A computational study of creativity in design: the role of society

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Abstract. Studies of creativity tend to focus on the isolated individual under the assumption that it can be defined as a characteristic of an extraordinary person, product or process. Existing computational models of creative behaviour have inherited this emphasis on 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 individuals, social groups and knowledge. To acknowledge the complementarity of evaluative processes by social groups, experts and peers, this paper presents experimentation with a framework of design as a social activity. This model is used to inspect phenomena associated to creativity in 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 effects on creativity. The experiments presented demonstrate ways in which the role of designers as change agents can be largely determined by how the evaluating group organises over time. A key implication is that the isolated characteristics of designers are insufficient to formulate conclusions about the nature and effects of their behaviour. Instead, causality could be at least partially attributed to situational factors that define not the designer but its evaluators.

Keywords. Creativity, innovation diffusion, social simulation, situated behaviour, design agents.

1. INTRODUCTION

Design is considered a creative activity. It is also considered a source of innovation and a foundation for social change (Gero 2000). However, our current understanding of creativity in general and in relation to design, innovation, and social change is limited. The last fifty years of research in creativity have been partly speculative with a vague level of theorising and inconclusive empirical evidence (Sternberg 1999). The present challenge is to use a combination of research methodologies to move from speculation to specification and explanation.

The main approach to the study of creativity has been based on an individualistic premise under which creativity is assumed as an isolated capacity, trait, or generative process. Under such an approach it has been difficult to capture a single or a consistent set of individual characteristics associated to creative designers or creative design solutions. In everyday discourse explanations are often circular: people tend to attribute exceptional performance to talent and to explain talent by exceptional performance (Howe et al. 1999).

The definition of historic creativity (Boden 1994) or creativity with a big-C (Gardner 1993) stresses the importance of evaluation by a social group. Consensus constitutes a kind of Turing-test of creativity where evaluation is determined by a group over time and not by the isolated individual generator. An increasingly accepted approach focuses on the relation between individual-generative and group-evaluative processes. Under this view, creativity is seen as a social construct or a communal judgment (Feldman et al. 1994) where a creative designer is considered not in isolation but in interaction with an environment of social and epistemological dimensions.

In this paper we explore some fundamentals of the relationship between designers and social groups. Our motivation is to understand how certain individual actions in design can be determined by collective conditions and in turn trigger structural social changes. The term *creativity* is polysemous and ambiguous. In the literature it implicitly refers to different ideas including aesthetic appeal, novelty, quality, unexpectedness, uncommonness, peer-recognition, influence, intelligence, learning, and popularity (Runco and Pritzker 1999). In this paper creativity in design is defined by a set of complementary processes including evaluation by a target population, selection by opinion leaders, and colleague recognition. Innovation is defined by the diffusion of a design solution across a social group (Rogers 1995).

This paper presents an experimental test-bed where qualitative generalisations about the nature of creative behaviour in design can be explored. This framework is based on the Domain-Individual-Field Interaction model (DIFI) (Feldman et al. 1994), which locates creativity outside the individual creator and places it in the interrelations of three main parts of a system: domain, field and individual. The domain consists of the set of solutions, knowledge, techniques, and evaluation criteria shared by the members of a given community. Fields include groups of individuals who share a common domain. The key implication of the DIFI model is that situated in a dynamic environment, creative designers are those who generate 'the right product at the right place and at the right time' where 'rightness' is largely defined by evolving social standards.

2. METHOD OF STUDY

One way to investigate creative design as a social construct 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 hypotheses in relation to the target system.

Multi-agent based simulation of social phenomena is the primary method of inquiry used with these types of systems (Gilbert and Troitzsch 1999). In this paper we define a framework of social agency based on the DIFI model which includes a small number of competing designer agents, large social groups of clients or adopter agents, and a cumulative repository of design solutions or artefacts that represent the design domain as shown in Figure 1.

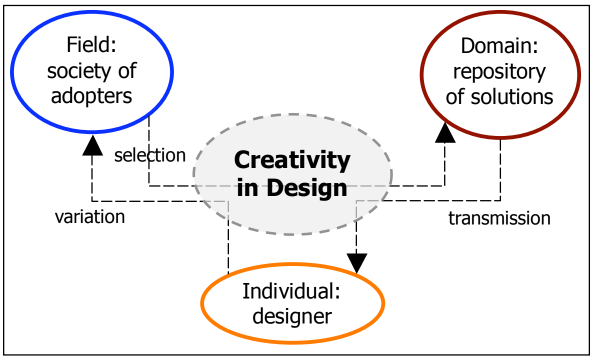

Figure 1 DIFI map: creativity as a system's property

The dominant architecture of rational agency divides agent systems into two explicit parts: agent and environment (Wooldridge 2000). The rational agent is the sole causal determinant of behaviour whilst changes in the environment may reflect the impact of actions by other agents or external effects. Under such view, social interaction is limited to indirect communication via the external state. However, the behaviour of more complex and social individuals is not expected to be hardwired as a reaction to environmental stimuli. For a social agent individual determinants are complemented by direct contact within a social environment.

In our framework social agency implies that decisions to adopt artefacts by members of a social group are not entirely determined internally but are subject to social influence. In other words, adopter agents are socially interdependent (Castelfranchi 2001). As a result, competing designer agents are required to adapt their behaviour to continuous changes triggered by the generation of new solutions and by a continuous process of social influence (Sosa and Gero 2003). In this paper this generative-evaluative interaction is analysed by modifying the characteristics of how adopters communicate and interact over time and observing consistent effects on design behaviour and domain configurations.

To support a social system of adoption, our agent architecture includes a range from individual to social mechanisms. Figure 2 shows a schematic definition of our architecture where agent-environment interaction is mediated by layers that range from individual to collective.

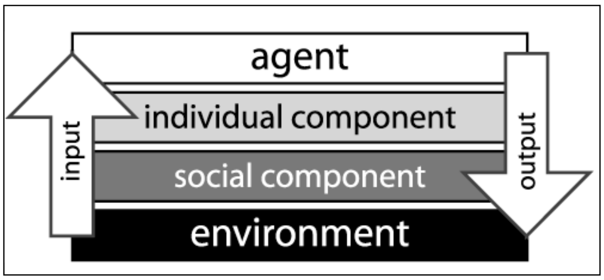

Figure 2 Social agent behaviour determined by a combination of individual and shared components

Agent behaviour (M) in an environment (E) is thus defined as:

$$M = \sum \left\{ m_n \left[S \left(m_n \wedge E' \right) \right] \right\} \qquad (1)$$

where individual behaviour (M) is determined by the sum of internal state components (m_n) and construed situation (S). Internal state components (m_n) include goals, perceptions, preferences, skills, knowledge, and actions. Environment (E) is perceived by a bounded agent as interpreted external state (E'). Situation (S) is in this sense a function of the combination of internal and interpreted external state.

For a social agent a perceived external state may be a measure of group pressure. However, perceived group pressure by itself does not determine individual behaviour inasmuch as it is a passive contextual feature. Perceived group pressure only becomes part of a social situation when construed in combination with a relevant internal state such as a certainty or extroversion threshold to publicly express an opinion (Asch 1955). In this way equivalent group pressure perceived by agents with different internal states may lead to the construction of entirely different situations, eg. compliance or assertiveness. Equivalent contexts may thus generate different behaviours within different situations. When situational factors are strong determinants, agent behaviour is normalised whereas if personal factors (m_n) dominate, behaviour is more differentiated across a population.

A situation can be defined at the individual level and it can also be shared by a group. A shared situation is perceived by a group of agents as a result of the combination of internal states and perceived external state. Extending the previous example, at the individual level a social situation may be one of compliance whilst at the group level it may be one of unanimity. The latter requires, by definition, the aggregate action of a group. These two levels of social situations are corresponding effects of one common contextual structure, i.e., group pressure.

Individual behaviour under this view is defined as a function of the agent and the situation. This approach supports equivalent agents acting differently within different situations, and different agents acting similarly within similar situations. In our system of designers and adopters this implies that given a common design artefact different decisions to adopt are possible from similar members of a social group.

To represent social groups, adopters are defined in a number of social spaces or configurations i.e., they have adjacency relations to other agents in simultaneous social environments. For instance, individuals have different positions in kinship and work structures within a society. Other approaches like cellular automata of social influence tend to conflate physical and social location into a notion of two-dimensional neighbourhoods. Here agents have *n* sets of neighbours in *n* social spaces. Such spaces are modelled with different parameters: social tie strength and number of ties are two structural properties defined and addressed later in this paper.

3. ADOPTION FRAMEWORK

A multi-agent system is implemented to model a population of adopter agents and their social interaction. Adopter behaviour consists of evaluating solutions generated by designers and deciding to adopt or abstain. Solutions are formulated in a simple linear representation as shown in Figure 3(a). This representation is chosen because it illustrates an evaluation function based on intuitive visual geometric features. It also supports multiple interpretations by adopters and shape emergence. The objective is to support some of the key aspects of design problems in multi-objective decision making.

Clients or adopters in this system evaluate artefacts according to individual thresholds of perception and preference. Variation of perception across a population enables different interpretations of artefacts as shown in Figure 3(b). Variation of preferences enables different decisions based on shared interpretations. In other words, differences of perception support adoption decisions based on different interpretations of an artefact whilst differences of preference support adoption decisions based on different evaluations of equivalent interpretations.

The process of perception by adopter agents is implemented by a shape-recognition algorithm executed by every individual adopter with a branch limit called perception (V). Starting from every point in the representation, adopters conduct this search following all possible paths until a number (V) of points is reached. This search produces a set (G) of singular closed shapes of (V) number of sides that stands for the artefact's features as perceived by each adopter. To allow for overlap of perceptions, a threshold (V±2) is defined.

Perception traits (V) are assigned from a Gaussian distribution at initial time. As the process of perceiving artefacts is computationally expensive, it is scheduled at intervals of adoption. We assume that whilst adopters take decisions continuously, they only update their perceptions periodically. This is consistent with evidence that suggests that social agents base their decisions on approximations that they update regularly. The perception of artefacts in our system refers to the idea that in human populations there may be a number of distinct but overlapping views of a design artefact's features, a notion illustrated by market segmentation.

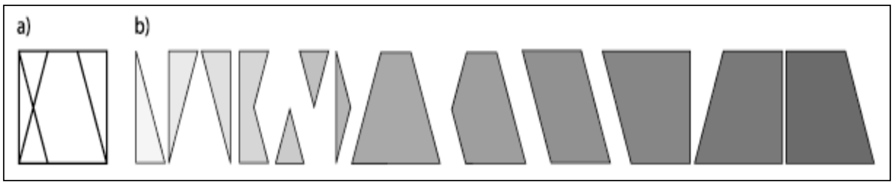

Figure 3 (a) Sample artefact and (b) a range of shapes that adopters may perceive

Variation of percepts across a population is controlled by the standard deviation of the percept distribution. Different studies may consider different percept variance assuming more subjective or more normalised interpretation across a target population.

3.1 Adoption Decision

The adoption decision process consists of a multivariate evaluation function where adopters seek to maximise conflicting geometric objectives. These criteria include number of shapes, shape alignment in horizontal and vertical axes, preferred number of sides, overlapping of shapes, and shape bounds. The evaluation or performance (P) of a design artefact is individually estimated by adopters following:

$$P = \sum_{i,j}^{n} \{g_{i,j}\} \qquad (2)$$

where artefact evaluation is based on an individualised set of geometric relations (g) between pairs of perceived features. These ratings (P) of artefacts under evaluation are compared by each adopter to determine an adoption decision where the criterion (g_{max}) that defines the adoption is defined by the difference between evaluations along that criterion:

$$g_{max} = (P_{max} - P_{mean})(b_i) \qquad (3)$$

where criterion for adoption (g_{max}) refers to the geometric relationship with the largest difference from the mean (P_{max} - P_{mean}) weighted by an individual preference or bias (b_i) between 0.0 and 1.0 assigned to adopters at initial time. This adoption decision process captures novelty preference since adopters tend to choose artefacts that they perceive to have the highest differentiation from the rest. Adoption is therefore a function of how competing artefacts compare at a given time. To be adopted an artefact needs to perform well in a criterion that other artefacts do not meet and it helps if such criterion is positively biased by adopters' preferences.

Preferences (B) evolve over time following a mechanism of habituation where bias (b_i) increases marginally as a function of g_{max}. Namely, as adopters choose artefacts, their preference for the geometric criterion best satisfied by an artefact is gradually increased. This mechanism 'pulls' group preferences towards criteria which artefacts best satisfy. Preferences (B) are defined as the set of biases for each evaluation criteria:

$$B = \sum \{b_{i \ldots n}\} \qquad (4)$$

3.2 Verification

This adoption framework provides a method to manipulate perceptions (V) and preferences (B) for verification purposes. Figure 4 shows a verification run where a set of three random artefacts are 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 that criterion.

As a result of this bias, adopter agents tend to choose the artefact with the highest performance in horizontal alignment, i.e., 83% of the decisions concentrate on the artefact where all perceived shapes are aligned. However, not all adopters converge since perceptions (V) are not homogeneous. 17% of the adoption decisions go to the other two artefacts possibly by adopters with very low or very high perception thresholds (V) that perceive atypical features.

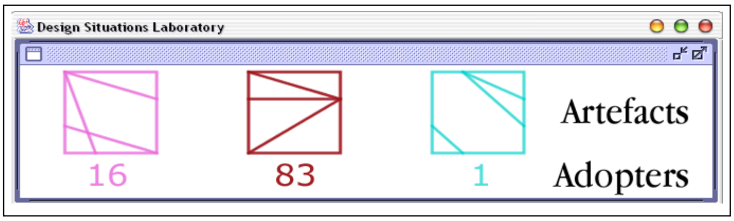

Figure 4 A verification run where most adopters are induced to adopt a particular artefact. The numbers refer to the number of adopters out of 100 adopting that shape.

3.3 Adoption Satisfaction

Adopter satisfaction is computed as a post-adoption coefficient of relative quality since it indicates agreement between adopters' preferences and artefacts' features. In the adoption decision, if the choice criterion (g_{max}) equals the leading preference of an adopter (b_{max}), its satisfaction level is set to a maximum in a scale of three possible values that represents 'very satisfied with the current adoption decision'. Else, if the choice criterion is one standard deviation above the mean of the adopter's preferences (B), then the satisfaction level is set to a medium level or 'satisfied with current adoption decision'. Otherwise, the adoption has been based in a criterion that is of little relevance to the adopter and its satisfaction level is set to a minimum or 'not satisfied with adoption decision'.

Lastly, an adopter may abstain from adoption if no difference is perceived between artefacts, i.e., if P_{i-n} is equal for all artefacts and (g_{max}) = 0.

3.4 Social Interaction

At every iteration step, adopters rely on social interaction to validate their perceptions, spread preferences and in general to conduct their adoption decisions. To this end different social spaces (L) are defined where adopters interact. At initial time, adopter agents are randomly assigned a location on each space. These social spaces have different rules of interaction and development. Two aspects addressed in this paper are social tie strength (T) and neighbourhood size (H).

Ties are normally defined as interaction links between nodes in a social network and represent the relationship between adopter agents (nodes) in a social space (Wasserman and Faust 1994).

Tie strength (T) has been associated to the probability that associated nodes may interact over a period of time (Granovetter 1973). Strong social ties usually exist between nodes in a kinship network, whilst weak ties characterise networks where casual encounters occur between strangers or acquaintances. H is determined by the number of links from a node - also called ego-centred networks (Wasserman and Faust 1994).

In our framework we implement a basic notion of tie strength as a probability $0.0 \leq T \leq 1.0$ that any possible pair of adopter agents will remain in adjacent positions at the next time step. When a social space has a strength $T \approx 0.0$, it supports higher social mobility. This means that adopter agents are shuffled more often and get to interact with different adopters over any given period. In contrast, when strength is $T \approx 1.0$ relations between adopters remain unchanged causing a decrease in social mobility, i.e., adopters interact with the same neighbours for long periods of time.

3.5 Influence Dominance

A social space (L_1) in this framework is set where adopters exchange preferences (B). Within a second social space (L_2) percepts (V) are traded. A third space is set where agents exchange adoption decisions (g_{max}). In all spaces neighbourhood size (H) has a constant initial value of 2 that varies during a system run according to the influence that an adopter exerts on others. More influential adopters have larger neighbourhoods. The strength of social ties (T) is the experimental variable discussed in this paper. With all other conditions kept constant including all random generator seeds, strength (T) is increased from 0.0 to 1.0 in increments of 0.1.

These assumptions can be changed by the experimenter according to the hypothesis under inspection. For instance, the purchase of cars may be shaped by influence interaction in kinship networks whilst that of mobile phones may be strongly influenced by peer networks.

In Figure 5 adopters are represented by rectangles and influence dominance by arrows. Vertical axis plots influence dominance (d) and neighbourhood size increases with dominance. Figure 5 shows an example influence structure where an adopter with high dominance (d) has a large neighbourhood H = 6.

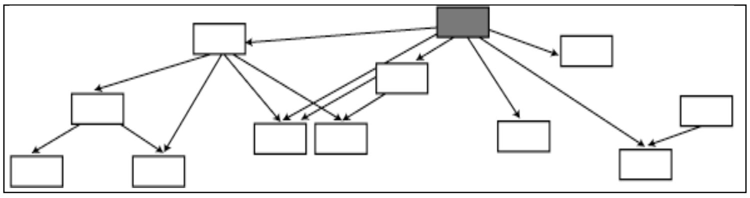

Figure 5 Influence structure in a social space.

The distribution of influence dominance (d) in an adopter population is measured in this framework by the Gini coefficient, which is a summary statistic of inequality. The Gini coefficient γ is used in studies of wealth distribution where limited group resources are 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.

The Gini coefficient ranges from a minimum value of $\gamma = 0.0$, where influence between all individuals is equal, to a theoretical maximum of $\gamma = 1.0$ in a population where one individual concentrates all influence dominance. The Gini index γ is calculated by:

$$\gamma = \frac{\sum_{i,j}^{n} \left| \mathrm{d}_i - \mathrm{d}_j \right|}{2\mathrm{n}^2\mu} \qquad (5)$$

where the average difference of every possible pair of dominance values (d_i - d_j) is divided by two times the average (n) of the mean size (μ) (Dorfman 1979). The larger the coefficient, the higher the degree of dispersion.

At initial time adopter agents are randomly assigned extroversion thresholds (X) in every social space. An adopter agent is assigned different extroversion (X) in different social spaces. Extroversion values are not fixed during a system run but change as a result of exerting influence over other agents.

Exchange between any pair of adopters starts by a comparison of their extroversion thresholds (X). In the social space where preferences (B) are exchanged, the adopter agent with the higher extroversion of the pair influences the less extrovert adopter on the criterion with the highest preference. A negotiation process occurs by which the influenced adopter increases its preference by half the difference between their preferences. However, if the chosen artefact of both adopters is the same and their preferences too similar, the more extrovert adopter changes its own focus of attention by shifting its preference to another criterion. This is a way to implement uniformity-avoidance and novelty-seeking behaviour, i.e. "b_i is an adopter's top preference until it perceives that b_i is commonplace". Within other social spaces different content is exchanged following a similar approach. Influence (I) between adopters *i* and *j* is of the form:

$$I_{i,j} \left| X_i - X_j \right| \Rightarrow B_j = \left(B_i - B_j \right) * 0.5 \qquad (6)$$

where the more extrovert adopter X_i influences less extrovert X_j. Negotiation occurs as the target preference B of agent *j* approaches agent *i* by a ratio of their difference, in this case 0.5. The exchange of percepts (V) and adoption choices (g_{max}) in their corresponding social spaces takes place in the same form.

Whilst the details of this interaction can be fine-tuned to match other assumptions, the key idea is that adopter agents exchange building blocks of their adoption process. This way even if an influential adopter is successful in spreading its preferences and percepts, the adoption decisions of influenced adopters need not converge. Namely, adopters with equal top preferences may still perceive artefacts differently and therefore reach different adoption decisions as demonstrated in Figure 4.

In ergodic systems such as 2-dimensional cellular automata, a population converges from any initial random configuration. In contrast, when exchange occurs in more than one social space, the population may not converge as time → ∞ due to random walks being transient (Sosa and Gero 2003).

3.6 Opinion Leadership and Gatekeeping

As a result of social interaction over time, adopter populations form hierarchical social structures. In this framework these structures are determined by exchanges of preferences, percepts, and adoption decisions. Opinion leaders are adopter agents whose dominance (d) increases as a result of social interaction. At initial time the set of opinion leaders is empty. The role of opinion leader is given to adopters whose dominance is greater than one standard deviation above the mean of group dominance. The role of opinion leaders in this framework is to enable interaction between adopters and designers. Firstly, leaders serve as adoption models providing designers with positive feedback for reinforcement learning. Secondly, they become *gatekeepers* of the field by selecting artefacts for entry into the repository, i.e. a collection of artefacts that defines the material culture of a population (Feldman et al. 1994).

Since the number of opinion leaders is by definition a small ratio of the adopter population, they are more likely to spend more real and computational resources in analysing available artefacts. With an adopter background, leaders follow the standard adoption decision process described above complemented by additional geometric evaluation criteria including rotation, reflection, and uniform scale.

The artefact repository is initialised with an entry threshold $\varepsilon = 0$. During a system run ε is increased supporting a notion of group progress by which the entry bar is raised with every entry. Two possible entry modes are addressed in this paper. Opinion leaders in their role as gatekeepers select artefacts that either increase the population's threshold of entry ε or perform well in different evaluation criteria than existing entries.

The nomination of artefacts by gatekeepers occurs at a control rate specified by the experimenter. Figure 6 shows sample repository entries as selected based on their geometric relationships. Geometric relationships can be recognised within these artefact shapes including scale, rotation, and symmetry. Entry threshold ε to repositories has a decay mechanism (α) of the form:

$$\alpha = \varepsilon - (0.05\varepsilon) \qquad (7)$$

where ε decays marginally over time when gatekeepers fail to nominate qualified entries above ε.

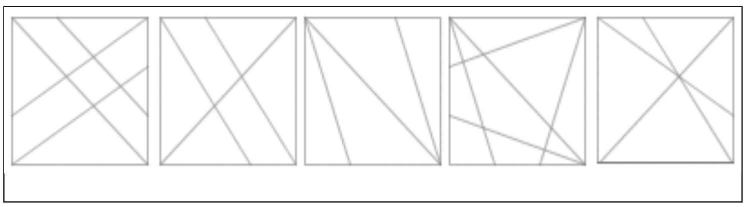

Figure 6 Sample entries to the repository.

Adopters and opinion leaders provide the first elements for our definition of creativity. In this framework a creative design must be firstly recognised and adopted by a population. Cumulative adoption of artefacts addresses a notion of popularity (Simonton 2000). It must also be selected by gatekeepers, i.e. experts representative of their social group (Amabile and Hennessey 1999). This selection is based on rules of entry that evolve as artefacts and societies change. Critics' choice addresses the idea that creativity is judged by relevant arbiters (Gardner 1993). Lastly, adoption categories enable classification on the basis of when in the diffusion process adopters choose an artefact (Rogers 1995).

4. DESIGN BEHAVIOUR

The size of a group of designer agents is determined by the experimenter as a ratio of the adopter population. At initial time artefacts are configured and assigned to each designer. Designer agents are given a set of standard constraints to which their artefacts must comply. Designers' knowledge and adopter bases, recognition levels, and repository entries are all set to zero at the beginning of a system run. Knowledge base refers to domain rules that designer agents generate and apply during a simulation. Adopter base is defined by cumulative adoption. Recognition is given by peer designers that imitate features of an existing solution.

The role of designer agents is to generate and present their artefacts for assessment by adopters and gatekeepers, if any. The details of the design task are determined by the adopter group decisions and the ability of competing designers to generate solutions. The goal of designers in this system is to consistently generate artefacts that are chosen by adopters, are selected by critics, and are imitated by peers.

In this framework design update and adoption rates are assumed to be periodic. Design takes place in these experiments at constant intervals during which adopters execute their decisions and interact socially. Variations of these assumptions are required to model different product markets and industries, requiring particular experimentation scenarios.

Designers may engage in different types of behaviour depending on a number of internal and external factors. Contingent design strategies can be seen as the product of the confluence of these conditions. The term *strategy* is used as adaptation of behaviour that appears to serve a function in achieving the goal of generating artefacts that are adopted, short-listed and influential. As determined by a strategy, design behaviour seeks to increment adopters' satisfaction levels and extend adopter base by capitalising on relative superiority (competition) or by maximising differences to other artefacts (differentiation).

Designer agents seek a type of contingent strategy where they learn a *design rule*, i.e. an instance of domain knowledge tied to the artefact representation. In this case condition → action rules are made by artefact feature → target criterion. Rules are generated based on the designer's model of the population's adoption process construed by retrieving preferences and choices of opinion leaders. This is a way to implement positive feedback since otherwise a designer would not have access to target criteria and target perception, i.e. an opinion leader may be an adopter of a competing artefact or may be abstaining from adopting. A designer can emulate the collective decision process by generating hypotheses of possible alternative artefacts.

Designers formulate hypotheses by evaluating and changing the configuration of their artefacts in order to improve performance along the modelled adoption criteria retrieved from opinion leaders. Namely, designers sort the lines of their artefacts according to their contribution to the formation of perceived shapes. Designers are able to delete or generate new lines as a function of adopter perception (V). Hypotheses consist of rules to change a current artefact. Features that do not contribute to good performance are replaced based on these hypotheses. They are then evaluated following the multi-criteria adoption function of equations 2 and 3 above.

A design rule λ consists of artefact changes that increase its performance along a target criterion.

$$\lambda = \left(g_h \rightarrow \Delta P\right) \qquad (8)$$

where a hypothesised feature (g_h) results in an increment of artefact performance (P). A positive value of Δ stands for the improvement ratio of λ.

Individual differences between competing designers are addressed as differences in processing and synthetic abilities assigned at initial time. Processing refers to the capacity of designers to generate and retrieve domain rules, whilst synthesis controls the number of hypotheses that designers can generate before having to transform their artefacts. In this paper designers are assigned constant abilities at initial time. However, abilities gradually increase as a function of design behaviour. This enables experimentation with the impact of individual factors on creativity, which is beyond the scope of this paper.

If during the design of a new artefact a designer is not able to generate new domain knowledge, it seeks a strategy to apply existing design rules λ. Here two assumptions can be explored: domain knowledge may have private or public access. If private, every designer agent only has access to their own rules, whilst in public mode all designers have access to all existing rules. In this paper public access is constant across all experiments. Existing knowledge is applied by:

$$\text{Apply}: \lambda \rightarrow \Delta P(g) \qquad (9)$$

where an existing rule λ that improves performance (P) in a target criterion (g) is applied to an artefact.

If a designer is not able to generate or apply relevant knowledge, the last option is to imitate other designers. Imitation is the simplest form of collective learning, i.e., blind learning since information about features, criteria, and perception is missing. Imitation is defined here as the transfer of random artefact features.

Designers whose artefacts have low adoption rates imitate artefacts with higher rates. This is acknowledged by a mechanism where peer recognition is given to the designer of the source artefact. Recognition from colleagues indicates the influence of a designer and further extends its processing and synthetic abilities.

Designers may address the perceived group's choice criterion or they may determine an alternative target criterion. This choice is a function of perceived adopter preferences (B') and estimated artefact performance (P'). If a designer considers that its artefact's performance is competitive (defined as equal or above mean adopter preference) capitalisation is chosen and design rules are built or applied to improve performance on the choice criterion (exploit relative superiority). If estimated performance is instead low on perceived adopter preferences then designers seek to differentiate their artefacts in a highly competitive industry by selecting their best performing criterion. Strategies of competition and differentiation are defined as:

$$\text{Competition}: P' \geq B'_{mean} \qquad (10)$$

$$\text{Differentiation}: P' < B'_{mean} \qquad (11)$$

where P' and B' are performance and preferences as estimated by the designer agent.

Designer agents in this system are not equipped with creative abilities per se. The aim is not to introduce special traits to assess the effects of agents' creativeness as defined by the experimenter. Instead, all designers are given equivalent sets of mechanisms. No extraordinary process within the individual is hardwired but in time agent interaction renders a social self-organised construct of how a designer may exhibit behaviour considered creative within its society.

The last mechanism addressed in this paper is a measure of difference between artefacts as perceived by adopters. Strategic Differentiation Index (SDI) is an index estimated collectively by adopters that reflects the perceived differentiation across the available artefacts (Nattermann 2000). With a design system initialised in a converged state, SDI = 0.0. As designers seek to generate artefacts that differ from other available artefacts SDI > 0.

$$\text{SDI} = \sum_{i \ldots n} \left(g_{var} \right) \qquad (12)$$

where SDI is the mean performance variance for all evaluation criteria as estimated by every adopter agent in the population.

These mechanisms of our framework encapsulate in a simple way some of the characteristics of design problems including ill-structuredness and interpretation; incremental solutions; hypothesis generation; nomological constraints; no right or wrong answers; and delayed feedback (Goel 1994).

Design behaviour complements our definition of creativity. Adoption rate is a trend measure used to determine what designer is imitated at a particular time step. 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 2000), learning and experience (Runco and Pritzker 1999). The number of hypotheses generated resembles idea productivity. The number of entries selected by gatekeepers gives a measure of a designer's contribution to the repository or domain (Feldman et al. 1994).

Experimentation with this framework consists of exploring the effects that the described individual and situational factors have on determining the creativity of designers. A designer is considered creative by its social group in this framework when its artefacts reach large adopter groups, its artefacts are entered into the repository, other designers imitate its artefacts, it transforms the design space by formulating knowledge, and its adopters have high satisfaction levels.

The framework has been implemented in a system built in Java 1.4.2 using the following libraries: Colt 1.3 (Hoschek 2002) for array operators and random number generators, Jxl (Khan 2004) for output data management and JGraph (Alder 2004) for visualisation.

5. EXPERIMENT: SOCIAL TIES

This experiment addresses the role of social ties in the formation of influence structures and the associated effects on design behaviour. Tie strength (T) is implemented as the frequency of contact between adopters (Marsden and Campbell 1984). A series of simulations are run where the initial configuration of adopters and designers is kept constant and the strength of social ties (T) is the experimental variable. Monte Carlo runs are conducted to explore the range $0.0 \leq T \leq 1.0$ over 7500 iterations in populations of 100 agents. This explores the range where agents remain in their social location at all times to where agents change locations at all times, respectively.

In social networks with weak ties ($T \approx 0$) 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 ($T \approx 1$) adopters are bound causing a decrease in social mobility, i.e., adopter agents interact within the same groups for longer periods.

Preliminary runs showed that dependent variables stabilise between 2500 and 5000 iterations. The resulting dataset is then filtered in order to exclude outliers defined here as 1.5 standard deviations from the mean. All the following results represent means of 30 simulation runs. Each simulation run is initialised in a converged state to avoid biases in the form of random initial artefact configurations.

Therefore at iteration step 0, adopters perceive no differentiation between artefacts and all abstain from adopting. It is only after designers first modify their artefacts that adoption commences.

5.1. Dominance Hierarchies

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 ≈ 1) a few opinion leaders become dominant (higher Gini coefficient γ). In contrast, as social ties become weaker (T ≈ 0) social mobility increases and agents have contact within a varying neighbourhood causing influence structures of dominance to be more distributed (lower γ). Figure 7 shows a scatter plot on a logarithmic scale of the relation of tie strength (T) and Gini coefficient (γ) with fitness = 0.927. Whilst cases with very strong social ties yield a high Gini coefficient, in most cases it is comparatively low. It is particularly interesting to obtain an exponential distribution by linear increments of an experimental variable. These types of patterns are prevalent in biological and social phenomena.

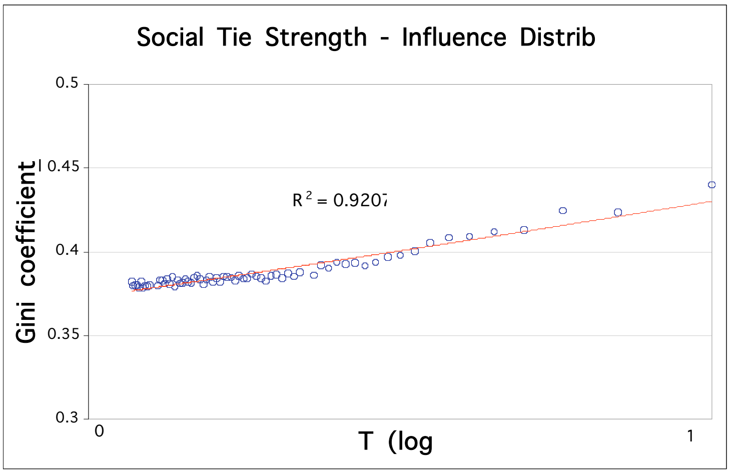

Figure 7 Exponential function for tie strength (T) and Gini coefficient (γ)

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 such groups 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 these groups.

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. Figures in following sections plot only the ends ($T = 0$) and ($T = 1$) since most (T) values yield similar results similar until ($T \approx 1$) at which point effects vary significantly.

5.2. Gatekeeping Effects

At the domain level, the formation of dominance structures shows unexpected effects: 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 8, (Pearson = 0.6706 $N = 30$ $p = 0.001$).

In societies with weak social ties ($T \approx 0$) a mean of 97 artefacts with a standard deviation of 43.4 are selected by gatekeepers, whereas in societies with strong social ties ($T \approx 1$) 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, evaluation criteria remain constant over time. As a consequence repositories tend to be smaller. In contrast, in societies with lower tie strength 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.

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.

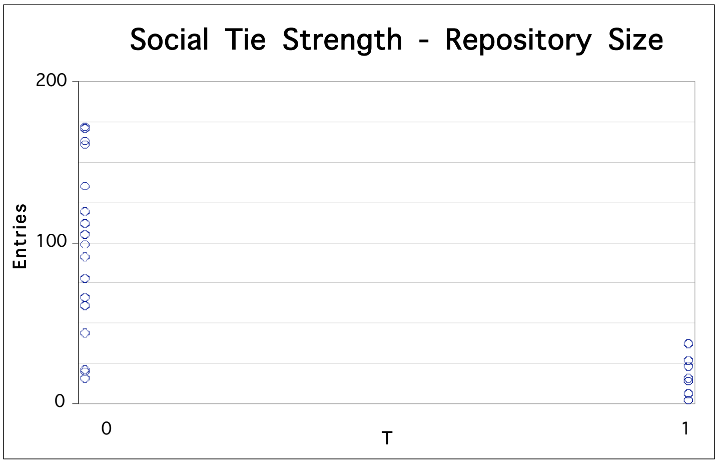

Figure 8 Social spaces with high tie strengths tend to produce smaller repositories.

5.3. Differentiation Effects

The differentiation of design artefacts is measured by the strategic differentiation index (SDI) as an aggregate measure of differences perceived by adopters. These experiments show that SDI is inversely correlated with the strength of social ties (T) as seen in Figure 9. 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).

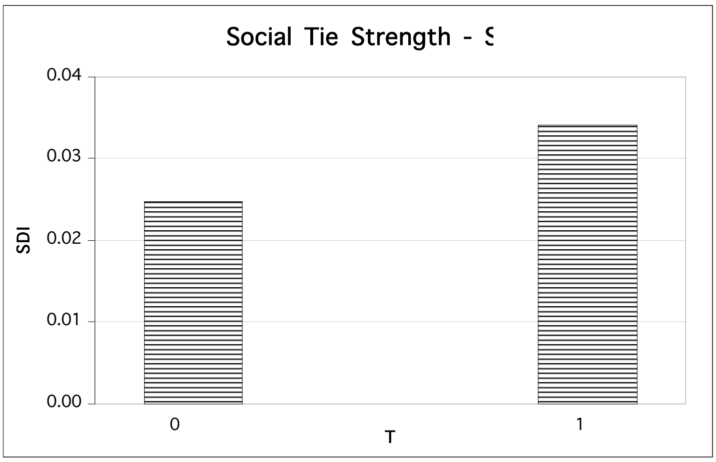

Figure 9 Effects of social tie strength (T) in SDI.

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.

5.4. Prominence Effects

Lastly, effects on the size and nature of adopter groups are addressed. Results show that tie strength (T) is positively correlated with adopter group size (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 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.

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 10 (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, strong ties (T ≈ 1) increase total adoption and concentration of choices around a few designers.

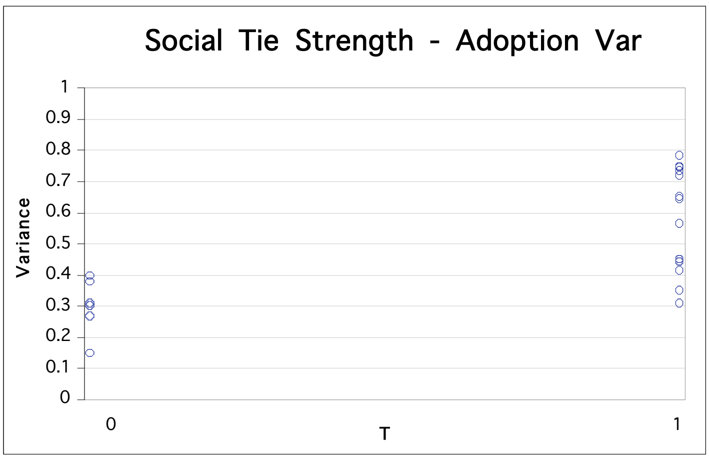

Figure 10 Strong ties (T ≈ 1.0) produce higher variation between adopter groups' sizes.

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. When within a society with weak links ($T \approx 0$) 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 ($T \approx 1$) one should expect higher and more consistent popularity levels and a higher concentration of prominence, i.e., a few designers concentrating most adoption choices.

5.5. Summary

According to the shape of the relationship between tie strength (T) and influence distribution (γ), 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.

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.

5.6. Extensions

The main aspects of this experiment have been replicated in order to demonstrate this framework's validity beyond any specific implementation. This replication makes use of the social net library in RePast (Collier 2004), a multi-agent simulation toolkit for Java.

A social network in this system can be defined by circular configurations of nodes connected by directional links. This makes possible to dispense with the extroversion threshold in the mechanism of social influence between adopters as defined above in Eq. 6 since with one-directional link source nodes always exert influence over destination nodes.

An additional parameter is defined in this replication defined by link density ($0.0 \leq \text{density} \leq 1.0$) that determines the ratio of connections between nodes in the social net. Figure 11 depicts a social net of 25 agents and density = 0.5.

The behaviour of these agents is analogous to the adopter agents described in this paper. At every iteration step source nodes exert influence over those nodes to which they are linked. Links are replaced as a function of tie or link strength (T).

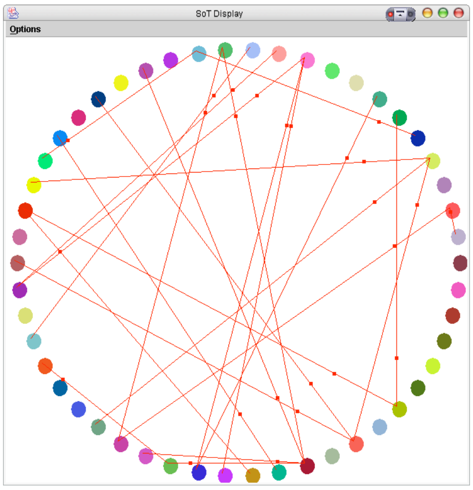

Figure 11 Replication using social nets. Marker represents link directionality between nodes.

Results are consistent with those shown in Figure 7: as soon as members of the evaluating group have low degrees of contact with a varying group, dominance rapidly decreases. Thus, social situations where the decisions of a few opinion leaders have large consequences in the creators' patterns may be unlikely.

6. DISCUSSION

The experiments presented in this paper demonstrate one way in which creativity transcends the individual domain. 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 an 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). Patterns of creative figures show that characteristics external to the individual may indeed determine who and how is considered creative in a society. Graham, Einstein, Picasso and Freud have been characterised as extraordinary creators. Whilst their personality traits and abilities have little in common (Gardner 1994), similarities exist between the structures of the fields within which they operated. Namely, a few powerful critics rendered influential judgements about the quality of their work (Feldman et al. 1994).

As demonstrated in this paper, 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.

These experiments illustrate a fundamental idea about the nature of creativity and innovation, i.e., that a situational factor that regulates the way in which adopters interact may have a significant effect on how both designers and social groups operate. There is an alternative interpretation of the relation between authority and creativity. 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.

The key implication is that by observing the performance of designers in isolation it is not possible to put forward conclusions about their individual characteristics. Instead, the cause of behaviour could be a situational factor that defines not the designers but their evaluators. In this paper a social framework for the study of creativity and innovation in design has been introduced and used to experiment with a situational factor of creativity in design. Factors that regulate aggregate behaviour of a population of adopters are shown to affect the way designers operate and their impact as change agents of their societies.

A corollary of these types of studies is that the understanding of creativity will require the extension of the unit of study outside the cognitive realm of the design process and into the social-psychology of design. Computational creativity has a fundamental role in supporting experimentation of socio-cognitive interactions. The concept of situations seems an adequate unit of analysis to model the link between design cognition and social change. A creative situation (i.e. one within which designers with different characteristics are likely to trigger a social change) could be typified in design to complement the dominance of studies that focus on the creative personality.

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REFERENCES

Alder, G. (2004). *JGraph, Open Source Java Graph Visualization*, http://www.jgraph.com accessed on 09/2004.

Amabile, T. and Hennessey, B.A. (1999). Consensual assessment, MA Runco and SR Pritzer (eds.), *Encyclopedia of Creativity*, Academic Press, San Diego, pp. 347-360.

Asch, S.E. (1955). Opinions and social pressure, *Scientific American*, **193**(5), 31-35.

Boden, M.A. (1994). *Dimensions of Creativity*, MIT Press, Cambridge.

Castelfranchi, C. (2001). The theory of social functions: challenges for computational social science and multi-agent learning, *Cognitive Systems Research*, **2**(1), 5-38.

Collier, N. (2004). *Repast: An Agent Based Modelling Toolkit for Java*, http://repast.sourceforge.net accessed on 08/2004.

Dorfman, R. (1979). Formula for Gini coefficient, *Review of Economics Statistics*, **61**(2), 146-149.

Feldman, D.H., Csikszentmihalyi, M. and Gardner, H. (1994). *Changing the World: A Framework for the Study of Creativity*, Praeger, Westport.

Gardner, H. (1993). *Creating Minds: an Anatomy of Creativity seen through the Lives of Freud, Einstein, Picasso, Stravinsky, Eliot, Graham, and Gandhi*, BasicBooks, New York.

Gardner, H. (1994). The creators' patterns, DH Feldman, M Csikszentmihalyi and H Gardner (eds.), *Changing the World, a Framework for the Study of Creativity*, Praeger, Westport, pp. 69-85.

Gero, J.S. (2000). Computational models of innovative and creative design processes, *Technological Forecasting and Social Change*, **64**(2-3), 183-196.

Gilbert, G.N. and Troitzsch, K.G. (1999). *Simulation for the Social Scientist*, Open University Press, Buckingham.

Goel, V. (1994). A comparison of design and nondesign problem spaces, *Artificial Intelligence in Engineering*, **9**(1), 53-72.

Granovetter, M. (1973). The strength of weak ties, *American Journal of Sociology*, **78**(6), 1360-1380.

Hoschek, W. (2002). *The Colt 1.0.3 Distribution: Open Source Libraries for High Performance Scientific and Technical Computing in Java*, http://cern.ch/hoschek/colt accessed on 08/2004.

Howe, M.J.A., Davidson, J.W. and Sloboda, J.A. (1999). Innate traits: reality or myth?, SJ Ceci and WM Williams (eds.), *The Nature-Nurture Debate, The Essential Readings*, Blackwell, Malden, pp. 258-289.

Khan, A. (2004). *JExcel: A Java library for reading/writing Excel*, http://jexcelapi.sourceforge.net accessed on 08/2004.

Marsden, P.V. and Campbell, K. (1984). Measuring tie strength, *Social Forces*, **63**(2), 482-501.

Nattermann, P.M. (2000). Best practice does not equal best strategy, *The McKinsey Quarterly*, **2000**(2), 38-45.

Rogers, E.M. (1995). *Diffusion of Innovations*, Free Press, New York.

Rudowicz, E. (2003). Creativity and culture: a two way interaction, *Scandinavian Journal of Educational Research*, **47**(3), 273-290.

Runco, M.A. and Pritzker, S. (1999). *Encyclopedia of Creativity*, Academic Press, San Diego.

Simonton, K. (2000). Creativity, *American Psychologist*, **55**(1), 151-172.

Sosa, R. and Gero, J.S. (2003). Social change: Exploring design influence, D Hales, B Edmonds, E Norling and J Rouchier (eds.), *Multi-Agent-Based Simulation III*, Springer, pp. 106-119.

Sternberg, R.J. (1999). *Handbook of Creativity*, Cambridge University Press, Cambridge.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*, Cambridge University Press, New York.

Wooldridge, M.J. (2000). *Reasoning about Rational Agents*, MIT Press, Cambridge.

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