers stabilises around 5. Figure 5.14a plots design rate D against recognition in the full range on the axes whilst Figure 5.14b plots this relationship in a log-log scale with a linear correlation. This reinforces the idea that without feedback from imitative behaviour, designer agents rapidly cease to generate rules.

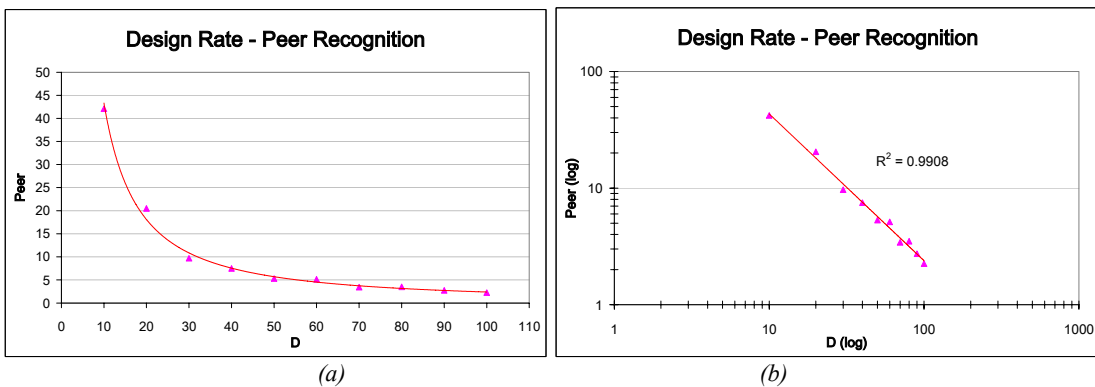


Figure 5.14 Effects of design rate D in peer recognition confirm the pattern seen with knowledge base sizes: (a) plots this relationship in full scale axes, whilst (b) shows the linear relation in a log-log plot. (c) plots design rate against differentiation strategies in a log-log scale.

The effects of design rate D in differentiation strategies are shown in Figure 5.15a in full scale and in Figure 5.15b in log-log axes. It can be expected from frequent design activity to cause designers to seek differentiation more often.

When designing takes place recurrently, $D = 10$, a mean of 250 strategies of differentiation are generated by designers. However, it is unexpected to observe that during an equivalent period of time but with design activity marginally less frequent, $D \geq 30$, the mean cumulative number of differentiation strategies rapidly decreases to a stable point below 50. With more sporadic design activity, changes of design rate have no significant effects on the generation of differentiation strategies.

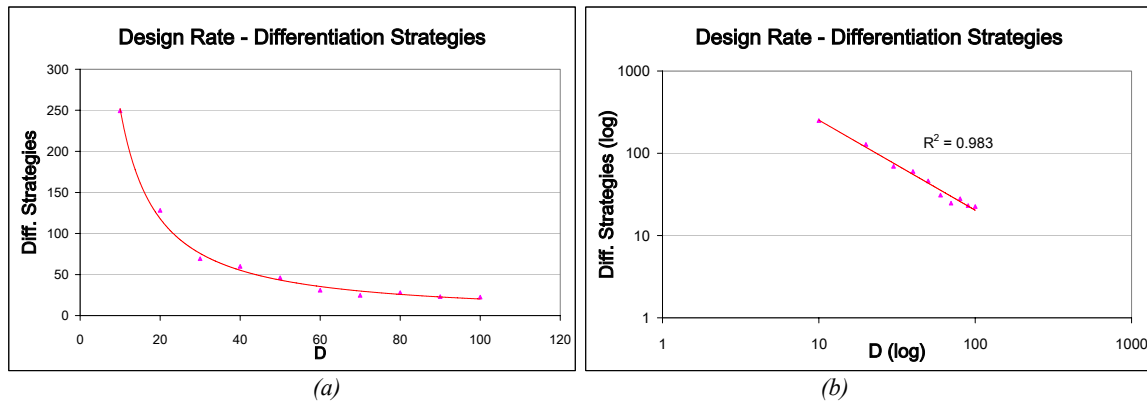


Figure 5.15 Effects of design rate D in strategies of differentiation in (a) full scale and (b) log-log scale.

Other significant effects are observed at the domain level. Whilst no substantial changes are observed on the size of repositories, their composition seems to vary consistently with design rate.

Firstly, domain variance is recorded during a simulation run by the distribution of contributions by designer agents. Namely, a low domain or repository variance indicates a run where selected artefacts are uniformly contributed by all designers, whereas a high repository variance indicates more concentration of gatekeepers' selections.

Figure 5.16a shows that repository variance increases with design rate suggesting that entries are selected from a wider range of designer agents when design behaviour is less frequent. Secondly, the mean score assigned by gatekeepers to entries is also recorded for every simulation run. Figure 5.16b shows that repository score decreases as design rate is increased.

This is confirmed in Figure 5.16c by the relationship between design rate and the independent measure of repository complexity which indicates that the types of artefacts designed are indeed different. These relationships fit least squares lines.

The implications at the domain level are that an infrequent scheduling of design behaviour causes gatekeepers to select repository entries from a less diverse range of designers. At the same time, the score assigned by gatekeepers and the inherent complexity of repository entries decays with sporadic design behaviour. The latter can be attributed to the idea that fewer changes of artefacts under inspection cause less diversity and lower quality of domains.

A factor to consider in regards to these trends is that the rate of gatekeeping in this experiment is kept constant. Thus, the decay of the domain entry threshold (Section 4.5.1) is expected to affect the selection process when gatekeepers keep evaluating but not selecting unchanged artefacts as $D \approx 100$.

Artefacts that would otherwise not be selected due to a high entry threshold become entries as $D \approx 100$. This also accounts for the lack of substantial changes in repository size: when $D \approx 10$, gatekeepers select artefacts with increasingly high scores, whilst when $D \approx 100$, selection does not decrease but shifts to artefacts of lower quality.

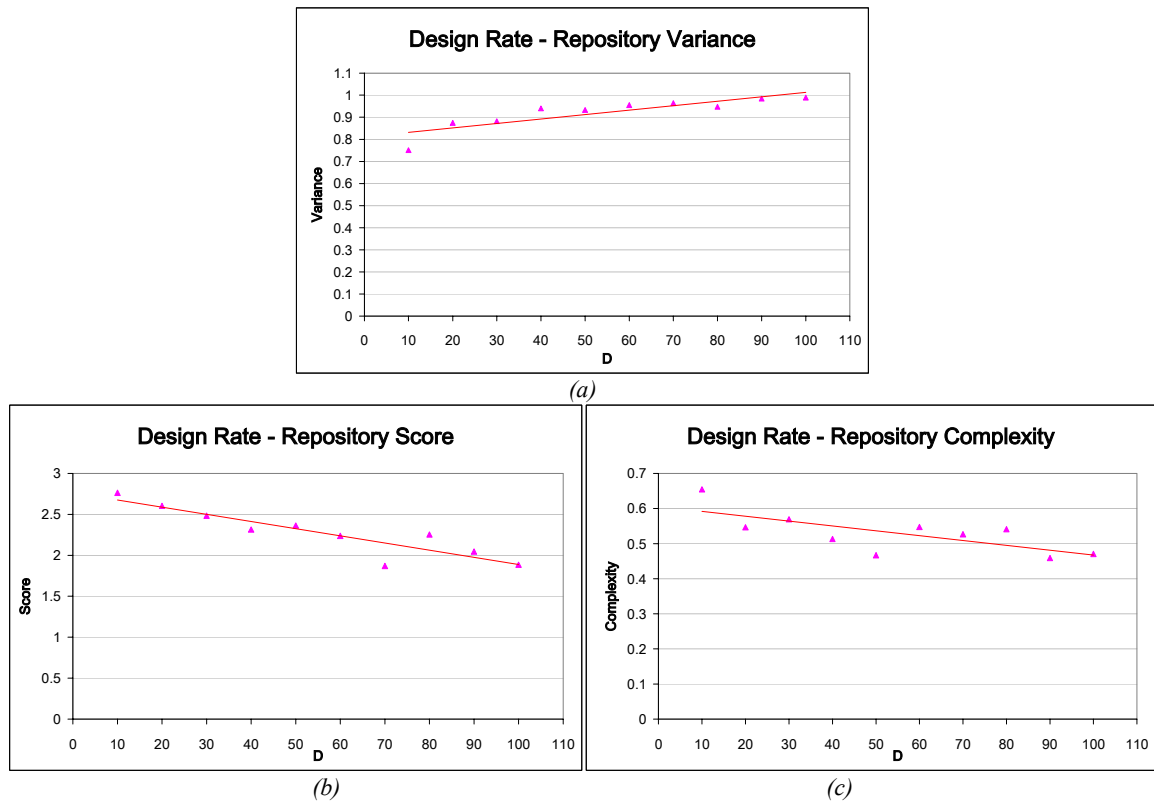


Figure 5.16 Effects of design rate D in domain variables. In (a) domain entries are selected from a lower number of designers. In (b) the scores and (c) the complexity of domain entries is negatively correlated with design rate. Domain size, however, is virtually constant.

5.3.2.2 Analysis

The effects of design rate can be summarised as follows: with everything else constant, more frequent design behaviour generates large knowledge bases, more instances of peer recognition, and domains that are of higher quality and complexity built by contributions from more designers. As the scheduling of designers' activities becomes sporadic, knowledge bases and peer recognition decline sharply to a stable low level. Likewise, domains receive entries of lesser quality and from few designers. When more adoption and expert selection takes place between design episodes a wider range of designer agents can be expected to contribute to the repository. However, these artefacts can also be expected to be of lower quality.

Extensions of design rate can be addressed as individual factors. To this end, designer agents can be assigned an individual rate of design which determines how often each designer agent is able to execute revisions and changes to their artefacts. As a situational factor, the rate of design need not be fixed during a simulation run. Further experimentation could be aimed at inspecting the consequences of an evolving design rate.

5.3.3 Gatekeeping Rate (G)

In this experiment the situational factor under inspection is given by the frequency of execution of the gatekeeping role. Gatekeepers periodically select artefacts for entry into the collective repository of the population. This nomination process is executed with a fixed rate during a simulation run and is defined as the gatekeeping rate G . When $G = 100$, gatekeeping is executed sporadically at every 100 adoption steps. When $G = 10$, gatekeepers evaluate entries more often at every 10 adoption steps. The assumption is that in different design fields there are different review and selection rates when compared to the rates of adoption and design. Periodic competitions and exhibitions are types of gatekeeping schedules in design.

In this experiment design rate D is left constant at $D = 10$, i.e., designer agents update their artefacts every 10 adoption steps irrespective of how often gatekeepers evaluate their artefacts. With all other variables unchanged, Monte Carlo simulations are run from $G = 10$ to $G = 100$ in increments of 10. Results reported are means of thirty cases per increment after outliers are excluded.

5.3.3.1 Results

As could be expected, the main effects of varying the rate of gatekeeping are at the domain level. Increasing gatekeeping activity generates larger repositories as shown in Figure 5.17. The reason behind this pattern could be simply that when gatekeepers consider entries to the domain more often, there is a higher probability that more artefacts are selected. However, the shape of this relationship is perhaps more surprising. The relationship between G and the mean size of repositories is non-linear, i.e., a small decrease in the rate of frequent gatekeeping rapidly generates smaller repositories down to a point after which as gatekeeping becomes more sporadic, rate changes do not have a significant effect on domain size. Figure 5.17a plots the range on the axes whilst Figure 5.17b shows the linear distribution on a log-log plot ($r^2 = 0.8361$).

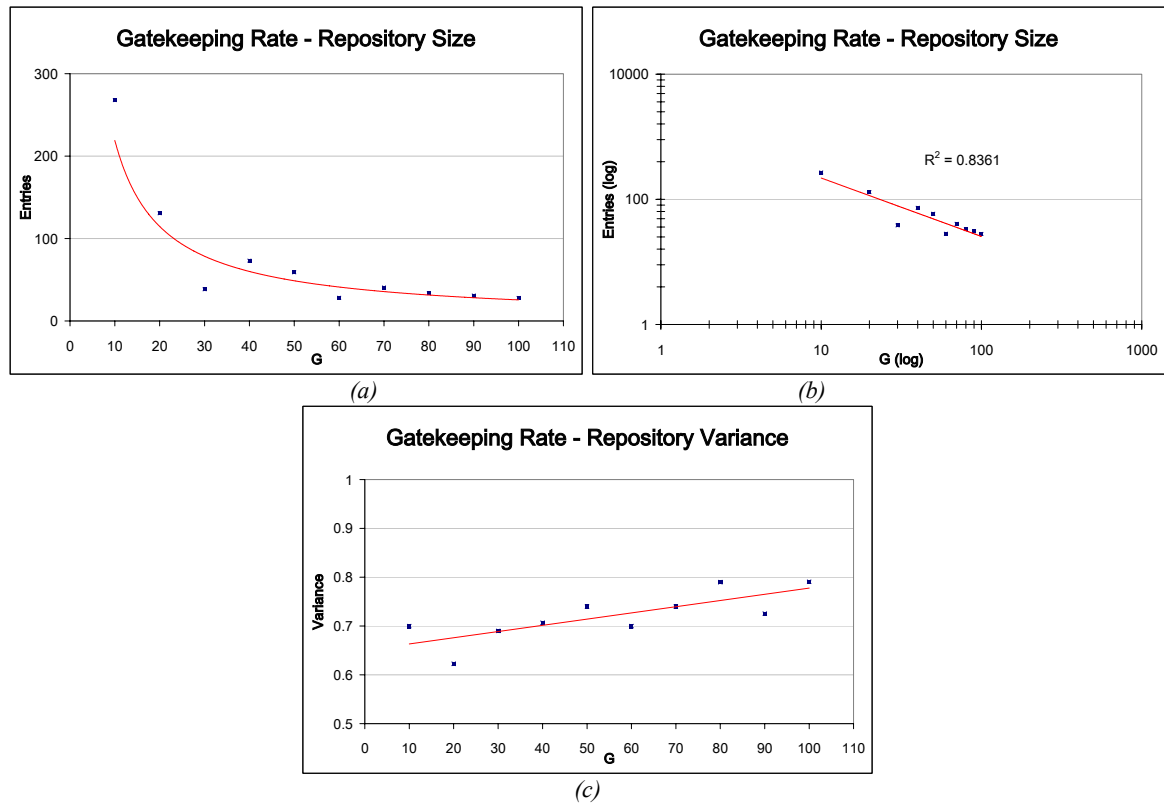


Figure 5.17 (a) The shape of the relationship between gatekeeping rate G and the size of the domain shows that small changes at high frequency of gatekeeping have a significant effect on the number of selected artefacts. In (b) the same pattern is shown in a log-log scale. In (c) variance of domain entries per designer are positively correlated with G .

To complement this finding, the variance of domain entries is seen to increase with gatekeeping rate G . Domain or repository variance is estimated from the number of contributions generated by each designer. A high domain variance indicates that the selection process concentrates on the artefacts of a few designers, whereas a low domain variance indicates a distribution of entries from all designers. Figure 5.17c shows that a gatekeeping rate of $G = 10$ generates low domain variance. This reveals that with frequent gatekeeping domain entries originate from a smaller number of

designers. In contrast, when gatekeeping is more infrequent in relation to adoption decisions, $G = 100$, a higher variance is observed. This indicates that with sporadic gatekeeping more entries are selected from more designers.

These effects of the frequency of gatekeeping at the domain level do not seem to permeate into the content of the repository. Neither domain scores nor the independent measure of complexity of domain entries yield discernible patterns.

One possible explanation for the independence of these variables is that more frequent gatekeeping, $G = 10$, is more likely to include entries with small increments to the entry threshold (Section 4.5.2). In contrast, more periodic gatekeeping, $G = 100$, can be expected to include artefacts with equivalent scores but in larger increments to the entry threshold. In other words, the smaller repositories tend to consist of fewer artefacts that make qualitative leaps, whilst large repositories created by frequent gatekeeping include a large number of artefacts of small qualitative increments.

5.3.3.2 Analysis

These results can be stated in a principle of gatekeeping and domains as follows: In fields where gatekeeping takes place frequently, larger domains can be expected with a limited number of designers contributing. This generates more concentration of prominence given by experts. When gatekeepers only select artefacts sporadically, the number of selections in the domain is smaller but the number of different contributors higher. In these cases prominence is more distributed across designers.

These variations, however, need not determine the mean quality of domain entries. Sporadic gatekeeping can be said to be more efficient since same-quality levels are reached by a smaller number of entries.

Extensions to the study of gatekeeping can be carried by relaxing the assumption that the rate of gatekeeping remains fixed during a simulation. To this end, the behaviour of gatekeepers can be tied to domain rules including the entry threshold or the size of the repository. Experiments could then be conducted on the role that designers can play in influencing the role of gatekeepers. This may be a viable way to establish a closer relationship between designers and gatekeepers, perhaps extending the role of the latter into more active promoters of the artefacts of their associates.

5.3.4 Adoption Rate (A)

Having considered the rates of designing and gatekeeping separately, the focus is shifted to variations of the adoption rate A . In this experiment the number of adoption steps between design and gatekeeping is manipulated. On one hand, adopters are required to take 10 decisions for every time that designers and gatekeepers execute their behaviours, i.e., $A = 10$. On the other, adopters are required to select artefacts as many as 100 times between design and gatekeeping episodes, i.e., $A = 100$. The twofold assumption is that some types of design artefacts are acquired by adopters in a variable frequency of combined design decisions and expert selection. For instance, disposable items are, by definition, chosen on a more frequent basis than non-disposable products. Given that other processes continue to operate—in particular the mechanisms of social influence—the objective of this experiment is to compare the patterns of cases in the range $10 \leq A \leq 100$.

With every other variable kept constant, in this experiment the single independent variable is adoption rate (A), traversed from $A = 10$ to $A = 100$ in increments of 10. Results analysed are based on means of thirty cases per increment.

5.3.4.1 Results

Some of the main effects observed in this experiment could be expected by the previous manipulation of design and gatekeeping rates. However, other patterns emerge that are not discernible in the previous two experiments. The most noticeable trends occur at the adoption process, the domain, and the differentiation of artefacts. Figure 5.18a shows that as the number of

adoption decisions taken between design and gatekeeping instances increases, $A \approx 100$, consistently higher adoption satisfaction levels and higher adoption variance are observed. Adoption satisfaction is estimated by the comparison of adopter preferences to artefacts' features every time an adoption choice is made (Section 4.4.2). The increase of satisfaction can be tracked back to the mechanism of gradual habituation to features (Section 4.4.1). Thus, this finding is consistent with such assumption and demonstrates its effects. When artefacts remain unchanged for long periods and no bias is introduced by the selection of domain entries by experts, the preferences of the adopter population tend to approach the features of the available artefacts. As a consequence, the satisfaction of adopters tends to increase.

Adoption variance is estimated by the distribution of adoption choices amongst designers. A high variance is indicative of cases where a few designers concentrate most adopters, whereas a low variance characterises a population where adoption is distributed across artefacts from all designers. Figure 5.18b shows that as adoption decisions increase between design and gatekeeping episodes, the variance of adoption also increases. One way to explain this is in relation to adoption satisfaction: the habituation mechanism draws adopters closer to the artefacts they adopt. Thus, adoption is more concentrated on a few designer agents as a function of adoption rate A .

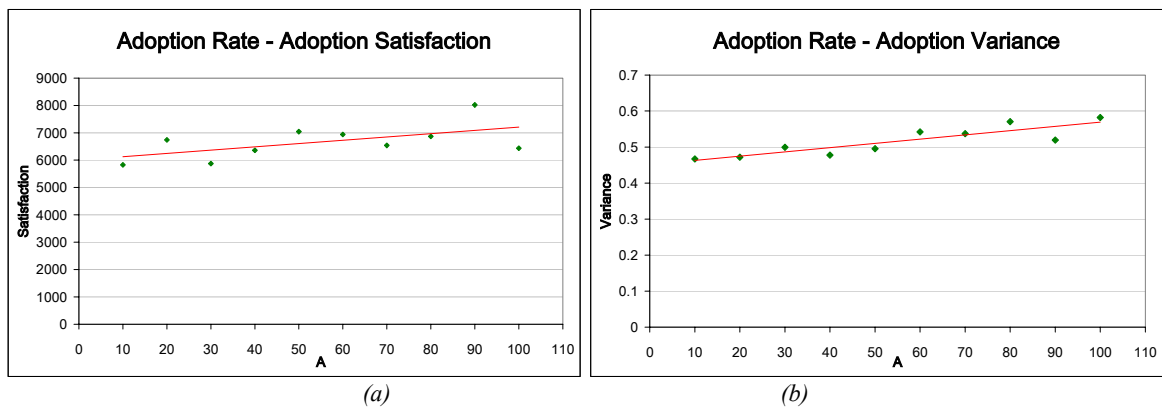


Figure 5.18 Effects of adoption rate A in the adoption process. (a) Adopters' satisfaction and (b) adoption variance increase with A .

At the domain level, the dependent variables where the effects of A are significant are repository size and repository score. Figure 5.19a and Figure 5.19b plot the non-linear relation between A and repository size in full scale and log-log scale, respectively. This relationship seems to be a consequence of varying the gatekeeping rate G (Section 4.5.2). It suggests that as the number of adoption decisions increases between the selection of artefacts, such selection process yields a smaller number of domain entries. On the other hand, Figure 5.19c shows the effects of adoption rate A that combine an additional result from varying the design rate D (Section 5.3.2). This effect yields a negative correlation between entry score and the rate of adoption decisions.

These results show that the more decisions taken for adoption, the lower the mean score of domain entries. In this experiment this effect could be due simply to the exponential decrease in the number of entries, which fails to raise the mean score of domain entries.

A further consequence of varying adoption rate is observed at the design level. Figure 5.20a shows that the differentiation of artefacts as perceived by adopters tends to decrease as the number of adoption decisions increases between the selection of artefacts. The differentiation of design artefacts is measured through the strategic differentiation index (SDI) (Section 4.3.6). This implies that infrequent design behaviour and gatekeeping selection generate an increase of similarity between artefacts. In order to confirm this finding, the mean number of strategies chosen by designers during a simulation run is analysed. Strategies of differentiation are chosen when the features of their artefacts do not address the perceived preferences of the population and designer agents aim to improve other features to attract adoption (Section 4.3.2). Figure 5.20b shows that the

total number of strategies of differentiation indeed decrease as a function of adoption rate A . The relation between adoption rate A and strategies of differentiation is non-linear, i.e., the number of this type of strategies rapidly declines as adoption rate increases up to a point after which large differences in A have marginal effects.

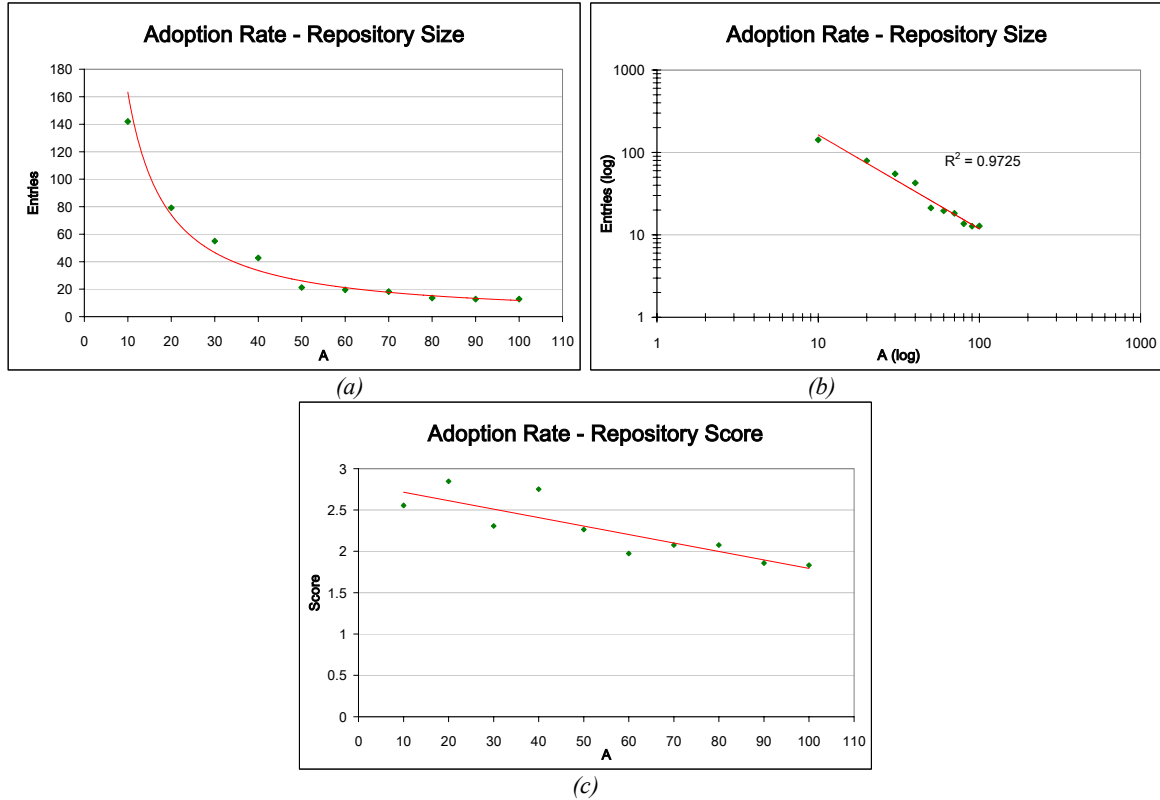


Figure 5.19 Effects of adoption rate A at the domain level where a combination of patterns is observed from the independent manipulation of design and adoption rates. In (a) and (b) the non-linear relation of adoption rate A and repository size is plotted in full scale and log-log scale, respectively. In (c) a decreasing repository score is observed.

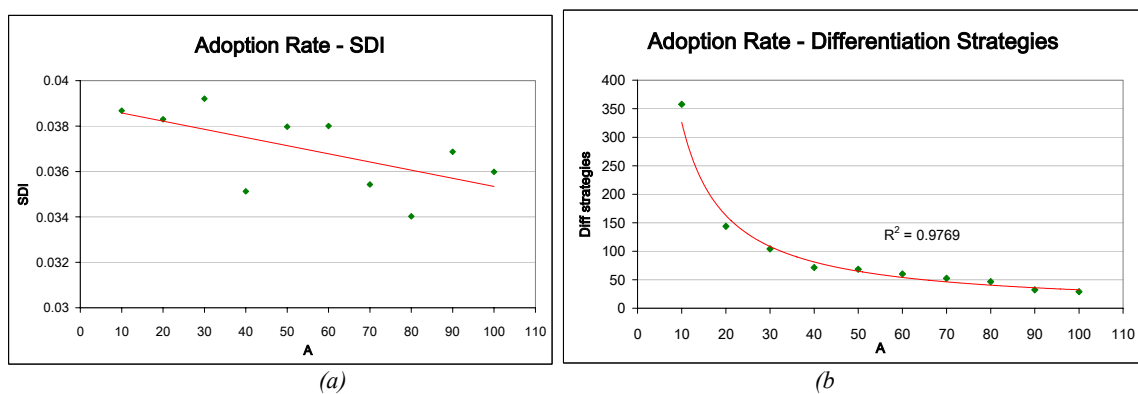


Figure 5.20 Effects of adoption rate A in design behaviour. As A increases, (a) adopters perceive more similar artefacts and (b) in general designers fail to differentiate their artefacts.

5.3.4.2 Analysis

This experiment illustrates the consequences of the habituation assumption (Section 4.4.1). Related to this issue is the trend of adoption variance that suggests that the less often that designers operate, the higher the concentration of adoption choices. These two findings may depict a simplistic

assumption that needs to be revised. In general, experimentation with the rates of behaviour of different actors in this framework could be extended to account for variations during a system run. The adoption rate is no exception. Inquiry could be aimed at establishing the mechanisms and conditions under which designers can influence the number of adoption choices (i.e., maximise or minimise them) or how they can adapt their behaviour to a varying adoption rate.

5.3.5 Population Size (P)

In this experiment the effects of varying the size of the adopter population are assessed. Population size P is given by the total number of adopter agents in a simulation run. P is defined at initial time and remains fixed during a simulation run.

The objective of this experiment is to assess the interaction between designers and adopters in cases where the ratio of designers and adopters varies. Whilst some effects can be expected to increase linearly due simply to the sum of more adoption decisions, there are other dependent variables at the domain and design levels where the effects are not so easy to visualise.

The results presented in the following Section refer to cases where the population consists of 10, 50 and 100 adopter agents, i.e., P is varied between $P = 10$, $P = 50$ and $P = 100$, respectively. In all experiments the number of designers is kept constant at 3.

In principle, larger P values can be studied but simulation times increase significantly making it impractical with existing computational power. Nonetheless, the patterns observed in this experiment give some indication of the consequences of varying population size in a system of this type. In these experiments all other variables remain unchanged including the number of designers, the strength of social ties, and design and gatekeeping rates. Results are based on mean values of one-hundred cases run per increment.

5.3.5.1 Results

Unsurprisingly, increasing the number of adopters in a population generates a linear increase of the mean size of their repositories as shown in Figure 5.21. This is a consequence of the definition of opinion leaders in our framework (Section 4.4.4). The number of opinion leaders increases linearly with P , i.e., a population of 100 adopters has, on average, 10 times more gatekeepers than a population of 10 adopters. This increase of gatekeeping activity yields an equivalent increase on the number of artefacts selected for the repository.

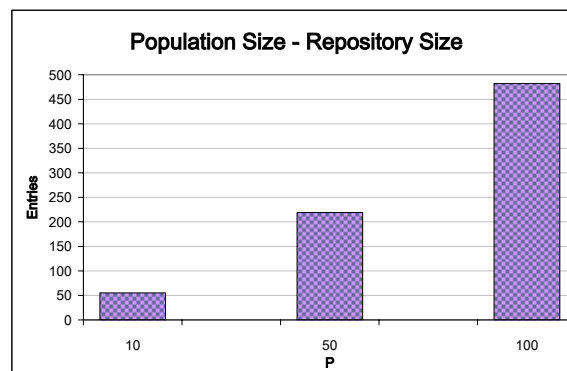


Figure 5.21 Linear relation between population size P and the mean size of repositories. Since the number of gatekeepers is a ratio of the population, an increase of gatekeeping activity in large populations generates proportionally large repositories.

Nonetheless, the quality of repository entries only varies marginally with P . Figure 5.22a plots the mean repository scores attributed by gatekeepers whilst Figure 5.22b plots an independent measure of complexity of the entries (Section 4.5.4). Both measures show that the qualitative difference of the selected artefacts is relatively small. The mean complexity of domain artefacts of

small populations, $P = 10$ is 0.52 whilst for $P = 100$ the mean score increases to 0.69. The reason for this increase can be directly attributed to repository size, i.e., since entries need to pass the entry bar, larger repositories can be expected to include artefacts of higher quality and complexity.

These results suggest that whilst large populations may generate proportionally larger domains, the mean quality of a large domain can be expected to be only marginally higher than that of smaller societies. In other words, since large social groups involve more gatekeeping, they tend to generate larger domains. However, large domains need not be of proportionally high quality. Small adopter societies can produce small repositories of comparable mean quality.

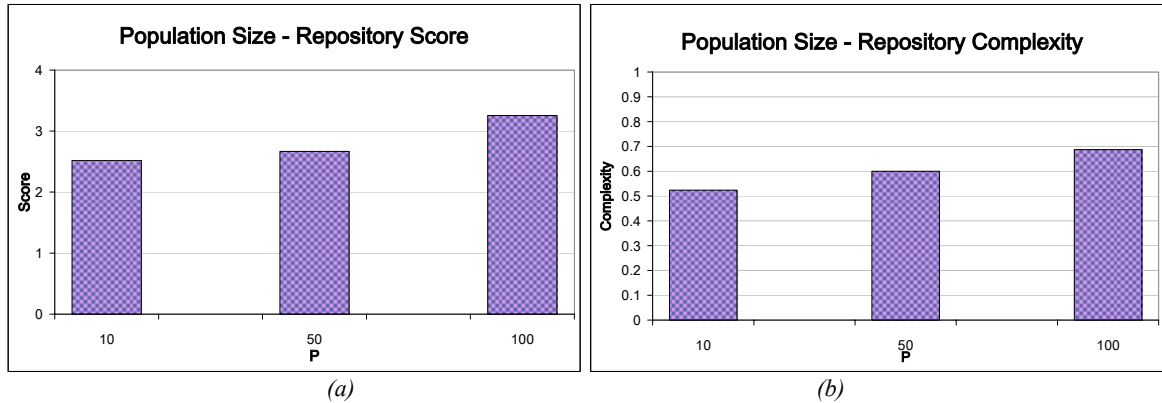


Figure 5.22 Effects of population size P in domain content. In (a) the relation between population size P and the mean score of repository entries is shown whilst (b) confirms the trend with mean complexity of repository entries. The mean quality of repository entries is relatively similar.

The effect of population size P in the level of satisfaction of adopters is demonstrated in Figure 5.23a. Satisfaction is recorded by the absolute number of adopters that reach a level of high satisfaction during a system run. When members of a group of evaluators belong to small societies of only 10 adopters a total of 6469 adopters reach high satisfaction levels, i.e., a ratio of 647. When equivalent adopters are part of societies of 50 and 100 members, this ratio increases to 709 and 804, respectively.

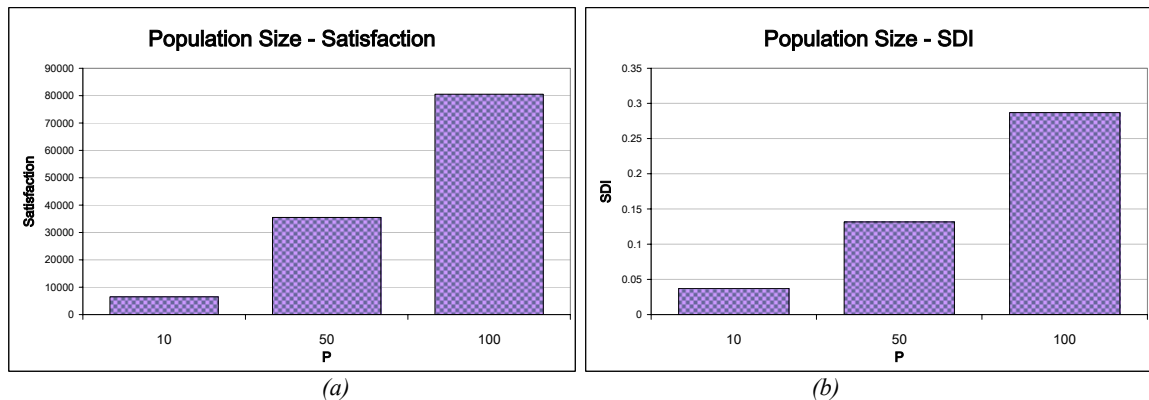


Figure 5.23 (a) Effects of population size P in the post-adoption index of satisfaction of adopters: equivalent adopters tend to have higher satisfaction levels when they are part of larger groups. This can be explained by (b) a positive correlation between population size and perceived differentiation (SDI).

A possible explanation for this pattern is provided by the effects of population size in the perceived differentiation coefficient measured by the SDI as defined in Section 4.3.6. High SDI values indicate adopter groups that perceive available artefacts as being more different to each

other than low SDI values. Larger populations yield a higher SDI mean value as seen in Figure 5.23b.

This pattern of association between SDI and satisfaction level is consistent with the effects of other independent variables such as the strength of social ties, i.e., Figure 5.11. It would be appropriate to conduct complementary experiments where the strength of social ties and population size are manipulated to evaluate whether small groups with strong social ties generate higher SDI values than same-size groups with weaker ties.

5.3.5.2 Analysis

The main consequences of varying the size of the adopter population in this framework are observed at the domain level. Whilst the size of repositories increases proportionally, the quality of repository entries is only marginally higher in large populations.

An interesting extension to this experiment is to explore the ratio between the size of the adopter population and the number of designers. A range of experiments could be implemented to address the notion of active and passive designers. As a function of adoption, peer or expert evaluation, designer agents could be ‘fired’ and ‘hired’ from societies. A hiring mechanism could be a further role of gatekeepers, i.e., they could be in charge of authorising the entry of more designers into a population. Likewise, the number of adopters in a society could be varied during a simulation as a function of design activity.

5.3.6 Access to Knowledge (K)

In this experiment the factor under inspection is the type of access that designers have to design knowledge (Section 4.3.3). This variable has two states: public or private access. In public mode, designer agents have access to the rules generated by other designers up to that time. In private mode, each designer is restricted to use rules from its own knowledge base.

Public access to knowledge refers to settings where designers cooperate by disclosing and sharing information. This resembles the phenomenon of ‘collective innovation’ (Allen 1983). In contrast, private access reflects a system where knowledge is concealed akin to a strong patenting system (Kingston 2001).

The objective of this experiment is to explore the role that a situational factor of a regulatory type can have in adoption, design, and opinion leadership. With all other variables kept constant, one hundred simulations are replicated for each scenario: private and public access to knowledge. Individual characteristics of designers and adopters are kept constant.

The dependent variables of interest in this experimental setting include the size and contents of repositories, rate and variance of adoption, and adoption satisfaction levels. Results are based on mean values of one hundred instances.

5.3.6.1 Results

Results are shown in Figure 5.24 for a number of dependent variables plotted in columns (A) to (I). To facilitate comparison of effects across different scales, the vertical axis of this graph is normalised, i.e., the maximum value for each variable is made equivalent to 1. This unit measure is compared against the output of the other type of access to knowledge. Bars show the difference ratio between the two conditions.

When designers have public access to knowledge, column (A) shows that adoption variance decreases 14% (to 0.861). Adoption variance is defined as the distribution of adoption decisions between designer agents. When adoption variance is high, adopters tend to concentrate their choices in artefacts from a few designers, whereas a low adoption variance refers to a more competitive environment where adopters distribute their choices across all designers. Adoption variance decreases from 0.50 in private mode to 0.43 in public mode. Thus, private access has the

expected effect of increasing the likelihood that adoption will concentrate on a few designers, i.e., those that individually generate more appropriate rules to transform their artefacts.

A similar effect occurs in the total number of adopters in column (B) where public access shows an equivalent decrease to 0.862, i.e., from a mean of 9513 adoption choices in private mode to 8197 in public access to knowledge. This indicates that private access generates not only higher adoption variance but also larger adopter groups or less abstention. Namely, more adopters concentrate their choices on artefacts from a small number of designers.

If adopter group size is taken as a measure of popularity then given the assumptions of this framework, societies where design knowledge is concealed can be expected to produce a few highly popular designers.

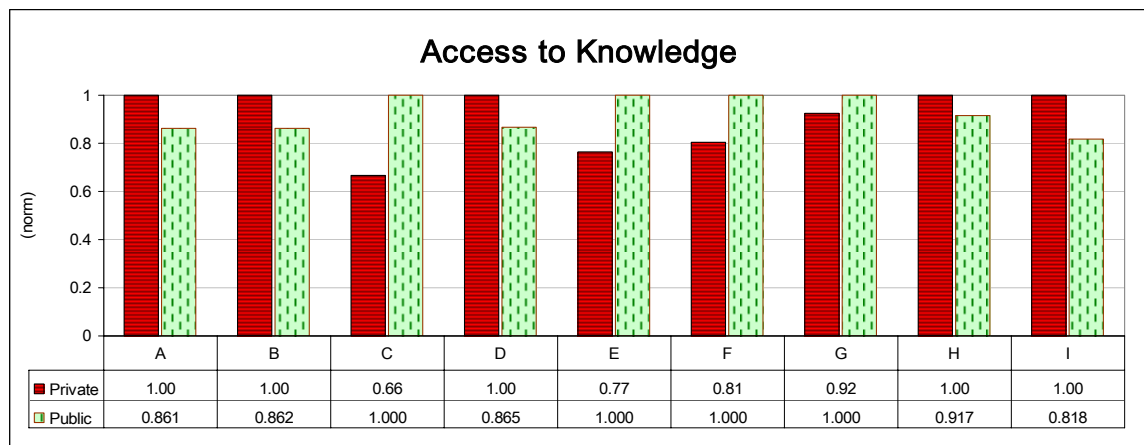


Figure 5.24 Effects of types of access to design knowledge in A = variance of adoption, B = total adoption, C = number of rules, D = variance of domain entries, E = total domain entries, F = mean domain score, G = mean domain complexity, H = total adoption satisfaction, and I = mean SDI.

The most significant effect of K is on the number of rules generated as plotted in column (C). In this case the maximum value is registered in public mode. A mean of 33 rules are produced when designers share knowledge compared to 21 rules in cases with private access. This mean decrease to 0.66 indicates that public access to design knowledge further encourages the generation of rules in this framework. A possible explanation is that when designer agents have access to others' rules they are able to build on existing knowledge. As a result a more dynamic design behaviour can be inferred where constant changes to artefacts are produced.

Domain effects are multifaceted as shown in columns (D) and (E). Private access causes a higher variance of contributors to the repository. However, it is public access to knowledge that generates more total repository entries. Domain or repository variance is estimated from the number of contributions generated by each designer. A high domain variance indicates that the selection process concentrates on the artefacts of a few designers, whereas a low domain variance indicates a distribution of entries from all designers. Domain variance decreases from 0.797 in private mode to 0.689 in public mode. Domain size is estimated by the sum of all repository entries. It increases from a mean of 31 in private mode to 40 in public mode. The apparent contradiction of these opposite effects can be explained by the notion that in private mode the selection process of gatekeepers concentrates on artefacts generated by a smaller number of designers, which renders less frequent selection. Still on domain effects, the mean score of artefact is plotted in column (F). Domain score increases from a mean 2.26 in private mode to 2.80 in cases of public access to knowledge. This trend is confirmed although in a lesser degree, by the measure of pattern complexity plotted in column (G). Domain complexity increases from 0.49 in private access to 0.53 in public access. This effect on domain score may be associated to knowledge base

size plotted in column (C). Namely, by collectively building more design rules in public mode, designers are able to generate artefacts of higher quality and complexity.

Lastly, the effects on adoption satisfaction in column (H) and industry differentiation in column (I) show that in private mode adopters are more satisfied with a higher artefact differentiation. Adoption satisfaction decreases from a mean of 7911 in private mode to 7257 in public access. SDI equally decreases from 0.377 to 0.308. In other words, in public mode there is a stronger ‘herding effect’ (Lux 1995; Nattermann 2000).

The scatter plot in Figure 5.25 shows the number of design rules generated in each of the one-hundred cases for both types of access to knowledge. The horizontal axis plots cases sorted in ascendant order. In all instances, when designer agents have public access to knowledge larger knowledge bases are generated. This result yields a seemingly paradoxical conclusion: having access to the knowledge of others promotes the generation of further knowledge. The reason could be that when designer agents have access to others’ rules they are able to build on existing knowledge.

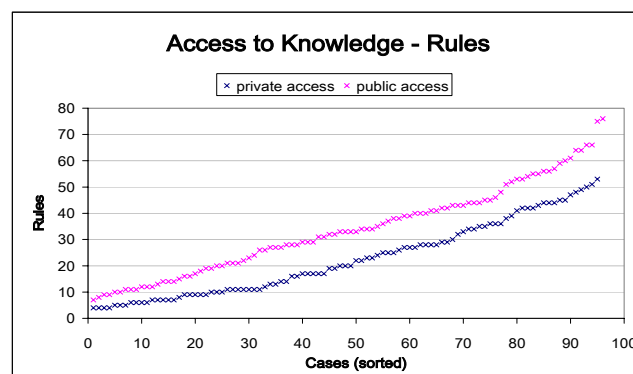


Figure 5.25 A detailed view of the effects of type of access to knowledge in the generation of design rules. Scatter plot of one hundred cases sorted in ascendant order. Public access consistently yields more rules.

5.3.6.2 Analysis

This situational factor has the largest range of effects on a number of dependent variables at adoption, design and domain levels. The collection of effects portrays a comprehensive role of the type of access to design knowledge. On one hand public access appears to promote the generation of further knowledge as well as the mean domain size and score. On the other, private access promotes adoption, increases adopter satisfaction and supports more differentiated artefacts.

A number of extensions to this experiment can be aimed at exploring the type of access to knowledge with incremental and sequential innovations (Godoe 2000). In addition, this situational factor can be transformed into an individual property by assigning one designer agent with public access whilst the rest of designer agents are constrained by private access to knowledge. The objective of such experiment could be to assess the possible consequences of piracy and copyright infringement for the various stakeholders of the system (Baer et al. 2003; Helpman 1993; Prasad and Mahajan 2003; Stokes 2002).

5.4 Conclusions

None of the results presented in this chapter are directly programmed in the framework. The patterns observed are side-effects of interaction between agents and emergent system structures. Whilst all are effects of the assumptions implemented, some could be expected whilst others are rather surprising. Nonetheless, once they are visible, we are directed to think about the full implications of every decision behind the framework and their consequences when placed in interaction with each other. Without computational assistance, this task would be extremely hard to

conduct and the results unconvincing without the hard evidence from the output data. The large number of integrated variables and the nonlinearities of their interaction make it difficult for humans, unassisted by computer simulations, to reason about such systems (Carley 1999).

The nature of this type of social simulation is explorative and to that extent, the results presented in this chapter assist in the understanding of a complex system of interactions where creators and evaluators interact.

5.4.1 Summary of Findings

Table 5.3 summarises the findings of these experiments.

Table 5.3 Summary of Findings

Independent variable	Dependent Variable	Pattern
Individual Factor: Processing abilities (m)	Adoption	Processing abilities of designers at the end of a simulation yield a relatively low correlation to adopter group size. In general, artefacts from designers with higher abilities can be expected to have more adopters but a large increase of processing abilities need not generate a significant difference of adopter group size.
	Designers	Due to the assumption of ability development, initial and end abilities yield a low correlation when initial differences are not large.
	Domain	Processing abilities of designers at the end of a simulation yield a relatively low correlation to domain contributions. In general, artefacts from designers with higher abilities can be expected to be selected by gatekeepers but a large increase of processing abilities need not generate a significant difference of expert selection.
Individual Factor: Synthetic abilities (t)	Adoption	Individual differences in synthetic abilities between designers do not have a significant effect on adoption even when such differences are large and their effects are observed in other parameters.
	Designers	The main effect of individual differences in synthetic abilities is on peer recognition. As the synthetic ability of a designer increases, it can be expected to be increasingly imitated by other designers. An associated effect is observed in knowledge. Higher synthetic abilities promote the generation of rules.
	Domain	Individual differences in synthetic abilities also account for the contribution to the domain. The artefacts of designer agents with higher synthetic abilities are likely to be selected by gatekeepers to be part of the collective repository. However, large increments of synthetic ability may have only a marginal increase in the number of entries selected from a designer.
Individual Factor: Adoption bias (W)	Adoption	When individual preferences play a strong part in the adoption decision process, the satisfaction levels of adopters is expected to increase but it also becomes harder to predict. When adopters give less emphasis to their preferences, the perceived features of artefacts have a stronger impact on these decisions and social influence is stronger, which results in increased aggregate adoption.
	Designers	When individual preferences are strong, design artefacts are perceived as having more similar features. Designer agents indeed develop less differentiation strategies when adoption choices are more individualised.
	Domain	The scores assigned by gatekeepers to domain entries are higher when adopters' choices are more individualised.
Situational Factor: Social ties strength (T)	Adoption	A power-law characterises the effects of social tie strength on structures of influence. A minimum degree of social mobility in highly static societies rapidly produces influence hierarchies to decrease. After this drop, making social ties weaker has no significant effect in the distribution of influence. Total adoption increases and is more stable in societies with strong ties. The distribution of adoption choices by designer increases with tie strength, i.e., more prominent designers are likely to dominate in social groups with strong ties.
	Designers	Consistent with the effects of individual adoption bias, SDI is inversely

Independent variable	Dependent Variable	Pattern
		correlated with the strength of social ties. Designer agents operating on strong social spaces where influence structures are stable tend to generate more similar artefacts.
	Domain	An inverse correlation is observed between tie strength and number of domain entries. In fields where social ties are strong and influence is concentrated, an unvarying group of gatekeepers generates smaller artefact repositories. In fields where social ties are weak and influence is more distributed, there is a high rotation of gatekeepers that generates a larger and less predictable domain size.
Situational Factor: Design rate (D)	Designers	When designing takes place frequently, designer agents generate a large number of rules. A small decrease in frequency of design behaviour is sufficient to reach a critical point where a sudden drop in rule generation is observed. As design becomes more sporadic, even significant changes on the rate of design have only marginal effects on knowledge production. When design rate is frequent, mean peer recognition amongst designer agents is high; as the behaviour of designer agents becomes more sporadic, instances of peer recognition slowly converge to a minimum.
	Domain	An infrequent scheduling of design behaviour causes gatekeepers to select repository entries from a less diverse range of designers. At the same time, the score assigned by gatekeepers and the inherent complexity of repository entries decays with sporadic design behaviour.
Situational Factor: Gatekeeping rate (G)	Domain	Frequent gatekeeping activity generates larger repositories and low domain variance. When gatekeeping is infrequent in relation to adoption decisions, a higher domain variance indicates that expert opinion centres on a few prominent designers.
Situational Factor: Adoption rate (A)	Adoption	As the number of adoption decisions taken between design and gatekeeping instances increases, consistently higher adoption satisfaction levels and higher adoption variance are observed.
	Design	The differentiation of artefacts as perceived by adopters tends to decrease as the number of adoption decisions increases between the selection of artefacts. The mean number of strategies chosen by designers during a simulation run decreases as more adoption decisions are taken between design and gatekeeping episodes.
	Domain	A large number of adoption iterations between the selection of artefacts generates smaller domains and lower scores.
Situational Factor: Population size (P)	Adoption	Adopters in larger populations have a higher mean satisfaction level than equivalent adopters in smaller evaluation groups.
	Domain	Increasing the number of adopters in a population has a linear effect on the mean size of their repositories. Nonetheless, the mean score assigned by gatekeepers and the independent measure of complexity show that large repositories have only a marginally higher quality than the smaller, more select repositories.
Situational Factor: Access to knowledge (K)	Adoption	Total adoption, adoption variance and adoption satisfaction are higher when designers have private access to knowledge. Abstention declines, adoption choices concentrate on a few prominent designers, and artefacts' features tend to address adopters' preferences.
	Design	When design rules are disclosed between designers and access to knowledge is public, a higher number of rules are generated. However, artefacts are perceived by adopters as being more similar.
	Domain	Public access to knowledge generates larger domains with higher mean scores and higher complexity. This type of access also discourages the concentration of experts' selections on few designers.

A twofold conclusion from results of experiments with individual factors is that a) individual differences can play a determinant role but that b) there are other determinants potentially equally important that tend to 'balance out' such differences. Learning and practice are basic processes that account for medium to low correlations between initial individual differences and final conditions. The likely role of other conditions implied by these experiments are explored as situational factors in the second part of the chapter.

5.4.2 Summary of Principles

Influential gatekeeping is likely to generate higher concentration of prominence in a small number of creators. This also occurs when designers conceal their knowledge from each other.

Adoption is in general stimulated by situational factors including strong social ties, larger populations, and private access to design knowledge. The presence of a highly skilled designer in a group can cause not only more adoption choices of its artefacts but may also stimulate adoption of other artefacts in general.

Adopters tend to concentrate their choices in a few popular designers when social ties are strong and when more adoption decisions are taken between design and gatekeeping episodes. Private access to design knowledge also generates higher adoption concentration.

Larger domains can be product of situational factors such as weak social ties, more frequent gatekeeping, larger populations, and public access to knowledge.

Domains with entries of higher quality ascribed by gatekeepers are observed when adopters' choices are more individualised, design behaviour is more frequent, a slow adoption rate between design and gatekeeping episodes, larger populations, and public access to knowledge.

Artefacts are perceived as more differentiated when individual abilities are high, when adopters' preferences play a marginal role in the adoption decision, when social ties are weak, under slow adoption rates between design and gatekeeping episodes, and in settings of private access to design knowledge.

The satisfaction of adopters' choices in a population is high when individual preferences play a strong part in the adoption decision process, when the number of adoption decisions taken between design and gatekeeping instances is high, and when designers have private access to knowledge.

Designers are likely to exchange more peer recognition as a consequence of high differences of synthetic abilities and when design behaviour is more frequent.

More knowledge is generated by designers when large individual differences of synthetic abilities exist, when designing takes place frequently, and when designer agents have access to public knowledge generated by others.

Chapter 6

Understanding Creativity and Innovation

This chapter presents a series of discussions of the results from our framework in light of relevant literature. The aim of these computational explorations is to support reasoning about creative design. In this chapter this reasoning is conducted through an analysis of our results in view of relevant empirical data in the literature. The results from the simulation studies presented in previous chapters are also examined in relation to other relevant models in the field. The assumptions of our models are compared to the contemporary understanding of these phenomena. Direct validation of these results is unfeasible, but a number of similarities between the nature of our findings and a number of research studies illustrate that with the contribution of computational simulation we are closer to understand the link between creativity and innovation in design.

This chapter starts by describing the types of validation suitable for these studies. Section 6.1 outlines the type and degree of validation applicable to results from computational simulations of social systems. In Sections 6.2 to 6.4 insights drawn from results presented in previous chapters are analysed under four main topics: designers as change agents, the role of the field in design and evaluation processes, and domain factors involved in the link between individual behaviour and social change. They help to understand the components of a systems view of creativity and innovation and the interactions between these components. This chapter ends with Section 6.5 where the concept of design situations is presented as a theoretical product of our investigations and their relation to existing knowledge.

6.1 Validation

In principle, the relation between computational modelling and target social systems remains an open question (Carley 1996, 1999, 2001, 2004). This relation is the controversial subject of scientific validation. In design research any model that claims to capture some aspects of design practice has to produce convincing evidence that validates such a claimed analogy. Cognitive

studies conducted in the laboratory may yield externally invalid results when the artificial conditions of the laboratory fail to represent the key components of the design task (Lloyd et al. 1996). This is of particular concern in studies of creative design, since the main experimental condition, i.e., repeatability, is by definition hard to guarantee. In relation to the study of innovation at the social level, the problem of validation is common to case studies, i.e., the results from a single case are not easy to generalise (Wejnert 2002). At best, models can be said to have a degree of validity. Results of a model are always open to further scrutiny, both in natural and social sciences (Kuhn 1981; Popper 1959). In the fields of creativity and innovation research, there are only a handful of general results widely accepted as sufficiently valid, some of which were discussed in Chapter 2 of this thesis.

In computational models there is a characteristic tension between transparency and validation or veridicality (Carley 2004; Gilbert 2002). Validation of computational models requires checking for matches between the simulated and the target systems, i.e., evidence linked to the system which the model claims to capture (Carley 2002). Throughout this thesis we have emphasised that the main aim of our models is to generate hypotheses and reason about the real system, i.e., qualitative understanding. The claim has been that by studying artificial systems of designers and adopters one is able to consider the principles behind a possible system, i.e., one that exists within a computer program.

To the degree that a) the assumptions that govern the actors and conditions under study are relevant, b) the system implementation is robust, and c) the variables manipulated yield noticeable and consistent changes in the behaviour of the system, we can claim that the ‘case study’ of the artificial society has some relevance to the general endeavour of understanding creativity and innovation in design.

The assumptions and results of our work have been presented in isolation in previous chapters. Their integration and discussion of their relevance are the tasks of this chapter.

6.1.1 Types of Validation

Four types of validation are considered of relevance in our studies: internal, conceptual, cross-model, and external (Carley 2004; Suleiman et al. 2000; Troitzsch 2004). The internal validity or correctness of the implementation of our models is assessed by sensitivity analysis and verification of the main algorithms obtaining consistent results in hundreds of simulations run for long iteration periods. Internal validation of cellular automata (CA) has been considered relatively simple in particular when results from different replications are compared (Axelrod 1997; Edmonds and Hales 2003). Cross-model validation or docking (Axtell et al. 1996; Edmonds and Hales 2003) refers to the comparison of results between other relevant models where assumptions and output data match to some extent. Particularly useful are comparisons between models based on different methods. Thus, one key aspect which we repeatedly focus on this chapter is how the findings from our model rate against other existing modelling approaches.

In particular Axelrod’s CA of social influence (1997) is implemented in Pascal and Visual Basic; both versions are available on the Internet (Axelrod 2004). Our replication in Java2 was shown to yield equivalent output under equivalent conditions as discussed in detail in Section 3.2.

The design and implementation of our multi-agent framework required an iterative process of programming and testing every separate mechanism in the model. An aspect of this process is presented in Section 4.4.5 to analyse the consistency of adoption decisions.

To increase internal validity our work makes use of several Java2 libraries including the Colt libraries for pseudo-random number generation (Hoschek 2002), the RePast multi-agent library (Collier 2002; Tobias and Hofmann 2004), and JExcel for data collection (Khan 2004). Consistent distributions are obtained throughout experiments where rates of behaviour are manipulated independently and in combination as observed between Figure 5.17 and Figure 5.19 where the effects of gatekeeping and adoption rate on the domain are plotted.

Conceptual validity refers to the soundness of the conceptual model, i.e., how the main assumptions of the framework rate against current knowledge in the field. For those aspects of the framework for which a satisfactory understanding of the isolated components exists, this can be a relatively direct process of checking for theoretical validity. For instance, it is widely accepted that humans organise in social networks and that these structures have some kind of dynamic behaviour (Wasserman and Faust 1994), thus the conceptual validity of organising our adopter agents in social networks with parameterised mobility as defined in Section 4.4.3 is relatively sound. However, there are several interpretations on the relationship between neighbourhood size and social influence (Florida 2002; Granovetter 1973) that support multiple possible mechanisms in the model. In such cases we define an experimental parameter in order to explore the contrasting assumptions, as in the types of access to knowledge defined in Section 4.3.3.

The more detailed a simulation model, the more complicated it is considered to assess the conceptual validity of the entire system. Whilst the isolated components may seem conceptually valid, it could be the case that their interaction is importantly determined by a further mechanism not included in the framework. Cellular automata (CA) models are so abstract that their conceptually valid is difficult to challenge. It is hard to argue against the basic assumption of *homophily*, i.e., that the longer people interact with each other the higher the probability that they share opinions (Axelrod 1997). However, this conceptual clarity is traded for concreteness and other types of validity, in particular external validity. CA are so general that their cells can be conceptually valid to represent magnetic particles, ants, and humans.

External validity is the main level of discussion in this chapter. It refers to the comparability between the computational model and the *real* world where ‘real’ refers to sound experimental and field evidence reported in the literature.

6.1.2 Levels of External Validation

The levels of external validation that this chapter addresses are face, parameter, pattern and distributional validity. Face validity is addressed by establishing the reasonableness of the main assumptions of the model when compared to agreements in the field. Parameters of the model are considered against aspects which are generally assumed to range between possible states. Pattern and distribution validity refer to the match of results from the models to patterns and distributional characteristics of results reported in the literature, respectively.

The studies presented in this thesis do not take numerical data from any particular case as input. Therefore, it is not possible to conduct validation on the accuracy or predictive power of these results. Due to limitations of the existing computational resources, these models simulate small social groups, account for simple individual cognitive processes, and include a restricted number of system variables. One of the main challenges in the field is to model specific cases for which sufficient information exists in order to validate their output (Gilbert 1999).

External validity is a matter of degree, i.e., simulation models are not simply valid or not valid but show a degree of validity (Carley 1999). Further, most phenomena can only be observed and measured clearly under highly controlled conditions. Thus, strong requirements for theory verification cannot be imposed to this modelling approach (Simon 1995).

6.2 Designers

To an extent, individuals can be considered the building blocks of creativity and innovation. Without individuals there can be no social group or field, no cumulative knowledge or ideas, and no behaviour to trigger social change. However, this assumption need not imply that individuals are predominant and that other components of the system are secondary.

Given the emphasis at the individual level in the literature, it is commonly assumed that social aspects of creativity are a posteriori, external influences to the more important process of creative thinking (Dacey et al. 1998). Although the study of building blocks in isolation renders valuable

knowledge about a system, it is insufficient to explain how a dynamic system works (Anderson 1972). For a complete understanding it is necessary to analyse the way individuals interact with each other and with other system components at different levels.

This Section revisits the properties or aspects of individual designers addressed in our studies, the parameters defined for experimentation, and the resulting patterns observed. The Sections of this thesis where they are addressed are listed in Table 6.1.

Table 6.1 Summary of results in relation to design variables

PROPERTIES	PARAMETERS	EFFECTS	SECTIONS
Change Agency	Dissent rate in convergent groups	The nature of marginality is demonstrated in the triggering of social change. Global effects to individual actions are exceptional by definition.	3.3, 3.4
Abilities	Individual differences	These are important but insufficient determinants under learning and development. Effects in dimensions such as prominence and contributions to the domain need not be proportional to initial individual conditions.	0, 4.3.5, 5.2.1, 5.2.2
Persistence	Confluence of individual and external conditions	Change agents are bound by existing external conditions and by aggregate effects of their actions. Inherent limits of change and group coherence are demonstrated.	3.2, 3.4
Opportunities	Favourable conditions.	Structural properties of minorities determine their probability to influence a group. Over long periods opportunities to trigger a change increase when evaluation includes dynamic preferences.	3.2, 5.2.1, 5.2.2
Imitative Behaviour	Competition and cooperation	Incremental learning: more knowledge may be generated when it is available to others. Spillover effects are observed between competitors.	3.2, 4.3.3, 5.2.1
Peer Influence	Rate of design activity.	Under all other independent variables considered, influence between peer designers remains constant. However, the effects of design rate in peer influence yields a linear correlation when plotted in log-log scale. When design activity takes place frequently the mean peer influence increases nearly six times higher than on average. As design activity slows down, peer influence rapidly approaches its standard value.	4.3.3, 4.3.6, 5.3.2
Differentiation strategies	Rates of design activity and adoption decisions.	Variations of all other independent variables yield a constant number of strategies during equivalent system runs. The effects of design and adoption rate in design strategies are non-linear. When design activity or adoption decisions take place more often in otherwise equivalent systems, designers generate four times more strategies of differentiation than on average. However, as these rates gradually decrease, the production of differentiation strategies decreases to normal levels.	4.3.4, 5.3.2, 5.3.4

6.2.1 Change Agency

One of the main aspects under inspection in our studies has been the role of designers as change agents of their societies. The results presented in Section 3.3.2 demonstrated in a simple model of decentralised collective behaviour that individual dissenters can trigger change cycles in a bottom-up direction in a social group. This potential is possible despite a vast majority of members of the population engaging in convergent behaviour. Or more appropriately, our results suggest that this potential is possible *due to* such extensive convergent majority.

The predominance of convergent behaviour in a population can be justified by its role as a key sense-making social element as models of collective learning suggest (Boyd and Richerson 1995). These results draw attention to the relation between individual behaviour and group structure suggesting that a combination of majority imitative behaviour and occasional dissent of a minority facilitates innovation. When at the local and group levels imitation exists, the result is convergent structure or *status-quo*. When at the local and group levels unrestricted dissent exists, no group formation supports social coherence.

Table 6.2 presents the notion supported by our results that a minority of dissenters and a majority of imitators yield recursive cycles of group formation and group change as shown in Figure 3.12.

Table 6.2 Change agency as marginal dissent supported by a majority of imitators

MINORITY	MAJORITY	COLLECTIVE RESULT
Imitates	Imitates	Convergent lock-in
Dissents	Imitates	Recursive innovation
Dissents	Dissents	Noise

According to the results presented in Section 3.3.2.1, ratios of up to 0.10 of dissent support group formation and cyclic transformations. When the possible number of individuals engaged in dissenting behaviour in human societies is considered, official census show that the ratio of creative occupations is a marginal proportion of the total population (United States Census Bureau 2000). Less rigorous definitions still yield a similar ratio of creative professions that aim to do things differently compared to “a vast majority engaged in doing the same things better” (Florida 2002). It is often considered that whilst most people, most of the time engage in convergent behaviour (Axelrod 1997), societies delegate to a minority tasks that deal with new, uncertain events (Morello 2000).

This view of a minority of practitioners as change agents of their societies is pervasive in the literature. The principle of marginality has been used to imply that asynchrony or dissent is associated with creative behaviour (Gardner 1993). Moreover, creativity has been defined as a ‘dialectical antithesis to intelligence’ (Sternberg 2001) where intelligence is measured by adaptation to the customs of a society and creativity by the transformation of these customs. An implication of such a view is that creative individuals are ‘a threat to the intellectual, social, and economic orders that societies create’ (Sternberg 2001).

When creative practitioners such as designers are regarded as a minority group of dissenters as these results suggest, the effects of manipulating the rate of dissent demonstrate that creativity is a property of systems rather than isolated individuals since increasing the number of dissenters does not increase the rate of collective change. Rather, as Figure 3.12 shows, there is a group-level ‘ceiling’ to the frequency of change that a group supports. Rates of dissent over this threshold impede the basic processes of communication that generate the formation of coherent groups.

The role of dissenters has been studied in other fields suggesting the importance of individual disclosure and dissent to prevent errors by a wide range of social groups (Sunstein 1999, 2002; 2003). The notion that creative behaviour benefits a society when it is limited has also been suggested in a model of ‘creativity’ in insect foraging (Heck and Ghosh 2000). Moreover,

creativity has also been considered as the ‘mutation’ rate in models of culture evolution, a value generally considered as marginal (Campbell 1960; Findlay and Lumsden 1988; Lumsden 1999; Simonton 1999, 1999). The basic conclusion from our studies in this respect is that within a social system of decentralised behaviour where many individuals interact, a select number of individuals have the potential to trigger global changes at the social level.

6.2.2 Individual Abilities

It is an intuitive step to assume that if only a few individuals in a population are able to trigger group changes, then such individuals must be special, i.e., there must be something extraordinary about them. This has been identified as the Fundamental Attribution Error, FAE, revised in Section 2.5. It is considered an error because it has been shown that abilities that yield seemingly exceptional behaviour need not be qualitatively different from those of ordinary people (Amabile 1989). Ceci et al (1988) present evidence from experiments where ordinary individuals who are given large amounts of training achieve exceptionally high performance levels. When uninformed individuals observe this behaviour, they tend to assume that the participants must have a special innate aptitude. On such grounds of *putative* talent, Simon (2001) insists on placing extraordinary achievements toward the upper end of a continuum of common human mental activities, without claiming that they are qualitatively different from more commonplace behaviour.

In Section 3.5.2 the study of individual differences in a simple model of social influence suggested that their role in triggering group changes may be less significant than could be expected. Of similar importance can be situational factors such as the environmental conditions that support individual behaviour as well as the conditions that determine the group impact of such behaviour. In that model, the introduction of new values by an individual is constrained by the detection of sufficient external conditions and the diffusion of new values is determined by the stochastic behaviour of the group.

Although these are extremely simple generalisations, the results are consistent with the low predictability found in relation to individual differences measured in isolation (Ross and Nisbett 1991). This is typically expressed by low statistical correlations between measured individual differences on a given trait and observed behaviour in a situation that plausibly tests that dimension. For most novel behaviours the predictive coefficient of individual differences is not significant (Mischel 1968). This is not to imply that individual differences do not matter, but to indicate that their treatment as a sufficient condition of high performance has been probably exaggerated and oversimplified (Csikszentmihalyi and Epstein 1999; Howe et al. 1999).

The role of individual differences was considered in Section 5.2 in an additional way. The study of two types of individual abilities of designers showed their insufficiency as predictors of task performance when individuals are considered not in isolation but as part of a dynamic group. In those experiments the idea that in complex systems causality cannot be conceived as linear is illustrated (Wagner 1999). Whilst initial individual differences stabilise over time due to contingencies modelled as stochastic processes, the inclusion of learning mechanisms further lessen the strength of initial individual differences. Thus, when designers are considered as part of a social system, more than individual isolated characteristics can be expected to matter.

Learning and development of abilities have been shown to allow individuals to circumvent their capacity limits, rendering some innate limitations irrelevant. The role of instruction, support and practice often appears to be more important than innate talent in expert performance (Ericsson and Charness 1995). The layperson view of talent, which concludes that successful individuals have special innate abilities and basic capacities, is not consistent with the reviewed evidence (Ceci and Williams 1999).

As shown in Figure 5.4, our studies suggest that an increase of individual traits need not be proportional to the effect of individual behaviour. For individual abilities of designers to adequately account for effects at the group level, differences between individuals would need to be considerably high. This would be inconsistent with what is known about distributions of

intelligence and skills (Sternberg 1985). More importantly, even when certain abilities may account for some aspects of behaviour and possible effects, these need not be related to creativity. An example discussed in Section 5.2.1.2 is knowledge production, where individuals with larger knowledge bases (more expertise) need not be more successful in measures potentially relevant to creativity and innovation than those with less knowledge available. Other researchers report these types of correlations between expertise and creativity (Ericsson 1999).

Furthermore, the increase of individual abilities may be associated to the improvement of competitors as shown in Table 5.2 where small and large differences are considered between competing designers. This observation can be related to the notion of *spillovers* in innovation (Audretsch and Feldman 1996; Stolpe 2002; Verspagen and De Loo 1999). When individual agents in those experiments were assigned extremely high abilities, competing individuals with otherwise constant abilities also increased their performance as a side-effect result of interacting with more able competitors.

Relevant studies by McGahan and Silverman (2003) conclude that competitors benefit from innovation within their industries regardless of its source. The general advance by rival firms within an industry in many cases tends to spill over to improve the performance of competitors. A consequence of this effect is when financial markets reward firms even when their direct rivals achieve breakthrough innovations (McGahan 1999; McGahan and Silverman 2003).

Other models of creativity from an evolutionary perspective have interpreted differences in creative activity among individuals as arising from a combination of innate and experiential factors (Findlay and Lumsden 1988). This view is consistent with the emphasis on the role of development. Our studies in this regard demonstrate that the exceptionality of individuals that trigger group changes can be explained by a combination of individual and situational conditions.

6.2.3 Persistence

Whilst our results suggest that change agents have the potential to trigger global changes, the results presented in Figure 3.10 illustrate that such task requires perseverance and point to the principle that change agents may be characterised by high amounts of persistence rather than extraordinary skills. In that experiment dissenting minorities triggered cycles of group change with very low probabilities determined by number of dissenters and minority structure. The rate of dissent with highest effects on change episodes was estimated at around 0.10 in Figure 3.12b.

These results suggest that independently from individual characteristics, change agents are bound by a) perceiving sufficient conditions to initiate a change and b) favourable subsequent interactions in the system. The reasoning behind this principle is that *triggering* as the term implies, is an unfinished process. To trigger a social change is to actuate, to initiate a process which the aggregate action of others eventually determines.

The emphasis on continuous attempts is made in the Investment Theory of Creativity (Sternberg and O'Hara 1997) where perseverance is the main personality trait of creative people. Similarly, Simonton (1997) finds that quality is a probabilistic consequence of quantity and that a Poisson distribution describes the number of influential works in any given time period revealing a process where the probability of a hit is very small and the number of trials is very high (Simonton 2003).

The famous quote of creativity being mostly 'perspiration' illustrates these findings at an anecdotal level. Given the complexity of the system, at present it may be best to deal with persistence as a probability increase in a stochastic process where the best predictor of creative output is productivity (Simonton 2003).

The high failure rates of R&D in industrial dynamics reinforce this principle. Out of 25,000 products introduced annually in the US most are doomed to fail (Goldenberg and Mazursky 2001). Sternberg and Lubart (1993) point out that most creative ideas are often initially rejected. Walsh et al (1992) report that most product innovations fail commercially.

A key implication is that if designers had access to the potential effects of situational factors in their behaviour, they could adapt accordingly. In the experiment presented in Section 5.3.6, if designers could forecast the effects of their type of access to knowledge they could modify their behaviour over time in order to achieve the desired outcomes in adoption and gatekeeping described in Figure 5.24. For instance, higher adoption variance and smaller domains would be induced by switching to private access to design knowledge. Modelling this adaptation to indirect causality is not trivial (Wagner 1999). At this stage we conjecture that the ability to become aware of the situation and its role in framing design behaviour are fundamental in creativity.

An instance of situational awareness is addressed by Ashton (2001) who reports that designers with high social capital are likely to obtain more information, to fuel their innovation and to improve their performance compared to those who are relatively isolated. A key role of computational tools for creativity could be as aids in this process of situation awareness. In addition to ‘provide the content and organisation of design knowledge’ (Gero and Maher 1993), computational support systems of creativity have the potential to provide the content and organisation of social knowledge that can be used to generate creative products.

6.2.4 Opportunities

The study of individual abilities as predictors of social change in Section 3.5.2 suggested that individual behaviour combines with favourable circumstances to trigger global changes. In that simple model of social influence such conditions are a product of the random location of cells on the environment. In contrast, the experiments presented in Sections 5.2.1 and 5.2.2 capture the idea that the appropriateness of design behaviour in a system of generation and evaluation of design is collectively defined by the social group within which designers operate. In social groups that yield favourable evaluations for designers with initial low abilities, these may close the initial gap and in some cases exceed the initially more able competitors.

These results can be used to understand the adage often attributed to Louis Pasteur that ‘chance favours the prepared mind’. In these systems causality of such favourable conditions is largely based on stochastic processes. In real cases a prime example of favourable conditions is the existing knowledge contributed by previous individuals. This is regularly expressed in the aphorism of the innovator standing ‘on the shoulders of giants’ attributed to Isaac Newton.

Theoretical foundations that acknowledge the combination of opportunities and individual traits include the Theory of Planned Behaviour (Ajzen 1991; Ajzen and Fishbein 1980) and the PRSVL model of interaction (Wagner and Sternberg 1994). It is significant that heritability estimates in the literature are considered as highly situational (Ceci and Williams 1999): genes and environment contribute to the expression of a trait in a specific group, place and time. However, the timely combination of opportunities and traits may be unusual inasmuch as the necessary individual and environmental characteristics rarely coincide. It has been suggested that this uncommonness is why prodigious performance is rare (Feldman and Goldsmith 1986).

Applications like the KARO agent framework (van Linder et al. 1998) model this intersection of knowledge, abilities, results, and opportunities. Nonetheless investigating this principle has been considered a hard task since the necessary conditions are often studied independently of one another (Edmonds and Candy 1998).

A key assumption in our studies is the combination of habituation and novelty-seeking behaviour of adopters as defined in Section 4.4.1. Habituation refers to the tendency of adopters to increase their preferences for features with high scores, whereas novelty seeking is the process that allows adopters to update their preferences as a result of social convergence. If a design solution is considered as a compromise between conflicting objectives, it is generally assumed that a new artefact will displace an existing one when adopters perceive an advantage that the new holds over the existing artefacts (Rogers 1995). However, it has been shown that people tend to adapt to inconveniences or problems associated with long-existing artefacts (Petroski 1992).

In our framework of design as a social activity, causality of group change is attributed in two complementary directions. Firstly, the novelty-seeking behaviour of adopters demands the generation of new solutions by designers. Secondly, designers as defined in Section 4.3.2 proactively seek new solutions that may reshape demand. This twofold mechanism in our model accounts for a type of *social drift* as discussed in Section 4.4.3.

The bases for this twofold assumption can be related to the classification of innovation processes based on the source of change (Glor 2001; Goldenberg and Mazursky 2001). On one hand market-based or market-driven innovation refers to the process where solutions are directed to perceived market needs. On the other, product-based or market-driving innovation is also known as ‘pioneering’ and is initiated by the ability to forecast or direct non-existent, future requirements. Under the latter type of innovation it is impossible to deduce truly new and surprising ideas from present conditions since the market is not yet aware of them and could not provide information about them (Goldenberg and Mazursky 2001).

Other models that acknowledge adoption as decision-making with changing evaluation criteria include Gul and Pesendorfer (2004), and Reinstaller and Sanditov (2004). However, more research is necessary to understand how innovations in design respond to social demand and how they may help mould the *zeitgeist* (Boudon 1986; Forty 1986; Lloyd and Snelders 2003).

6.2.5 Imitative Behaviour

The effects of types of access to knowledge in the relation between designers and adopters as presented in Section 5.3.6 help to reconsider the role of imitative behaviour in design. Imitation is generally regarded as unacceptable in design. Purcell and Gero (1996) found that arguably due to their education, creative designers may actually become ‘fixated’ on being different. In creative fields in general imitation is considered forgery and penalised by intellectual property legislation. However, as Figure 5.24 shows, imitative behaviour can be seen as a way of cumulative learning given that in our experiments more knowledge is generated when designers share resources.

The role of imitation in learning has been characterised as a key social role in particular under new and uncertain situations (Byrne 2002; Byrne and Russon 1998). When creative solutions are seen as extensions to the existing space of possible designs (Boden 1994; Gero 1996), the largely imitative process of incremental search identified as ‘normal practice’ by Kuhn (1962) is a necessary condition of space extension. Kirton (1994) emphasises this type of complementary relation of innovation and imitators or adaptors. Whilst the first are considered necessary to ‘do things differently’, the latter are regarded as equally indispensable to ‘do things better’.

The assumption under which designer agents in our framework resort to imitative behaviour when unable to learn individually described in Section 4.3.3 is grounded in the literature on cultural learning (Tomasello et al. 1993). Tomasello (1999) defines ‘the ratchet effect’ as the cumulative cultural evolution resulting from innovation and imitation. This cumulative selection acts on knowledge rather than on genes.

Models of collective learning have captured the advantageous role of imitators in avoiding costly learning trials (Boyd and Richerson 1995). These models concur that a balance between imitators and non-imitators is necessary for a population to adapt to a changing environment effectively. When individual learning is sufficiently costly a population adapts to the environment when a small fraction is engaged in individual learning.

A related tension can be found in the debate of innovation and industrial development. Whilst some firms choose to spend more resources on developing new technology, others choose to develop and distribute solutions by applying existing technology and focusing on small improvements (Lohr 2004). Anderson and Tushman (1990) suggest after a longitudinal study of three industries spanning over a few decades that revolutionary innovations are crude and experimental when introduced. A period of experimentation ensues where organisations struggle to absorb the innovative technology. This is called the stage of *ferment* and is characterised by imitation and gradual development.

Related work on modelling has stressed this relationship between innovation and imitation in the spread of creative ideas and cultural evolution (Mansfield 1961). This link has also been of interest in evolutionary models (Iwai 2000) that describe the development of an industry's state of technology as an aggregate outcome of innovation and imitation.

6.2.6 Peer Influence

An important component of creativity has been identified in the process of peer judgement (Amabile and Hennessey 1999). Influence between competitors in design is addressed in our studies mainly through the concept of peer influence as defined in Section 4.3.3. During a system run the cumulative number of instances where a designer receives recognition from imitative peers is recorded.

The strongest effects in peer influence were registered from variations of design rate in Section 5.3.2. In that experiment, the frequency of design activity produced a linear correlation to peer recognition when plotted in a log-log scale. When design activity takes place frequently in comparison to gatekeeping and adoption processes, mean peer recognition recorded increased nearly six times higher than on average. As design activity gradually slows down, recognition between peers rapidly approaches the standard value recorded under all other independent variables considered.

The effects of design rate in peer recognition were paralleled by the effects of design rate in the generation of knowledge as seen in Figure 5.13. Namely, frequent design behaviour yields large knowledge bases and a high level of recognition between designers. This match confirms the analysis elaborated in Section 6.3.4 where imitation is associated to an increase in knowledge production as a way of collective learning (Mansfield 1986; Silverberg and Verspagen 1994).

6.2.7 Design Strategies

The process of designing studied in this framework includes the formation of strategies by designers as a function of evaluation by an adopter group as described in Section 4.3.2. Three types of strategies were accounted for following the literature (Cross et al. 1996; Langdon and Rothwell 1985): competition, differentiation and diversification. Variations of most independent variables in our studies yielded a constant number of strategies during equivalent system runs. However, design and adoption rates generated significant effects in design strategies of differentiation as shown in Figure 5.15 and Figure 5.20, respectively.

When design activity or adoption decisions take place more often in otherwise equivalent systems, designers generate up to four times more strategies of differentiation than on average. However, as these rates gradually decrease, the production of differentiation strategies decreases to normal levels.

This variation in design strategies is likely to be associated to equivalent changes in artefact differentiation as perceived by adopters at least when adoption activity is frequent. In contrast, when design activity is frequent the observed increase in strategies of differentiation may indicate the pressure created by a rising rate of imitative behaviour as shown by patterns of peer influence in Figure 5.14.

6.2.8 Summary

An interdependent relationship between individual behaviour and the conditions and effects at the social level is observed in a number of findings regarding designers as change agents. To trigger a global change based on local behaviour, the actions of a change agent are importantly determined by necessary conditions that lie outside its control (i.e., previous knowledge). Once these adequate conditions exist, they ought to be perceived by the individual who has to be sufficiently able to execute the corresponding action. The frequency, independently of the actual content, of the action can determine influence between peers and the decisions and strategies in the design process.

Our studies demonstrate that effects of design behaviour can be subject to a range of social conditions. The entire process can be seen as a match or adaptation between the individual and the social levels. This confirms the cautionary note that giving emphasis to either part of this chain of causation is misleading; an example being the recurring controversy whether causality of creativity originates at the individual (Lloyd and Snelders 2003) or at the social level (Forty 1986).

6.3 Field

Creativity is often defined in terms of novelty and a standard of quality or utility (Boden 2003; Eisenberger and Cameron 1998; Gardner 1993; Runco 2004; Runco and Pritzker 1999; Simon 2001). In the literature the field is defined as the collection of individuals that participate in the definition of this standard of what constitutes novelty and quality or utility (Csikszentmihalyi 1988; Feldman et al. 1994). The field is composed by competing designers and social groups of evaluators in our studies.

The role of the field is determinant not only after new solutions or artefacts are created by individuals, but it includes conditions which may support specific generative processes. One of the aims in this type of studies is to show that equivalent individuals and solutions can be considered creative or not by equivalent social groups depending on situational factors. This is an important challenge that would demonstrate that the creativeness of a solution is not an inherent property but one ascribed over time by others in a process which is subject to a range of circumstances. In this Section those aspects targeted in our work are analysed.

A summary including the relevant Sections of this thesis where they are addressed is presented in Table 6.3. Field effects can determine aspects of creativity that a reductionist view would assume to be entirely due to the actual solution. They show that the impact of a design artefact cannot be explained based only on its inherent properties. The outcome may not depend on the evaluator: the same solution assessed by equivalent evaluators can receive significantly different ascriptions depending on factors such as the way in which the group organises, its structure, contact between members, and rules imposed to creators.

Table 6.3 Summary of results in relation to field variables

PROPERTIES	PARAMETERS	EFFECTS	SECTIONS
Group Structure	Social networks	The 'degree of separation' of a group determines the diffusion of ideas. Diversity is likely to emerge and be maintained in groups where neighbours-of-neighbours are not mutual. Similarly, populations where members are part of various contact networks are more likely to support the emergence of new values.	3.2.2.2, 4.4.3
Mobility	Displacement	Interaction between groups promotes diversity. Whilst spatial (social) structures may remain unchanged over long periods, value (cultural) organisation can evolve frequently.	3.4
Organisation	Tie strength	The type and rate of contact between members of an evaluating group determine group structures of influence. As a result, the size of domains can vary significantly as well as patterns of adoption and competition.	5.3.1
Opinion Leaders	Hierarchies of influence	High levels of authority can promote some aspects of creativity and innovation such as the prominence of a few designers. The stability or variety of decisions from influential	4.4.4, 5.3.1, 5.3.3

		individuals can affect who becomes creative.	
Rules	Access to knowledge	Social norms that regulate the management of information during the design process have a range of effects. Norms of concealment promote total adoption, perceived quality and concentration of prominence. Norms of disclosure promote new knowledge, larger domains and higher grades from experts.	5.3.6
Evaluation Distribution	Social influence	The distribution of adoption decisions across designers can be determined by social factors such as the frequency of contact between adopters. When social mobility is halted, variance of adoption increases significantly. However, small amounts of social mobility are sufficient to normalise this distribution.	3.4, 5.3.1
Satisfaction	Rate of adoption	The frequency of adoption decisions in relation to design and expert opinion determines the level of satisfaction in a group of evaluators.	4.4.2, 5.3.4

6.3.1 Group Structure

The size of a social group has key effects on the interaction between generators and evaluators of solutions. Section 3.2 reviewed the idea that very small populations do not support interaction between different individuals limiting the diffusion process. The apparent reason is that in smaller groups insufficient diversity yields incompatibility between evaluators that influence each others' decisions. In contrast, large populations where only local interaction takes place do support the exchange of opinions but take exponentially long periods to form consensus.

A clear implication from this result could be that large populations are likely to develop means of mass communication as a way to promote group coherence, an aspect that remains to be explored in these types of simulation studies.

Whilst group size yields no further qualitative differences in our models, a constant population size was found to cause substantial differences when the arrangement of its members varies. One aspect is that with a constant type of local neighbourhood, different common neighbours or 'friends-of-friends' network configurations have different effects (Boissevain 1974).

In Section 3.2.2.2 experimentation with different grid structures showed that besides local configuration, the degree of contact between individuals has an important effect on how new ideas are disseminated. This is consistent with current work on network structure and diffusion of knowledge (Cowan and Jonard 2004). When the neighbours of individuals are unlikely to be in contact with each other, diffusion can be expected to require substantially longer times and have qualitatively different outcomes than when the 'degree of separation' is lower.

The degree of separation can be measured by the ratio of common neighbours between individuals in a social network. These results are consistent with recent developments in network research (Barabasi et al. 2001; Watts and Strogatz 1998) where equivalent effects of structure rather than size of networks have been investigated.

In Section 4.4.3 emphasis was made on a social system of multiple simultaneous structures. Models where social interaction takes place in one and two dimensional spaces have been categorised as ergodic systems (Liggett 1985, 1999). In such types of structural arrangements random walks ensure that the system reaches convergence from any initial configuration. However, as the number of dimensions increases, this probability rapidly approaches zero.

In our studies this is explored in a system of three simultaneous social networks as described in Section 4.4. On each network a different aspect of evaluation takes place having as a result a type of social drift.

An implication of these findings is that the outcomes of design as a social activity are likely to depend largely on the structure of the society within which designers operate. In other words, similar actions and decisions by a designer could potentially have very different effects as a function of the organisation of the social group. The role of social network structure in design is largely an open question in the literature.

Studies of field structure served as a basis for the type and strength of social relations implemented in our studies. These assumptions are based on the widely accepted notion of the strength of social ties (Granovetter 1973). Ties represent the contact between social actors represented by nodes in social networks (Wasserman and Faust 1994).

One way to define the strength of social ties is by their duration over time, i.e., the probability that two nodes in a social graph remain connected over a period of time (Marsden and Campbell 1984). By incorporating these assumptions into our agent framework, we aim to account for the observation that for any given design field, potential adopters interact in a number of different social networks with different tie strengths such as kinship networks (strong ties) and acquaintance networks (weak ties).

As a result, a number of effects are reported in Section 5.3.1 including patterns in the design and adoption of artefacts and the distribution of prominence for designers. In sum, our results support the idea that populations where members are part of various contact networks are more likely to support the emergence of new values.

Recent studies of entrepreneurs consistently report that the most creative individuals spend more time than average networking with a diverse group that includes acquaintances and strangers (Ruef 2002). A combination of strong and weak ties is thus proposed as conducive to creativity. A similar interpretation suggests that weak social ties facilitate the introduction of novel ideas (Florida 2002).

In our studies, behavioural variety is supported by weak social ties where diversity of adoption opinions is higher than in equivalent social groups with strong ties. Relevant studies suggest that societies that support more behavioural variety tend to go through rapid adoption cycles of new artefacts (Reinstaller and Sanditov 2004). These studies further confirm that both the speed and scope of diffusion highly depend on the structure of a society.

6.3.2 Social Mobility

In Section 3.4 cellular automata models of social influence were extended to support the displacement of individuals. With large lattice sizes effects of between-group interactions suggest that occasional contact between groups supports a) the exchange of different values across group boundaries and b) the recursive influence and transformation of values. This insight points toward an additional source of change agency in design: the transfer of ideas from other fields and the ensuing adaptation of old and new solutions, of which distant analogies are an example (Qian and Gero 1995; Wolverson 1994).

Social mobility in the agent system was explored in Section 5.3.1 as a result of the strength of social ties. Frequent changes of neighbourhood composition cause even hierarchies of influence. These changes of influence exchanges had an unexpected effect not only in the emergence of opinion leaders in the adopter population but more importantly in the patterns of decisions of adopters and the type of behaviour by designers.

6.3.3 Opinion Leaders

The behaviour and effects of opinion leadership in our studies contribute to the discussion of the link between individual designers and their societies. Based on a careful analysis of the lives of seven creative individuals, Gardner (1994) suggests that in more hierarchical fields (i.e., “where a few powerful critics render influential judgments about the quality of work”) it is easier for a small number of creators to emerge and gain recognition and influence (Gardner 1994). This proposition is congruent with the patterns observed in Section 5.3.1 where the emergence of hierarchies of

influence was observed. Specifically, as demonstrated in Figure 5.9, in agent societies with strong social ties uneven hierarchies generate powerful opinion leaders that exert the role of gatekeepers to the domain. In contrast, in social networks with weak ties, influence is distributed among adopters and the expert judgements tend to vary over time. Consistent with Gardner's (1994) observation, the former social arrangement generates higher variance in the distribution of prominence whilst the latter yields more egalitarian distributions.

The mechanism of opinion leadership is consistent with concepts from the literature of diffusion and social networks (Valente 1995, 1996). In network models of diffusion of innovations, opinion leaders are defined as individuals with significant influence on the rate of adoption. In addition, perceived expert choices by adopters, tend to influence their adoption behaviour.

The underlying assumption of opinion leadership in our framework is based on threshold models of collective behaviour (Granovetter 1978). These types of models postulate that individuals determine their behaviour based on the proportion of people in the social system already engaged in the behaviour. An individual's influence by a collective behaviour can thus be defined as a function of the behaviour of others in the group or system (Young 1998). Individuals with lower thresholds tend to engage in collective behaviour before individuals with higher thresholds.

Nonetheless, there is an alternative interpretation of the relation between authority and creativity. Several authors refer to the widespread assumption that authoritarian environments hinder creativity (Dacey et al. 1998). Rudowicz (2003) presents a review of several empirical studies that support the idea that educational practices in hierarchically organised societies tend to promote behaviour that is incompatible with creativity, i.e., conformism and conventional thinking. This discrepancy indicates that further research is necessary to fully understand the role of structures of authority in creativity and innovation.

6.3.4 Rules

The situational factor with the widest range of effects across all dependent variables in our agent framework is related to the types of rules that fields impose to designers as depicted in Figure 5.24. An instance of this type of rules in design is intellectual property legislation (IP). A range of findings in our studies depicts a complex role of these types of field conditions in creativity and innovation.

The two variants of type of access to knowledge addressed in our studies present advantages and disadvantages for different stakeholders capturing some aspects of the current debate in the literature (Granstrand 2003).

When designers were allowed to draw from a shared pool of knowledge, more new knowledge was collectively generated and larger domains of higher perceived quality developed as shown in Figure 5.24. The increase in these three domain aspects represent the largest effects of this experimental parameter amounting for a mean of nearly 40% increase. However, when information between designers was concealed during equivalent system runs, total adoption increased as well as variance of adoption, satisfaction and perceived differentiation.

Public access to knowledge seems to impact on mechanisms of design activity and domain contributions whilst private access plays a determinant role in field patterns. These results demonstrate internal validity of these studies inasmuch as it is plausible to consider that when artefacts are perceived as being different by adopters, high satisfaction indices show that their individual preferences are met. Likewise, the increase on domain size can be associated to an increase in overall selection scores due to the 'raising-bar' mechanism that expert selection is based on as described in Section 4.5.1.

Our results support a multifaceted relation between patenting and innovation (Kingston 2001; Mansfield 1986). A recent report suggests that a balance between protection and disclosure of information are likely to promote innovation (US Federal Trade Commission 2003). Advantages of sharing information among competitors have been identified in the literature including a positive

feedback that allows for high innovation rates and fast knowledge accumulation (Cowan and Jonard 2004). In this vein Lagenfeld (2002) proposes an optimal degree of IP protection that portrays well the compromise between different stakeholders in our studies as shown in Figure 6.1. Strong IP protection is likely to benefit a few prominent providers by increasing adoption and the concentration of adoption choices. In contrast, weak IP protection may promote competition and support a variety of choices and a richer material culture.

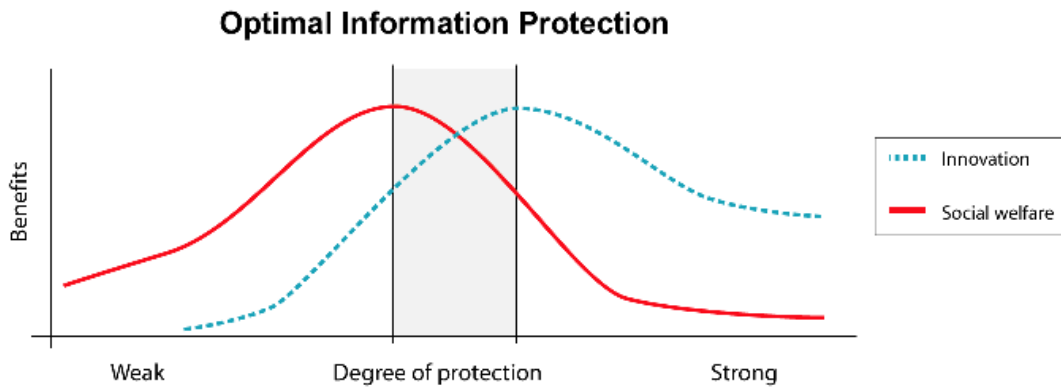


Figure 6.1 Optimal degree of intellectual property (IP) protection (Lagenfeld 2002)

It has been shown that when information is too well protected, the incentive for firms to innovate decreases (Rayna 2004). An instance of information disclosure is piracy. It has been proposed that piracy pushes firms to innovate since they are incited to innovate in order to maintain a difference of quality. Since the quality gap between the original and the copy often tends to be reduced, piracy places firms in a highly competitive environment. Future studies could explore the optimal ratio of piracy for innovation, which has been estimated as high as 45% for artefacts that require to trade-off fast adoption and legal adopters (Prasad and Mahajan 2003).

6.3.5 Evaluation Distribution

During each of our studies the adoption decisions of each member of a population are recorded. When the stopping condition is met, this record shows the distribution of adopters by designer. As a result the experimenter can identify what experimental conditions affect the patterns of adoption over a number of cases. If the variance of adoption is high, then the artefacts generated by a few designers concentrate a high proportion of the adoption choices during a simulation run. If the variance of adoption is low, then adopters are said to distribute their choices across all available artefacts. In the former case prominence and differentiation are expected to be high whilst in the latter competition indices are likely to be high.

As shown in Figure 5.12, the distribution of adoption decisions is importantly determined by social factors such as the frequency of contact between adopters. In our studies when social connections between members of an evaluation group are replaced, social mobility is determined by the rate of link replacement. When no social mobility is possible, our studies show that variance of adoption rapidly increases to a mean level of 100%. However, even small amounts of social mobility proved sufficient to normalise this distribution.

These differences in adoption variance are consistent with parallel effects of social ties in opinion leadership and domain characteristics. Moreover, they are consistent with what other researchers have speculated inasmuch as unvarying social structures are likely to support the emergence of more powerful experts, i.e., with stronger influence (Gardner 1993).

6.3.6 Satisfaction and Differentiation

A measure of satisfaction is incorporated in our studies as an index of quality. Satisfaction levels are measured by adopters as a function of the distance between their choice and their list of

preferences as described in Section 4.4.2. Aggregate satisfaction indicates how close were the adoption decisions of a group to their evolving set of preferences over time. A basic principle - which was not previously considered- emerged from our explorations with a range of independent parameters.

This principle associates artefact differentiation as perceived by adopters with their satisfaction levels and was confirmed in the experiments with social tie strength in Section 5.3.1, population size in Section 5.3.5, and access to knowledge in Section 5.3.6. Perceived differentiation of artefacts is measured by the strategic differentiation index, SDI following Section 4.3.6.

These cases yield a positive correlation between satisfaction levels and perceived differentiation suggesting that the larger the differences perceived in available artefacts by a group, the closer the adoption decisions are to the preferences of its members. This can be explained by the notion that diversity suits a broader range of adopters than uniformity. In these experiments this is a consequence of stronger social ties, larger population sizes, and private access to knowledge, respectively.

However, effects of adoption rate in these parameters are apparently inconsistent with this finding. In such case satisfaction and SDI are negatively correlated as observed in Figure 5.18 and Figure 5.20. When adoption decisions are taken more frequently, satisfaction levels are low but SDI is high. As adoption activity becomes more sporadic, satisfaction increases whilst mean SDI tends to decrease.

A possible explanation is that with frequent adoption activity, adopters evaluate an unvarying set of artefacts since design activity is scheduled more sporadically. Therefore, the key factor between satisfaction and perceived differentiation could be the response of designers to dynamic adoption preferences. When designers are able to adjust their behaviour to convergent preferences in a group, satisfaction and differentiation can be expected to increase. In contrast, when no timely design response is produced as in the experiments with adoption rate in Section 5.3.4, differentiation is likely to decrease while satisfaction can be determined by social influence.

This finding is further confirmed by the association between satisfaction levels and adoption variance in Figure 5.18 which suggests that adopters become more similar in preferences -which determine their satisfaction coefficients.

To elucidate this point it would be appropriate to conduct complementary experiments where the rate of adoption activity is manipulated together with the strength of social ties or with population sizes. An expected result is that frequent adoption in societies with strong ties would cause a decrease in levels of satisfaction.

6.3.7 Summary

Design behaviour has been addressed in the literature mainly as a cognitive phenomenon. This has advanced our understanding of creative design at the individual level but has shed little understanding on this activity as part of a social system.

The general conclusion from our exploration of design as a social activity is summarised by the proposition that the 'creative act' does not end with the specification of a design solution. The synthesis of an artefact is only the starting point of a poorly understood process where creativity turns into innovation in the link between individual and social action, i.e., 'design is a cognitive and a social process'.

The social forces acting on the creative individual can be classified in two periods, i.e., the earlier period in the production of ideas and the later period in their dissemination and evaluation (Gruber and Wallace 2001).

The relationship between collective factors and individual expression is extremely complex (Rudowicz 2003). Arguably, the main insight of situated behaviour is the principle that the same individual design behaviour can generate solutions that are regarded as creative within one social setting but not within a different one. In other words, macro conditions may provide the bases for

particular generative processes, or they may facilitate particular effects on evaluative processes. The strongest evidence for this principle is the extemporaneous recognition of creativity. Whilst design artefacts remain unchanged, the social and cultural conditions may evolve to the point where evaluators are ready for such solutions.

6.4 Domain

Domains represent the epistemological level in a systems model of creativity (Csikszentmihalyi 1988). Whilst no formal criteria have been proposed for identifying a domain, in our studies design domains are defined as repositories or collections of artefacts and knowledge accumulated by a population over a period of time.

A key threefold aspect of domain content is that it is generated by designers, it is influenced by the adoption patterns of the field, and its content is ultimately determined by experts. The concept of design domains can be compared to the material culture of a group (Rochon 1998) and to the concept of ‘disciplinary matrix’ (Kuhn 1974), i.e., the set of beliefs, values, methods, examples and techniques around which a field or community is defined. In this sense domains are the set of standards of what is valid, accepted and valued by those who share them.

Our studies carry the assumption that certain *rules* of domains have significant effects in the interaction between individuals and fields. These aspects are manipulated by the experimenter and can be defined in top-down or bottom-up directions.

In this Section domain aspects addressed in our work are analysed, what mechanisms had an effect of them and how they affected the behaviour of individuals and field conditions. Table 6.4 sums up these results and indicates the Sections of this thesis where they are addressed.

Table 6.4 Summary of results in relation to domain variables

PROPERTIES	PARAMETERS	EFFECTS	SECTIONS
Knowledge	Design rate and disclosure of information	When design rate is very frequent, new knowledge is produced collectively. With small decreases in frequency, the size of knowledge bases stabilise. Norms of disclosure support knowledge generation.	4.3.3, 5.3.2, 5.3.6
Gatekeeping	Score and complexity, adoption bias	Disclosure of information renders larger domains with higher mean scores and higher complexity. This type of access also discourages the concentration of experts’ selections on few designers. Scores assigned by gatekeepers to domain entries are higher when adopters’ choices are more individualised. Large adopter groups produce large domains that have only a marginally higher quality than smaller domains of smaller groups.	5.2.3, 5.3.5, 5.3.6
Domain Size	Gatekeeping and adoption rates, social ties, and information disclosure	Increasing the number of adopters in a population has a positive effect on the mean size of their repositories. When either expert selection or adoption decisions take place more frequently artefact repositories are larger. Disclosure of information is related to more instances of expert selection. In fields where social ties are strong an unvarying group of gatekeepers generates smaller artefact repositories. In fields with weak social ties a high rotation of gatekeepers generates a larger	4.5, 5.3.1, 5.3.3, 5.3.4, 5.3.5, 5.3.6

		and less predictable domain size.	
Domain Distribution	Design and gatekeeping rates, and concealment of information	With frequent design activity or expert selection the variance of expert selection increases, i.e., decisions concentrate on one designer. Same occurs when knowledge is concealed during the design process.	5.3.2, 5.3.3, 5.3.6
Artefact Structure	Diffusion speed and scope	The composition or structure of artefacts can determine the speed and scope of diffusion. An artefact with high compatibility and low complexity is likely to speed rapidly and reach a large segment of a population.	3.2, 3.3
Artefact Representation	Interpretation	Artefacts that support ambiguity and interpretation during the diffusion process are more likely to be accepted.	3.3

6.4.1 Knowledge

The learning mechanisms of design agents described in Section 4.3.3 generate knowledge in relation to the transformation of artefacts. Our studies address two types of access to this knowledge or information generated during the process of designing. These are defined by rules of protection or disclosure of information. A series of experiments produced consistent and significant variations in the rate of generation of knowledge and its effects in the system.

When design activity is very frequent the generation of new knowledge increased as reported in Figure 5.16. With small decreases in frequency of design activity, the size of knowledge bases reaches a stable level. The mechanism at work seems to be the collective production of knowledge.

A parallel pattern is observed when designers have access to the knowledge generated by others. Disclosure of information causes an increase in generation of knowledge as shown in Figure 5.24. Moreover, in both experiments other associated effects are observed: frequent rates of design activity and public disclosure of information yield lower variance of domain entries as well as higher domain scores and complexity. Seemingly, higher quality may be associated to the contributions of various sources supported by the disclosure of knowledge.

6.4.2 Gatekeeping

In practice, gatekeepers are individuals authorised to qualify the merits of creative solutions including their novelty and feasibility (Subotnik et al. 2003). Apart from patent examiners, other types of gatekeepers in design include venture capital firms, exhibition curators, journal editorial committees, and competition juries. Approval or endorsement of gatekeepers may be necessary to turn a new idea into an available product.

Nonetheless, little is known about the role of gatekeeping in a) promoting or deterring the generation of creative solutions and b) initiating or promoting their diffusion and the social ascription of the 'creative' label to their creators. Gatekeepers such as patent examiners base their decisions *prima facie*, on references to other patents and ordinary skills, and on declarations from experts in the field. However, articulating these evaluations is often problematic and in many cases criteria are updated or made explicit based on litigations (United States Patent and Trademark Office 2001).

Gatekeeping in our studies is considered an emergent role that adopter populations assign to some of their members as an aggregate result of social interaction. In particular, influence of adoption opinions is taken as the condition to allocate the gatekeeping role, i.e., influential adopters become gatekeepers of the domain as defined in Section 4.5.1.

Whilst this enables the study of bottom-up processes of gatekeeping, future research could be extended to address other aspects including the view of experienced designers as gatekeepers (Subotnik et al. 2003; Walsh and Roy 1985). Our models show that the role of influential adopters

as gatekeepers can be important in the rate and quality of design behaviour and the relation between designers and adopters.

In particular disclosure of information was shown to render larger domains with higher mean scores and higher complexity in Section 5.3.6. This type of access also discourages the concentration of experts' selections on few designers. Therefore, under systems of high protection of information experts can be expected to concentrate their choices and facilitate the emergence of prominent figures (Gardner 1994). Scores assigned by gatekeepers to domain entries are also higher when adopters' choices are more individualised as shown in Figure 5.7. Finally, larger adopter groups were shown to produce larger domains with only a marginally higher quality than smaller domains of smaller groups in Figure 5.22.

The effects of population size and of types of access to knowledge are not only parallel in direction but also in scale. Whilst domain size varies considerably, the scale of variation of domain scores and domain complexity is significantly smaller in both cases.

A number of insights are motivated from our exploration of gatekeeping. Firstly, higher rates of gatekeeping generate a higher number of domain contributions and a decrease in the variance of contributors. This lower concentration of prominence is interpreted as more designers being responsible for contributing to the domain. This is in contradiction to the Price Law which states that the square root of N , where N is the number of contributors in the field, is the number of individuals who will account for 50 percent of creative contributions (Price 1965; Simonton 2003).

Further research is necessary to understand the conditions under which these apparently contradictory patterns may occur. Secondly, strong social ties are believed to create stable and influential gatekeeping that draws contributions from a few designers. This can be interpreted as consistent with the estimation that fields with few influential gatekeepers tend to concentrate recognition on a small number of creators (Gardner 1994). Likewise, to stimulate group creativity it has been proposed that evaluators of new ideas should constitute a heterogeneous group (Karni and Shalev 2004).

6.4.3 Domain Size and Distribution

The selection of entries by gatekeepers in our studies is assumed to be based on an incremental scale where once a solution is presented and chosen for inclusion in the domain, other solutions even with identical features are not considered of merit. In fields of creative practice these are in fact labelled as forgeries (Goodman 1976). The score assigned to an entry becomes the new entry threshold for future candidates as defined in Section 4.5.1. For new artefacts to gain access, two conditions are considered in our studies: entries must receive a higher score in the same features than existing entries or they must present advantages in features other than those by which previous artefacts were chosen (Berlyne 1960).

An additional mechanism implemented in our framework addresses the decay of the entry threshold. The assumption is that as simulated time lapses, with no new entries being selected the entry bar gradually decays. These conditions prove sufficient to model the continuous selection of domain artefacts. An evolving set of adoption preferences and perceptions subject to social influence generates a continually changing set of criteria for generation and selection of artefacts. This can be considered as a way to capture the observation that as societies evolve, so do their standards of what is creative (McLaughlin 1993).

Some aspects of the entry mechanism in our agent framework can be compared against the standard procedure of patenting examination (United States Patent and Trademark Office 2001). On the one hand utility is given by the criterion that a person of ordinary skill in the art appreciates why the invention is useful based on the properties or applications of the product or process, and whether such utility is 'specific, substantial, and credible' (United States Patent and Trademark Office 2001). On the other hand, novelty is established if no conclusion of obviousness exists. Obvious subject matter is, again, determined by some suggestion or motivation in the knowledge referenced in the application or generally available to one of ordinary skill in the art. The examiner

must present a line of reasoning as to why the artisan would have found the claimed invention to have been obvious in light of the existing skills (United States Patent and Trademark Office 2001).

The main consideration on domain characteristics in our studies centred on their role as dependent variables. Various aspects in our models are found to determine the quantity and quality of domain entries including individual differences and situational factors such as rates of behaviour and type of access to knowledge.

Our findings suggest that quantity (number of domain entries) and quality (score and complexity of domain entries) need not be correlated. For instance, as Figure 5.7 shows, the scores assigned by gatekeepers to domain entries are higher when adopters' choices are more individualised but no significant changes in domain size are observed. However, more frequent adoption as shown in Figure 5.19 generates both larger domains and higher scores.

This effect is mirrored by frequent gatekeeping behaviour as depicted in Figure 5.17. When designers have public access to knowledge, larger domains with higher mean scores are generated as shown in Figure 5.24. Increasing the number of adopters in a population has a positive effect on the mean size of their repositories. Lastly, in fields where social ties are strong an unvarying gatekeeping group generates smaller artefact repositories. In fields with weak social ties a high rotation of gatekeepers generates a larger and less predictable domain size as shown in Figure 5.10.

In sum, situational aspects that may facilitate domain entry include frequent adoption decisions, frequent expert selection, disclosure of information between designers, number of adopters, and the strength of their ties.

These results depict a more complex relationship between productivity and quality of work than that suggested by Simonton (2003). His conjecture that quality (influential works) is a function of quantity (productivity) is used to define creativity as stochastic behaviour. Our findings suggest that under different circumstances, the correlation between quality and quantity can vary from positive to inverse to nonexistent. Therefore, personal prolificity (Simonton 1997) may also be a result of conditions other than individual characteristics including the aforementioned situational factors.

It follows that the recent increase of inventions patented shown in Figure 6.2 need not tell us anything about changes in the individual attributes of inventors and designers (World Intellectual Property Organization 2004). There are other likely causal sources in the field and domain levels (von Hippel 1988).

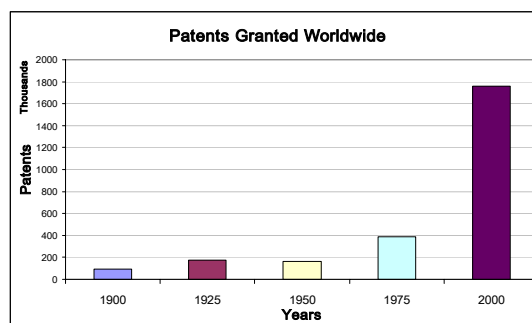


Figure 6.2 Increase of patents granted worldwide in the last 25 years. Quantity and quality of domains may have different effects under varying situational factors.

Lastly, according to the Price Law larger domains tend to decrease the variance of contributors, i.e., disciplines tend to become more elitists as they grow in number of participants (Price 1965). However, all our findings relating domain size and variance indicate otherwise, i.e., that disciplines start being more elitist and tend to be more inclusive as they mature. This is an issue that requires further attention in design research.

It is necessary to address in future research the impact of other domain characteristics in design behaviour. An example of an empirical finding to explore is the relation of population size and domain quality. Therrien (2003) found that innovation patterns of firms differ by the size of the city in which they are located and suggests that establishments located in cities of less than 50,000 inhabitants are likely to have a smaller impact than those located in larger cities. An open question is the type of assumptions that must be included to replicate such patterns.

6.4.4 Artefact Structure

In Section 3.2.2 the effects of manipulating the composition of solutions or artefacts in a simple model of social influence were addressed. The main conclusion is that under equivalent processes of diffusion, values that consist of a few variables a) tend to spread rapidly through a population, but b) reach only a segment of the population. In contrast, artefacts that are formed by a large range of variables require longer periods to be spread but provide a large number of options of which gradual acceptance is supported. Table 6.5 summarises the notion that the structure of the value being spread can determine the speed and diffusion of diffusion.

Table 6.5 Artefact type against time and scope of diffusion

ARTEFACT TYPE	DIFFUSION SPEED	DIFFUSION SCOPE
Few variables	Fast	Small
Many variables	Slow	Large

Number of variables of an artefact refers to the range of possible features that can be assigned a number of values. Examples of this distinction in design artefacts are first-generation of consumer products such as bicycles, cars, digital cameras, telephones and personal computers which have tended to have a minimum of options whereas in subsequent versions more product features and optional accessories become available. This principle suggests that artefacts such as early consumer products would tend to be adopted relatively fast but only by small segments of the market whereas second and third-generation products would take longer but would reach a wide spectrum of consumers. This is consistent with the basic construct of market penetration (Magnusson 1994).

As shown in Figure 3.7, increasing the number of variables or features of an artefact and not the range of values or traits for each variable is likely to affect the diffusion process. The result is that artefacts with a combination of more features and less traits present a balance between diffusion time and scope. As more features are added, diffusion times increase without changes in scope. Likewise, increasing the number of traits causes minor changes in diffusion times whilst significantly affecting the scope of diffusion. A balance between number of variables and value range is expected to provide optimal conditions for diffusion.

One way to explain this assumed optimal balance is through the study of compatibility and complexity in innovation studies. In the literature, *compatibility* is defined as the perceived degree of consistency between existing and new solutions, whilst *complexity* of an innovation generally refers to the degree to which an innovation is perceived as difficult to understand and use by potential adopters (Rogers 1995).

The general assumption in the literature is that high compatibility and low complexity facilitate innovation (Rogers 1995). These two requirements support our findings since design artefacts with more potentially common features can be expected to be more compatible with existing solutions. On the other hand, artefacts with a smaller range of values per variable can be expected to be perceived as less complex.

Table 6.6 summarises the notion that artefacts that spread relatively fast and have a larger scope of diffusion would consist of more features and less traits per feature. Such artefacts would be potentially highly compatible with existing solutions, yet have low complexity.

Table 6.6 Characteristics of artefacts with potentially rapid diffusion speed and large scope

ARTEFACT TYPE	DIFFUSION SPEED	DIFFUSION SCOPE
High compatibility + low complexity	Intermediate	Medium

Related to the time and scope of innovation is the shape of the sigmoid or S-curve of innovation (Baptista 1999; Mahajan et al. 1990) and the so-called tipping point (Gladwell 2001). *Tipping point*, *critical mass* (Ball 2004; Marwell and Oliver 1993) or *chasm* (Moore 1999) are terms that refer to the critical stage at which a sufficiently large number of early adopters cause a rapid acceleration of the adoption process, i.e., when diffusion ‘takes off’. Rogers (1995) defines it as the point at which enough individuals have adopted an innovation so that the innovation’s further rate of adoption becomes self-sustaining.

Our findings suggest that design artefacts with a large number of variables require longer initial stages of adoption, or a larger critical mass of early adopters to reach the tipping point. In contrast, the diffusion of artefacts with a small number of variables would reach this point with a smaller group of early adopters.

The time at which the tipping point takes place in our experiments follows this principle as seen in Figure 3.7. The tipping point in the case of artefacts with a small range of variables seems sufficient to reach only a small portion of the universe of potential adopters. For artefact structures with more features, diffusion only takes off later but it reaches larger adopter groups.

The importance of this distinction is that it only takes into account the type and number of characteristics of the artefacts being adopted preceding any consideration of their actual values, their designers, or the adoption population. This is a claim to be cautiously interpreted since the latter factors are not trivial in shaping the diffusion curve (Oude Wansink 1995).

Consensus exists in the literature that the diffusion curve takes off somewhere between the 5 and 25-percent level of adoption (Rogers 1995). The relationship that we suggest between artefact structure and diffusion can be seen as one possible source for this 20 point range. When this idea is compared to standard product diffusion models, it amounts to adjusting the likelihood of adoption potential due to factors that are external to the process of social influence, i.e., in this case the intrinsic properties of artefacts. The Bass model (Bass 1969) suggests that the probability of adoption at time t is a linear function of the number of existing adopters. This is expressed as:

$$N_t = N_{t-1} + p(m - N_{t-1}) + q \frac{N_{t-1}}{m} (m - N_{t-1}) . \quad (6.1)$$

Where the conditional probability of adoption N_t is a function of aggregate adoption N_{t-1} , the coefficient of external influence p , the coefficient of social influence q such as ‘word-of-mouth’, and market potential m (Mahajan et al. 1990). Whilst this linear model fits some empirical data, a more flexible model is necessary to account for different diffusion patterns including nonsymmetric rates of adoption (Easingwood et al. 1983; Srinivasan and Mason 1986; Strang and Tuma 1993). A modified formula for non-linear growth that models our observations can be expressed as:

$$N_t = N_{t-1} + p(m - N_{t-1}) + q \frac{N_{t-1}^\delta}{m} (m - N_{t-1}) . \quad (6.2)$$

Where the impact of adoption N_t , is not proportional with the number of existing adopters and the term δ represents a nonuniform influence factor. This model of non-linear diffusion implies that the coefficient of social influence does not remain constant over time, which is consistent with behavioural changes across adopter categories (Rogers 1995).

Figure 6.3 shows that lowering the coefficient of external influence p and varying δ in the range 1,0 the modified Bass formula with market potential $m = 100$ models the delayed tipping point and a slower but larger market penetration observed in Figure 3.7. In one extreme, an initially high but decreasing influence leads to a rapid initial acceleration of adoption with low market penetration. In contrast, a low and constant external influence yields a slower but higher peak in the

level of adoptions. This model captures the intuitive idea that artefacts with a large number of features may take a longer initial period of diffusion but provide more points to sustain persuasion.

Phases of innovation and routinisation or commodisation in design such as those presented in Figure 3.14 can be explained as ‘cycles of creative destruction’ (Kash and Rycroft 2002; Schumpeter 1939; Sengupta 2001; Stein 1997). The exhaustion of a design space may take place as the novelty of solutions gradually decreases. The transformation of the design space is interpreted from this perspective as the introduction of a creative exemplar (Kuhn and Horwich 1993). New exemplars redefine the space of possible solutions (Gero 1990) triggering a new cycle of innovation. However, an important distinction in regards to design artefacts needs to be made.

Unlike scientific paradigms, new solutions in design need not be incommensurable, i.e., the old space of solutions need not be superseded by the transformation of the design space. From this perspective, design fields can be defined as multi-paradigmatic (Kuhn 1969). One of the bases for this distinction is that design artefacts are open to multiple interpretations, both by adopters and by subsequent design processes. The principle suggested in this analysis is that artefact reinterpretation plays a key role in cycles of innovation.

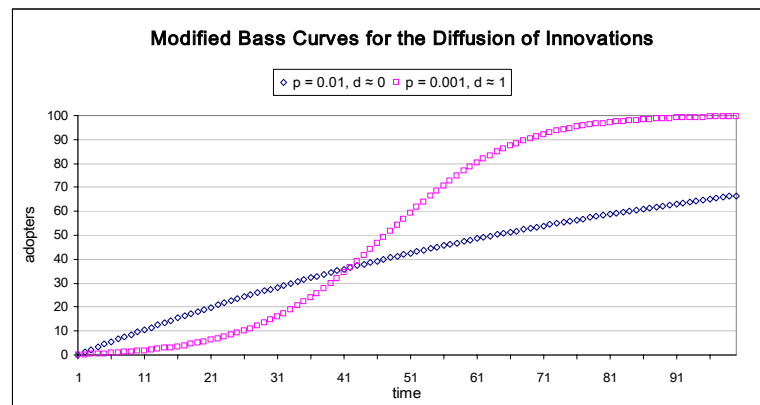


Figure 6.3 Modified Bass formula with varying coefficient of external influence p and influence factor δ . Diffusion with decreasing influence (i.e., artefacts with a few variables) yields a rapid initial adoption with low market penetration whilst diffusion with constant external influence (i.e., artefacts with more variables) yields a slow but larger scope of market penetration.

6.4.5 Artefact Representation

Artefact representation can be fundamental to determine innovation. When the structure of an artefact supports the emergence of multiple variations during the diffusion process, instances of opportunistic innovation can be expected. In Section 3.3.2.3 this type of innovation was shown when an artefact that shares characteristics with other competing artefacts benefits from the spread of compatible artefacts.

Examples abound of design artefacts that achieved recognition as they were re-interpreted for applications different from those originally conceived for. Thomas A. Edison’s original cylinder phonograph took off when cylinders were replaced by discs and its original use for voice recording was replaced by the more popular function of music reproduction (Israel 1998). Alexander Graham Bell’s telephone came as a direct result of attempts to improve the telegraph by transmitting multiple simultaneous messages over the same wire (i.e., United States Patent No. 174,465 for the telephone is indeed entitled “Improvement in Telegraphy”). More recently the Polo Harlequin by Volkswagen was originally intended as an April Fools’ Day joke (Goldenberg and Mazursky 2001), and the Sony Walkman came about incidentally from the failure of the monophonic Pressman (Goldenberg and Mazursky 2001).

One way to understand unexpected consequences of diffusion is by the capacity of artefact configurations to support multiple interpretations. In this sense a design artefact is not finished by design practitioners, the process is finalised by its impact and transformation in the field.

Trialability and observability are two well-researched aspects that help explain the possible link between interpretation and innovation (Rogers 1995). Trialability is defined as the degree to which an innovation may be experimented with on a limited basis. It is increased by allowing adopters to appraise the potential of the new solution and their capacity to assimilate or integrate it into their experience. Observability is the degree to which the results of an innovation are visible to potential adopters. It normally refers to access to the intended results of an innovation but it could be extended to account for the construction of new interpretations and applications.

Based on the results presented in Section 3.3 where values with longer representation structures support more adoption and transformations during their diffusion, we suggest the principle that artefacts that support more reinterpretation are more likely to gain recognition by potential adopters and by peer designers, who can build on the new solution. From the designer's point of view, however, the obvious drawback is that the creator gives up control over the artefact, which consequences tend to be unanticipated and indirect (Rogers 1995).

Figure 6.4 illustrates the principle that artefact representations with more variables support the generation of multiple alternatives over the course of diffusion.

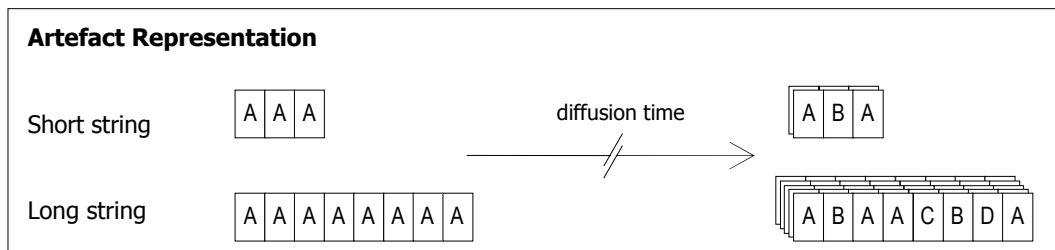


Figure 6.4 Artefacts with longer feature strings support more 'room for interpretation' during diffusion

To maximise diffusion artefacts should be sufficiently versatile to support compatibility, yet their complexity should be on the number of variables rather than on the possible values of these as demonstrated in Figure 3.7. This is why artefact representation in our studies supports reinterpretation as described in Section 4.3.1. Any model of design needs to account for artefacts sufficiently complex to support solutions with multiple perceptions. The two-dimensional line representation shown in Figure 4.8 is the simplest of such configurations we devised.

In the literature the extreme end of artefact reinterpretation is explained by *convivial tools* (Fischer 2000; Illich 1973). These types of artefacts promote user participation in extending their possible features. Future extensions to adoption models could address this range from passive to active consumer to users and power users to designers (Fischer 2003).

6.4.6 Summary

Our studies reveal a comprehensive role of domains in the link between individual behaviour and social change. These collections from which individuals retrieve existing information and fields incorporate changes may have significant qualitative and quantitative differences depending on a number of factors, most of which have been only marginally addressed in the literature.

A prevalent assumption is that creativity can be estimated from the creator's total output or from the number of works commended by experts (Gardner 1993; Simonton 2003). However, individual differences are only one of the factors that determine the quantity and quality of a domain. The 1,093 patents granted to Thomas A. Edison (Israel 1998) need not indicate much about his individual characteristics. Some of the factors addressed in our studies that may be responsible for such exceptional contribution include a) spillovers from other inventors, b) social characteristics that value and promote production, c) frequent rates and diverse sources of

gatekeeping including investors, d) rapid increase of target population size, and e) disclosure of new knowledge. The combination of these factors is likely to determine the output and distribution of prominence across competitors.

These situational effects characterise cases where various individuals independently make the same contribution. Westrum and Simonton (1979) document over 500 instances of multiple inventions.

Extensions to these models include more than one society having contact through their domains enabling the study of distant analogies (Qian and Gero 1995; Wolverson 1994). Between-group interaction was found to be a key source of innovation. Other extensions include the inclusion of further domain mechanisms such as when a new solution renders some or all past entries obsolete.

6.5 Design Situations

The implications of our computational studies in view of the literature point towards a promising line of inquiry focused on the complex relation between individuals, fields and domains. At present there are still more questions than answers (Cropley 1999), but the types of questions being asked change when based on an alternative understanding of creativity and innovation as part of a complex multi-level system. The most important theoretical construct that frames this interaction is the notion of *design situations*. Amabile (1983) recognises that as a result of the dominant individualistic focus in the literature, important questions have been underemphasised, specifically the study of ‘creative situations’, which she defines as ‘circumstances conducive to creativity’.

A design situation represents the combination of individual and external factors as construed by the designer. Based on the factors explored in our studies, a situation in design can be defined as the confluence of individual and external conditions within which behaviour is determined. When individual and situational conditions combine, a subsequent behavioural pattern can be expected from actors within such situations.

To illustrate the dynamic interaction of situations and individuals, a classic example in the literature is the intuitive notion of ‘dangerous situations’, i.e., conditions under which individuals are likely to generate unsafe behaviour with undesired effects such as car accidents (Argyle et al. 1981; Ross and Nisbett 1991). Dangerous situations can range from being strongly determined by individual factors (i.e., unskilled driver of a car), or by external conditions (i.e., slippery surface). Translating this into our models, situations can be characterised as conducive to a number of effects including prominence, influence upon peers, increased rates of creation, rapid diffusion curves, etc.

The key idea when considering creative situations is that the observed output is likely to take place as a combination of individual and external characteristics. This is true in two ways: a) a range of individual differences are likely to generate the behaviour of interest and b) a range of behaviours are likely to generate the effects of interest at the social level.

Figure 6.5 presents a framework of design situations. Aggregate agent interaction generates emergent collective structures (Langton 1989) that in turn feed back into individuals in second-order emergence (Conte et al. 2001; Gilbert 2002). The combination of individual and perceived external state can be characterised as situation-types. When sufficient individual and situational conditions combine, agents within that situation are likely to trigger collective changes and thus be characterised as ‘change agents’. When no information is known about the situation, it is reasonable to attribute extraordinary behaviour to internal properties of the change agent (Fein et al. 2001). However, when the agent is considered within a situation, the resulting behaviour becomes unsurprising. The exceptionality of the observed behaviour is explained by the uncommon combination of specific individual and situational conditions.

The term ‘design situation’ has been previously used as a synonym of system state (Hubka and Eder 1996). System state refers to the description of all properties of the artefact being designed, all

properties of the design process, and ‘all factors influencing the product and the process’ (Reymen 2001).

In addition, a methodology called “Situated Design” has been formulated (Lueg and Pfeifer 1997) in which the main assumption is that it is not possible to objectively define situations. The following Section presents a series of examples of design situations within our computational framework of design as a social activity.

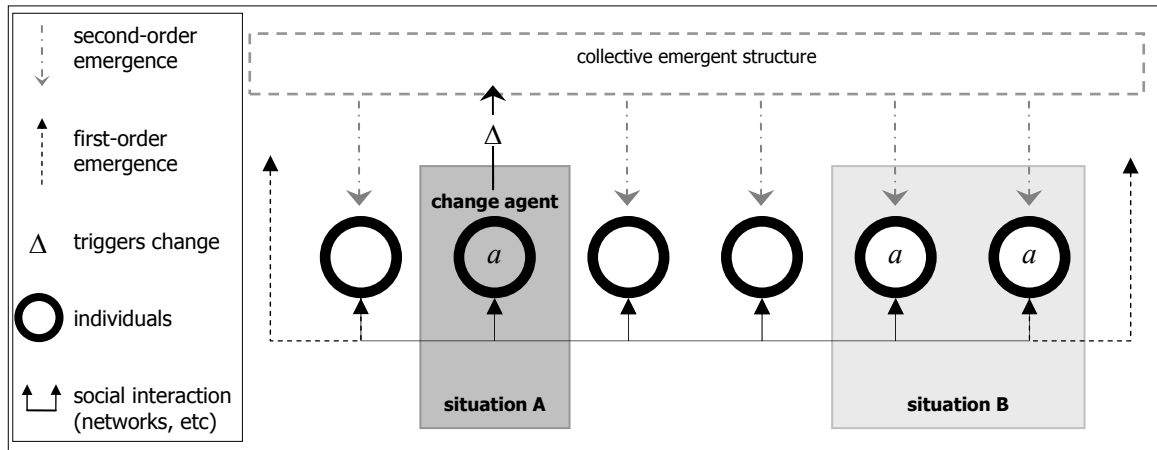


Figure 6.5 Framework of design situations: Aggregate social interaction creates emergent structures (domain) which feed back into individuals (adopters and designers). When individual characteristics (a) combine with conditions conducive to change agency (situation A), a change is triggered.

6.5.1 Types of Design Situations

An important implication of the notion of design situations is the degree to which individuals are able to choose and manipulate aspects of the situations within which they operate. An important role of individual differences may be in the disposition to choose or transform certain situations (Ross and Nisbett 1991). In this Section different scenarios are described based on the discussion presented in this chapter. Within these conditions, the patterns of individual behaviour and collective effects of interest are obtained independently of other conditions. The external validity of these situations is to be tested and they are presented as research hypotheses. The terms and mechanisms involved in these descriptions are given in detail in Chapter 5.

6.5.1.1 Situations where designers are likely to receive high peer influence

With other conditions equal, it is possible to engineer certain aspects of the framework to obtain instances of designer agents that receive high levels of peer influence or recognition. In our model recognition from peer designers is assigned when features of an exemplary artefact are copied by other designers.

The first way to get this pattern is through an individual trait: to have large differences of individual synthetic abilities between designers, i.e., when a designer is considerably more productive than the rest, it is likely to receive high levels of recognition from peers.

A second situation where high influence between designers is observed is when the rate of design in the field is high for all designers. Rate of design is defined as how often designers are able to launch new products measured by number of adoption decisions. The design of mobile phones is an example of a frequent design rate, whereas the design rate of staplers is more sporadic. However, when very frequent design rates decrease marginally, peer influence rapidly decreases to its minimum. This suggests that this situational factor may be very unlikely, only possible at an extremely high rate of design.

6.5.1.2 Situations where one designer is likely to concentrate adoption choices

The distribution of adoption choices by designers does not seem to be significantly affected by individual differences across designers in our framework. Namely, even when a designer agent has considerably higher abilities than the rest, the corresponding increase on number of adopters is only marginal. However, other situational factors are likely to cause adoption choices to be skewed towards the artefacts of one designer.

Societies of adopters with strong social ties are likely to concentrate their adoption decisions on the artefacts of one designer. Strong social ties between adopters are characterised by a lack of social mobility where influence hierarchies develop with a few dominant influential opinion leaders.

When a design field requires designer agents to conceal knowledge, adopter groups tend to converge in the adoption of artefacts from one designer. Under these conditions, designer agents have access only to the rules that they create during a simulation run. In contrast, when designer agents disclose their rules and build a public knowledge base, adoption choices tend to distribute among all designers.

6.5.1.3 Situations where one designer is likely to concentrate domain contributions

In fields of frequent design rate, contributions selected by gatekeepers to enter the domain originate from a small number of designers. In contrast, in fields where gatekeeping takes place sporadically, an equivalent concentration of expert choices is observed.

A third formula that yields high concentration of experts' selections is when designer agents have private access to knowledge.

6.5.1.4 Situations where adopters are likely to be more satisfied

When the individual bias of adopters is a strong factor of the adoption decision, their satisfaction is likely to increase, but it is also very unpredictable.

A second situation where adopters are likely to be more satisfied with their adoption choices is when adoption rate is high, i.e., when many adoption decisions and social influence take place between design and gatekeeping instances.

Thirdly, private access to knowledge is likely to generate more satisfied adopters.

6.5.1.5 Situations where more domain contributions of high quality are likely

Where quality is defined by the scores assigned by gatekeepers to domain contributions. The scores assigned by gatekeepers to domain entries are higher when adopters' choices are more individualised.

The score assigned by gatekeepers and the inherent complexity of repository entries decays with sporadic design behaviour.

A large number of adoption iterations between the selection of artefacts generates smaller domains and lower scores.

Lastly, public access to knowledge generates more domain entries that receive higher mean scores and are of higher complexity.

6.5.2 The Power of Situations

Situational factors need not be externally imposed but could be chosen and modified by designers as a result of their experience. Namely, a designer could choose to target smaller/larger populations, to target groups with stronger/weaker social ties, to exercise design updates more/less frequently, to encourage opinion leaders to manifest their opinions more/less frequently, etc. Obviously these are factors only partially accessible to the designer, some require external change or negotiation with other stakeholders. In addition, these are illustrative factors that may determine

creativity and innovation. This research aims to draw attention into these types of factors. Research should be extended to include situational factors that can determine creativity and innovation in important ways.

The likely effects of a range of situational factors can be identified, however the power of the situation has been regarded as variable (Bem and Allen 1974). The researcher would not expect everyone to perform uniformly on a fixed set of traits in a fixed set of situations. Instead, individuals are expected to manifest dispositions only in the particular subset of relevant situations for that individual.

Chapter 7

Conclusions and Future Work

This concluding chapter reviews how the objectives of the research presented in this thesis have been met. Future work is divided into short and long term extensions and contributions to the discipline of design research methodologies. The chapter ends with a discussion on controversial aspects of this type of research.

The goal of this research has been to contribute to the current understanding of creativity and innovation in design. The objectives of this research were met in the following ways:

- 1) To explore change agency in a basic computational model of social influence.

An inclusive literature review in Chapter 2 revealed a gap between existing knowledge about creativity at the individual level and innovation at the social level. The problem was defined as a complementary process of change at the individual and the collective levels. Existing computational models in this area tend to inherit such methodological gap: most models address generative processes or collective evaluation in isolation. The need was established to explore computational models that address the micro-macro link of change agency.

Exploration with a basic cellular automata CA framework of social influence in Chapter 3 provided a number of insights on general principles of individual and group divergence without a direct relation to design processes. The nature of marginality of dissent and the relation between innovation cycles and group coherence were analysed based on extensions to this cellular automata. Domain factors were included in particular the role of artefact structure and representation in determining the compatibility and complexity of innovations. Other aspects of diffusion studied in this Section included social mobility and between-group interaction. Lastly, a basic notion of the role of individual differences in change agency was addressed.

- 2) To explore generative and evaluative processes of design as part of a social system in a comprehensive framework of design agency

Relevant target phenomena were identified based on our initial explorations and on evidence and debates from the literature. The need for a computational framework that included the

generation and evaluation of design artefacts was formulated. To this end a multi-agent framework was introduced in Chapter 4 to study some aspects of social influence, gatekeeping, peer recognition, and intellectual property. This framework is based on a systems view of creativity where three main components are defined: individual designers, their social group or field, and a set of knowledge and solutions collectively developed, or domain.

Two series of experiments were designed in Chapter 5 to explore the effects of individual and situational factors in phenomena usually associated to creativity and innovation including patterns of adoption, prolificity, expert evaluation, and prominence. Individual factors were defined for exploration including differences of abilities between designers and differences of preferences between adopters. Situational factors were inspected including the strength of social ties, rates of behaviour; population sizes and domain rules.

- 3) To develop an understanding of how phenomena generally related to creativity and innovation can be understood as the result of individual and situational factors

A number of factors in a system were identified that may contribute to the emergence of phenomena associated to creativity and innovation in Chapter 6. At the individual level the role of individual differences, persistence, opportunities, imitative behaviour, peer influence, and design strategies were discussed. At the field level determinants analysed include group structure, social mobility and organisation, emergence of opinion leaders, established rules and norms, and distribution of adoption and quality assessments. Lastly, domain aspects that influence the interaction between designers and their social groups included the generation and access to knowledge, activities of gatekeeping, domain size and distribution, and artefact structure and representation.

These insights were discussed in view of current findings and relevant modelling approaches in the literature. Whilst a number of assumptions and results were validated, others contribute to ongoing debates and suggest specific mechanisms and parameters for future experimentation.

7.1 Future Work

The circular causation between individuals and groups in design is captured by the dialectic observation that designers ‘are producers as well as products of social systems’ (Bandura 2001). Some aspects of this complex relationship can be further explored in future work in two categories: short and long term extensions. The former refer to experiments that can be conducted with minimal modifications or additions to the current framework as described in this thesis. The latter are directions of research identified during this work which would require significant changes to the methods and tools of inquiry.

7.1.1 Short-term Extensions

7.1.1.1 Alternative Adoption Schemas

Alternative types of adoption could be explored in addition to the optional adoption schema addressed in these studies. Other types include collective decisions, i.e., made by consensus among the members of a system; authority decisions, i.e., made by a relatively few individuals who possess power, status, or expertise; and contingent decisions, i.e., choices made only after a prior decision. These types of adoption schemas may range on a continuum, i.e., more than one type of decision for a given design field may change over time (Rogers 1995).

7.1.1.2 Additional Types of Individual Differences

Extensions to our experiments with differences between individual designers can be devised in a relatively straightforward way. One question worth exploring is the point at which individual differences fail to make a significant difference in aspects such as adoption distribution, peer

recognition, and domain contributions. The hypothesis to explore here would be that at a certain point synthetic ability would give the maximum advantage to a designer agent after which higher abilities do not affect the outcome.

Another possible way to further explore these results is to test some of the assumptions in the framework in order to isolate the mechanisms that would make individual differences of design abilities have a more determinant role. This would require a process of replicating the experiments repeatedly by ‘turning off’ the mechanisms of the framework such as imitation, learning, adopters’ preferences, and social interaction. Arguably this could yield the ‘necessary conditions’ under which individual traits are sufficient to determine performance. This could lead to a more comprehensive framework that captures the possibility that in different design fields or at different stages within a field, the role and impact of individual factors vary.

Other individual traits of designers that can be explored in this framework include differences of imitation and motivation. The former can be parameterised by assigning individual thresholds of imitation and observing the effects of differences between designers. Would designers that prefer to imitate be able to trade recognition from peers for more adopters or domain entries? Extensions to explore motivation could address the relation between internal and external motivation of designer agents (Amabile 1996).

In addition, future experimentation should address in more depth the role of learning in individual differences between designers. Namely, the role of quality and not only quantity of domain knowledge calls for further attention.

7.1.1.3 Additional Types of Situational Factors

In relation to the strength of social ties, extensions could explore its relationship to neighbourhood size. In this framework neighbourhood size is assumed to increase with social tie strength (Section 4.4.3) based on the Theory of Social Impact (Granovetter and Swedberg 1992). However, an alternative interpretation worth investigating is that neighbourhoods become smaller as the strength of social ties increase, i.e., with limited time resources, individuals have to distribute their time between their relationships (Florida 2002). The issue then is to observe how a negative or inverse relationship between social tie strength and neighbourhood size affects the observed outcomes.

Extensions of design rate can be addressed as individual factors. To this end, designer agents can be assigned an individual rate of design which determines how often each designer agent is able to execute revisions and changes to their artefacts. As a situational factor, the rate of design need not be fixed during a simulation run. Further experimentation could be aimed at inspecting the consequences of an evolving design rate.

Extensions to the study of frequency of gatekeeping can be carried by relaxing the assumption that the rate of gatekeeping remains fixed during a simulation. To this end, the behaviour of gatekeepers can be tied to domain rules including the entry threshold or the size of the repository. Experiments could then be conducted on the role that designers can play in influencing the role of gatekeepers. This may be a viable way to establish a closer relationship between designers and gatekeepers, perhaps extending the role of the latter into more active promoters of the artefacts of their associates.

Extensions to the study of population sizes could explore the ratio between the size of the adopter population and the number of designers. A range of experiments could be implemented to address the notion of active and passive designers. As a function of adoption, peer or expert evaluation, designer agents could be ‘fired’ and ‘hired’ from societies. A hiring mechanism could be a further role of gatekeepers, i.e., they could be in charge of authorising the entry of more designers into a population. Likewise, the number of adopters in a society could a function of design activity.

A number of extensions the study of knowledge protection can be aimed at exploring the type of access to knowledge necessary for incremental and sequential innovations (Godoe 2000). In addition, this situational factor can be transformed into an individual property by assigning one

designer agent with public access whilst the rest of designer agents are constrained by private access to knowledge. The objective of such experiment is to assess the possible consequences of piracy and copyright infringement for the various stakeholders of the system (Baer et al. 2003; Helpman 1993; Prasad and Mahajan 2003; Stokes 2002).

7.1.1.4 Variable Conditions

To facilitate experimentation, experimental parameters in these studies have remained fixed during a simulation run. A future step is to reconsider the dynamic character of these parameters and enable their adjustment over time. This may be determined in two possible directions: as a response to emergent conditions produced by aggregate behaviour or as a top-down control mechanism by appropriate roles. A simple way to achieve this would be to give designers the capacity to change the level of protection of their knowledge as a function of their performance including how well their artefacts are evaluated by adopters and gatekeepers.

7.1.1.5 Combined Experiments

The work presented in this thesis has addressed a range of independent parameters in isolation. A future step is to design experiments where independent parameters are explored in combination based on the analysis of the effects of these variables. One key issue identified in our studies is the interaction between the strength of social ties and population size. The combined effect of these variables could confirm the presumed relationship between small/large groups and weak/strong ties in determining artefact differentiation as perceived by adopters and the ensuing satisfaction of adoption. This type of experiments would extend further the internal validity of the framework.

Other mechanisms associated to adoption satisfaction in the literature can be implemented to explore their interaction with independent parameters. A number of studies of adopter satisfaction could suggest ways to reconsider its role in adoption and social influence (Athanasopoulos 2000; Babin and Griffin 1998). For instance, satisfaction levels could determine the direction of influence between adopters to account for positive and negative word-of-mouth effects.

7.1.1.6 Extensible Artefacts

The current artefact representation has been useful to explore notions such as interpretation, popularity, peer recognition, and gatekeeper evaluations. However, a future mechanism could be developed to support more radical changes of design space.

An artefact representation that captures the notion of transformation of design spaces would be advisable (Gero 1990). At present, the generation of design rules can be interpreted as incremental changes to artefacts, but by determining possible mechanisms to overcome the original constraints, the system could address radical transformations to the design space.

One simple way to achieve this would be to extend the learning mechanism of designers to enable them to generate new coordinates within the two-dimensional grid. New coordinates could be based on the extension or intersection of existing lines.

In Figure 7.1a a point is created in the intersection between two existing lines. In Figure 7.1b new lines are generated using the new coordinate and existing points. In this way a designer can generate new shapes that meet the evaluation criteria established in this framework, i.e., geometric relations such as rotation, scale, alignment, and reflection.

Shapes based on new coordinates could transform the original constraints and define a new design space. The existing imitation mechanisms would spread the use of new coordinates among designers. Experiments could be directed at exploring the effects of these transformations in adoption patterns, competition, and peer influence. However, new coordinates may fail to have these effects in cases where resulting shapes are not valued by the adopter group.

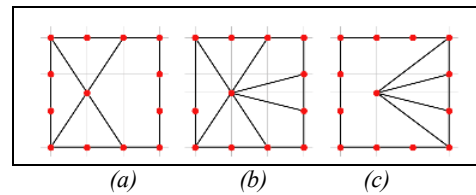


Figure 7.1 Possible extensions to the artefact representation described in Section 4.3.1 Designers generate new coordinates from (a) the intersection of existing lines. New points are used to (b) generate new lines and (c) new shapes with geometric relationships such as reflection.

7.1.1.7 Case Modelling

With a better understanding of the interactions of these types of systems, applications should be developed to study concrete case studies. Particular assumptions can be built, and an iterative process of executing and fine-tuning the framework could serve to identify the mechanisms and conditions in a particular design industry. For instance, the mobile phone industry is an interesting example where design rates are high, artefact differentiation is low, and adoption variance is very high (Green et al. 2001). Our framework could reveal some of the potential mechanisms at work sufficient to generate such combination of results.

This type of experimentation is necessary to assess the shape of patterns such as tie strength and adoption in Section 5.3.1. Where non-linear relations are observed between two variables, it is convenient to conduct curve-fitting to find functions that best approximate the data points. This would be particularly appropriate in simulations of specific target phenomena where numeric and distributional values are significant.

7.1.1.8 Extend CA with design agency

Due to the simplicity of representation and flexibility of results of cellular automata (CA), a number of extensions are conceived for that approach. A type of learning can be included in the investigation of heterogeneous CA. A basic version of this was in fact conducted and the results did not seem to vary from those presented in Section 0, i.e., that individual differences are only moderate predictors of behaviour when individuals are part of a social system where dependencies emerge. However, different mechanisms of learning deserve further consideration.

The role of top-down interactions was not considered in the current CA explorations. This has notorious disadvantages particularly in large populations where bottom-up change requires very long interaction periods. The role of top-down mechanisms of communication such as mass media in triggering group changes could be addressed. Arguably, access to such channels of distribution could be tied to mechanisms of gatekeeping.

7.1.2 Long-term Extensions

This research has identified a set of interactions that can be expected to occur between individual and situational factors in creative design. The long-term goal of this line of inquiry is to capture the details of naturally occurring situations. This can be done by matching field and laboratory studies with computational modelling (Morone and Taylor 2004; Newell and Simon 1976). For instance, our studies of gatekeeping suggest that social groups with weaker ties tend to distribute prominence in assessments made by experts. This could be used as a hypothesis in the design of laboratory experiments or historiometric studies. Likewise, during the evaluation of design artefacts strong individual preferences yielded higher satisfaction levels, less artefact differentiation, and higher scores for domain entries. This can be inspected in control and experimental groups of generative and evaluative processes.

7.1.2.1 Laboratory and Field Validation

Laboratory and field experiments are convenient to test the veridicality of these types of frameworks as explanations of human behaviour. In addition, computational models can provide

new ideas for the design of ‘in vivo’ and ‘in vitro’ tools of inquiry as shown in Table 7.1. One basic type of experimentation focuses on evaluation: where equivalent artefacts are given to equivalent evaluation groups to assess their creativeness.

Experimental conditions of interest include the mechanisms of deliberation between members of the group: strong ties can be implemented by allowing each member of the evaluating group to have contact with only one peer evaluator whilst in groups with weak ties evaluators are allowed to exchange opinions with all other members of their group.

The type of artefacts submitted for evaluation can be another experimental parameter to inspect the roles of compatibility and complexity in diffusion. The overall aim of these studies would be to investigate in human groups the foundational idea that creativity is a property of systems and varying different system components or the way in which equivalent components interact can generate quantitative and qualitative different results. More advanced studies that include the generative and the evaluative processes could be addressed.

Table 7.1 Approaches to the study of creativity and innovation

IN VIVO	IN VITRO	IN SILICO
Biographic and Historiometric case studies	Cognitive and social experiments	Simulation and forecasting applications
Mostly for innovation	Mostly for creativity	Apt for the link between both

Extensive multi-disciplinary work is going to be necessary in order to build a veridical and verifiable model of design that provides specific, measurable output for the decision-making of design management and product development.

7.2 Conclusions

The work presented in this thesis drew attention to the principles by which determinants of creativity may combine between individual and situational factors. Its scope is delimited by the following aspects. Firstly, the number and extent of behaviours under study are restricted. This is a necessary limitation in order to keep simulation times feasible and observation of effects tractable. Whilst agent-based methodologies facilitate the description and implementation of heterogeneous behaviour routines, results become hard to analyse. The execution and analysis of large populations of interacting agents becomes computationally expensive as their behaviours become complex.

Secondly, results are not directly comparable to empirical evidence as discussed extensively in Section 6.1. This research can be seen as a ‘case study’, i.e., the study of an artificial society as a way to generalise and build theory about ‘all possible societies’ (Pattee 1996). A third limitation is related to the modelling of design behaviour. The term *design* transcends any single discipline and there is no consensual definition.

7.2.1 Skeptic’s Corner

Ben Shneiderman (2002) usually rounds up with a ‘skeptic’s corner’ to address challenges and sketch lines of response. The following issues are acknowledged in this thesis:

- “*Design is a reach and complex phenomenon that is not captured in a computational system*”. The complexity of any phenomenon does not invalidate its study. Models are caricatures which concentrate on salient aspects (Holland 1995). This thesis makes emphasis on aspects that have been considered of key importance in studies of creativity and innovation, and that we speculate are of importance in creative design.
- “*There is no relevance between these systems and real human societies*”. Arguably, the same argument can be used against any modelling approach. The validity of laboratory studies has been equally challenged, however it is likely that different methods of inquiry will inform complementary aspects of the target system.

- “*Social context comes after creativity; first we need to understand creative cognition*”. There is an increasing consensus that human behaviour in general cannot be explained in isolation. This research considers creative design as a social phenomenon inasmuch as most definitions of creativity include generation and evaluation by distinct entities.
- “*If creativity is captured in a computer program it will lose its ‘magic’*”. This can be called the fallacy of the mechanisation of creativity and is a long-standing concern (Schumpeter and Clemence 1989). However, the growth of economic and technical knowledge has shown no sign that creativity is becoming predictable and routine (Langlois 2002). Moreover, many people may not want to be more creative (Shneiderman 2000). Similarly, many processes do not need to be more creative. Creativity is the property of open systems, so even when we get to understand it, by definition it is not under complete control. Lastly, several findings suggest a natural ceiling for creativity as part of a social system. Studies show that it takes about ten years for individuals to gain mastery and exert influence in their domains. The ten-year period suggests that, independent of individual behaviour there may be a limit to the number of innovative ideas or artefacts that a society can assimilate over a period of time (Gardner 1993).
- “*Simulation is only output of all well-known inputs*”. There are many instances, particularly of social systems, where simulation yields unexpected, emergent results (Epstein and Axtell 1996; Pattee 1996). Stochastic simulation is used in scientific inquiry to explore ill-understood phenomena and to approach more formal, analytical treatment (Strogatz 2003). In the study of complex systems, emergence refers to results that are not equal to the weighted sum of such ‘well-known’ inputs and are qualitatively different and at a different level of analysis.
- “*Patterns observed are only artefacts of a series of underlying mechanisms*”. This point has a twofold implication: it may refer to the internal or to the external validity of our studies. The former can be addressed in an easier way than the latter. In this thesis we have offered several instances of consistency of outputs with assumptions and between results. In addition the most effective way to guarantee internal validity is replication, which has been also included. Inasmuch as future computational simulations replicate the findings reported in this thesis their degree of internal validity will increase. Inasmuch as research on human designers and their societies confirm them, they will constitute externally valid contributions to understand the complex system of creativity.

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Appendix A

Publications Arising from this Research

Book Chapters

- Sosa, R and Gero, JS: 2003, Social change: Exploring design influence, in D Hales, B Edmonds, E Norling and J Rouchier (eds), *Multi-Agent-Based Simulation III*, Springer, Lecture Notes in Artificial Intelligence 2927, 106-119.
 - This paper explores some aspects of group divergence based on principles relative to design disciplines. Extensions to an elementary cellular automata model are used to explore the relation between divergence and social influence mechanisms previously employed to explain group convergence. The emergence of change agency is investigated.

Journals

- Sosa, R and Gero, JS: 2004, Diffusion of creative design: Gatekeeping effects, *International Journal of Architectural Computing*, **2**(4), pp. 517-531.
 - A computational framework for design is presented to show that certain social structures can determine how novel solutions are created and spread. This paper suggests that creativity transcends the individual inasmuch as situational factors such as the role of gatekeepers can determine who is considered creative in a society.
- Sosa, R and Gero, JS: 2005, A computational study of creativity in design: the role of society, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing AIEDAM*, **19**(4), forthcoming.
 - Computational models of creative behaviour tend to limit their focus to generative processes. However, an increasing multi-disciplinary consensus regards creativity as a systems property and extends the focus of inquiry to include the interaction between generative individuals and evaluative social groups. To acknowledge the complementarity of evaluative social processes, this paper presents a model to inspect the interaction between designers and their societies. In particular, this paper describes the strength of social ties as a concept of social organization and explores its potential relation to creativity in a computational social simulation. These experiments illustrate ways in which the role of designers as change agents of their societies can be largely determined by how the evaluating group organises over time. A key potential implication is that the isolated characteristics of designers may be insufficient to formulate conclusions about the nature and effects of their behaviour. Instead, causality could be attributed to situational factors that define not the designer, but its evaluators.

Conferences and Workshops

- Gero, JS and Sosa, R: 2002, Creative design situations, in A Eshaq, C Khong, K Neo, M Neo and S Ahmad (eds), *Computer-aided Architectural Design Research in Asia*, Prentice Hall, New York, 191-198.
 - This paper presents the outline of experiments with a behaviour-based computational model of creativity in

design called Creative Design Situations. This model aims to allow the study of social creativity through the computational implementation of a community of creative design agents.

- Sosa, R and Gero, JS: 2002, Cellular automata models of creative design situations, *in* JS Gero and F Brazier (eds), *Agents in Design 2002*, Key Centre of Design Computing and Cognition, University of Sydney, Australia, 165-180.
 - This paper presents a series of computational models based on a cellular automata voter model as applied to the study of social influence as a model of creative situations. Preliminary findings related to creativity and innovation in design and their possible implications in agent modelling are presented.
- Sosa, R and Gero, JS: 2002, Creative individuals or creative situations, *in* PL Hippolyte and E Miralles (eds), *SIGraDi*, Ediciones Universidad Central de Venezuela, Caracas, 31-34.
 - Computers can be used as a key research tool because they allow us to do things that have been difficult or unfeasible in the past. This potential could facilitate discussion of ideas in new ways. This paper presents preliminary findings of a computational model that may contribute to extend our presently limited understanding of creative phenomena in design. As part of an extensive modelling effort, it offers initial insights that may shift the current focus in individual creativity to a more extensive view where the situations within which designers operate play a key role in the occurrence and definition of creativity.
- Sosa, R and Gero, JS: 2003, Design and change: A model of situated creativity, *in* C Bento, A Cardoso and JS Gero (eds), *Approaches to Creativity in Artificial Intelligence and Cognitive Science*, Acapulco, 25-34.
 - This paper describes current research on the computational modelling of change phenomena in design. In particular it introduces a tutorial view of the model of design situations (DS) as a methodological basis for experimentation with change processes at the individual and the collective levels of an agent society. Creativity in the DS model takes place within the situated interaction of individuals in a social environment transcending its conventional characterization as purely a cognitive process.
- Sosa, R and Gero, JS: 2004, A computational framework for the study of creativity and innovation in design: Effects of social ties, *in* JS Gero (ed.) *Design Computing and Cognition '04*, Kluwer Academic Publishers, Dordrecht, 499-517.
 - This paper describes a socio-cognitive framework to study the interaction between designers and social groups. Experimentation with situational factors of creativity is presented. In particular, social ties in a population of adopters are shown to shape the way in which designers are considered as change agents of their societies.
- Sosa, R and Gero, JS: 2004, Diffusion of design ideas: Gatekeeping effects, *in* H Soo Lee and J Won Choi (eds), *Computer-Aided Architectural Design Research in Asia*, Yonsei University Press, Seoul, 287-302.
 - This paper presents a computational framework of design as a social activity where the final outcome is the impact that generated artefacts have in a social group. The research aim is to gain understanding of the role of designers as change agents of their societies. The experiments presented in this paper support the idea that creativity transcends the individual domain. Patterns of creative figures show that characteristics external to the individual may determine who and how is considered creative in a society. A generalisation can be formulated as follows: In more hierarchical fields prominence tends to concentrate on a few creators. Under such conditions, imitation of valued solutions increases whilst differentiation between available solutions decreases. In such fields the resulting domain tends to be smaller and to consist of solutions that have lower perceived value.
- Sosa, R and Gero, JS: 2004, The role of gatekeepers in creativity, *in* P Gervas and K Moy Gupta (eds), *Computational Creativity Workshop*, Universidad Complutense de Madrid, 257-268.
 - This paper investigates some principles of gatekeeping in creativity. It presents results of a computational framework based on a systems view of creativity applied to design. In this multi-agent system individuals are designers of artefacts, the field is composed by adopters and opinion leaders, and the domain consists of a collective repository of selected artefacts. The adopter population is organized in social networks where adopters influence the adoption decision process of others. Opinion leaders emerge as a result of this form of social interaction and become responsible for selecting entries to the collective repository. With these simple elements, a number of interesting phenomena are demonstrated in relation to gatekeeping in creativity. The findings suggest that the emergence of creative figures can be better understood when situational factors are considered, such as the role of the field.