How Different Models of Value Change Affect Emergent Patterns in Design Practice: Agent Based Simulations

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Abstract This paper reports on a computer simulation based approach to studying longitudinal patterns in social emergence of design practice. Design practice is an emergent and not a well-understood social phenomenon, especially in terms of understanding how values associated with different design disciplines influence their design practice. A society of agents, called design agents, representing designers with different design backgrounds, interact with each other and with the concepts associated with different disciplines. The design agents within each discipline are modelled to be attracted towards concepts, knowledge mode, as well towards the other design agents, knower mode. The force of attraction towards the knower or concepts varies between disciplines. A bottom up simulation approach is used to study how different models of value change affect emergent patterns of behaviour. The findings from these simulations have implications for how we can use computation models to study complex social behaviour in design societies.

Keywords Design practice · Legitimation code · Design values · Agent based simulation

1 Introduction

Design societies and communities, like societies in general, can be described and discussed in terms of their values and practices. In design societies, the underlying design values typically guide design practice, as well as determining what is

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considered as good design and what designers aspire to. The differences in design values across different design disciplines are reflected in the academic literature as well the wider public discourse within each of these disciplinary communities. For example, in engineering design the established value assessment approaches emphasize behavioral characteristics of the designed artefact such as performance, reliability and robustness. These assessments are typically disassociated or distanced from the designer. In contrast, in disciplines such as fashion design and architecture, the value assessment often puts considerable emphasis on aspects such as individual expressions or uniqueness that are considered as much a critic of the designer as that of the designed artefact, leading to comparatively greater pull towards the values associated with iconic designers or designs.

In order to better understand and manage design practices in any community, it is important to better understand the dependencies between design values and design practice. However, changes in design values and design practice occur gradually over an extended period of time, which means data over longitudinal periods is needed to observe these changes and the mutual dependencies between design values and the design practice. Observing such trends is data and resource intensive, and often extremely challenging in terms of obtaining sufficient data within the span of a single research project. Nonetheless, the study is important and critical, because many decisions about managing and improving design practices are often based on our limited understanding of the relationships between design values and design practice. For example, recently there has been a greater push for creating multi-disciplinary design societies, which among other benefits, are expected to facilitate exchange and sharing of design values across different disciplines, in the belief that shared values will enrich design practice. It is often not clear which design values we expect to be exchanged or shared through these multidisciplinary societies, and we do not have an adequate understanding of the long-term implications of these expected exchanges of values. Typically the effects of such multidisciplinary design environments are studied through short-term projects, with significant challenges in avoiding noise around the research variables and parameters. While such empirical studies provide useful insights into differences across disciplinary silos and multi-disciplinary environments, the short duration of these studies and experiments provides little opportunity to study long-term patterns.

The research reported in this paper focuses on the longitudinal patterns of changes in design practices resulting from the changes in design values in a multi-disciplinary design environment. This ‘what-if’ study focuses on trying to understand the global trends that are likely to emerge as a result of changes in design values over time at individual levels, rather than on the mechanisms of value change at the individual level. Agent-based simulations are used to carry out a longitudinal study. A computational model is created to simulate a society of designers, who interact with each other and the design concepts utilizing the value systems of their respective design disciplines. The design values and concepts are defined at an abstract level such that the simulation results need to be interpreted in a context that can be broadly approximated to these abstractions. These abstractions are based on our current understanding of the relative design values across the three exemplary societies of fashion design, architecture and engineering, studied through the lens of legitimation code theory [1, 2]. For example, based on Carvalho et al. [2], it is assumed that fashion designers have a greater attraction towards leading designers (knowers), compared to engineering designers, who have a greater attraction towards design concepts (knowledge) than towards the leading engineering designers. Assumptions such as the force of attraction become the key parameters of the computational model, which are then varied across different simulation cases. This paper describes this simulation model, the conceptual basis guiding the underlying assumptions in the model, and preliminary results from the different scenarios studied by varying some of these parameters.

2 Background

The simulations are built on an existing computational model developed and previously reported in Singh and Gero [3, 4]. Legitimation code theory (LCT) [1, 2] is adopted as the underlying framework to model the relationships between design values and design practice. A brief background to LCT and use of computational models in social simulations is provided.

2.1 LCT, Design Values and Social Influence

Legitimation describes what is acceptable or normative in a society, typically viewed as some form of unwritten 'rules of the game' [5]. LCT provides the theoretical basis to explain how unwritten rules of normative practice emerge in and guide a knowledge society. Carvalho [6] and Carvalho et al. [2] use LCT to explain how design practice and recognition within a social group are driven through both knowledge and knower modes [7], i.e., the design practices emerge and evolve under the influence of the social structure as well as the knowledge structure. For example, in engineering disciplines design values are mostly associated with the knowledge structure, whereas in fashion design and architecture, design values are equally linked to social structure so that design values are also influenced by knowers and their design values.

2.2 Agent Based Models and Social Simulations

Computational social simulations are an established method to test and generate socially-related hypotheses [8, 9]. These simulations aim to provide a complementary research method and infrastructure that can reduce the time, cost and resource requirements when generating and testing promising theories, especially in scenarios that require longitudinal studies.

3 Description of the Simulation Model and the Experiment Design

Building on Carvalho et al. [2], a society of design agents with different design backgrounds is modelled such that all design agents are attracted towards concepts, i.e., knowledge mode, as well towards the other design agents, i.e., knower mode, which influences their design values. The force of attraction towards the knower or concepts varies across disciplines. The emergent design practice is shown through a plot in a two dimensional space defined by the social and knowledge axes. Design agents higher up the social axis exert higher knower force while the concepts higher up the knowledge axis exert higher knowledge force.

The computational model is implemented in MASON [10], a java based multi-agent system. Following Carvalho [6], the three disciplinary backgrounds considered are architecture, fashion design and engineering. The key assumptions in the model, already described in previous papers [3, 4], are reiterated briefly in Table 1.

The social influence exerted on any agent (A^i) by another agent is described in Table 1. This influence is a function of the distance between them, and their InfluenceRadius, which defines how socially influential they are. Similarly, agents are also attracted towards concepts (C^i), which have an InfluenceRadius. Agents are attracted towards other agents who are higher in their social dimension, and pushed upward with relatively lesser force by agents that are behind them along the social dimension. Similarly, agents are attracted towards concepts that are higher than they are along the knowledge axis. A disciplinary factor, constant K, is used to account for the relative knowledge and knower pulls across the different disciplines. As an initial assumption K is set to be one order different between fashion design and architecture and between architecture and engineering.

Additional assumptions made in these simulations about the change in values are listed in Table 2.

The gap (G) between two agents is the distance along their social axis (agents' position being A^i_x). G is positive if the other agent has a higher position along the

Table 1 Key assumptions in the simulation model

Aspects to model	Assumed relationships	Assumed values
Knower mode Agent (A^1) − agent (A^2) attraction	$K \times$ (InfluenceRadius $A^1 \times$ InfluenceRadius A^2)/(sq. of social distance between A^1 and A^2)	For design agents IF discipline is architecture $K = 100$; IF fashion $K = 1$; IF engineering $K = 1{,}000$
Knowledge mode Agent (A^1) − concept (C^1) attraction	$K \times$ (InfluenceRadius $A^1 \times$ InfluenceRadius C^1)/(sq. of distance $A^1 - C^1$)	For design agents IF discipline is: architecture $K = 100$; IF fashion $K = 1$; IF engineering $K = 1{,}000$
Growth of concepts Concept (C^1) − concept (C^2) attraction	$K \times$ (InfluenceRadius $C^1 \times$ InfluenceRadius C^2)/(sq. of distance $C^1 - C^2$)	IF C^1 and C^2 belong to same discipline $K = 100$ ELSE $K = 1$

Table 2 Assumptions in the simulation model for studying the role of design values

Aspects to model	Assumed relationships	Assumed values
A status gap G is required for agent A^1 to influence agent A^2 $G = A_x^2 - A_x^1$, i.e., gap in Social positions of $A^1\left(A_x^1\right)$ and $A^2\left(A_x^2\right)$	G has to be greater than the minimum influence threshold T^i such that $G > T^i \times A_x^1$	T^i is the first simulation parameter varied across different cases
Disciplinary influence is mediated by value change. A coefficient of Value Change V^c is introduced. Each agents V^c at any given time is measured across three dimensions V^{cA} (architecture), V^{cE} (Engineering), and V^{cF} (fashion)	Value change ${}^1V^c$ of A^1 while interacting with A^2 (with value change ${}^2V^c$) is $V^c = W_A \times^1 V^{cA} \times^1 V^{cA} + W_E \times^1 V^{cE} \times^1 V^{cE} + W_F \times^1 V^{cF} \times^1 V^{cF}$ where W_A, W_E and W_F are disciplinary weight distribution such that $W_A + W_E + W_F = 1$	Weight distribution, i.e., $W_O{:}W_S{:}W_T$ ratio is the second simulation parameter varied across different cases

Number of interactions between A^1 and A^2 also determines V^c. This factor follows a bell curve. As interactions increase the influence increases exponentially followed by an exponential decay social axis, such that an agent is likely to be influenced by and attracted towards the other agent. However, it is assumed that there needs to be a minimum gap threshold (T^i) between the two agents for an agent to be attractive to the other. For example, if T^i is assumed to be 1.2 in a given simulation, then for an agent at position 100 units along the social axis, the other agent must at least be at the position 120+ units to be attractive and influential for the first agent. Threshold is taken as a parameter to understand how perceived status gaps and thresholds may influence the emergent social patterns.

In addition, a coefficient of value change (V^c) is introduced such that an agent's value change is the weighted average of its values associated with each of the three disciplines (Architecture-V^{cA}, Fashion-V^{cF}, Engineering-V^{cE}). This assumption is conceptually critical, because if we assume that in a multi-disciplinary society agents are likely to be influenced by the design values across the other disciplines, we are implicitly assuming that they have some intrinsic recognition and understanding of the values of the other disciplines. How much weight the agents give to the design values across the other disciplines may vary. Accordingly, the value change coefficient for an agent is assumed to be the weighted mean of the value change coefficients across the three disciplines (own discipline—W_O: second discipline—W_S: third discipline—W_T). For an architecture agent $W_O = W_A$, for engineering agent $W_O = W_E$, and for a fashion design agent $W_O = W_F$. This weight distribution ratio is taken as the second the parameter, whose influence will be studied to determine how design values emerge in a multi-disciplinary society as a function of interdisciplinary and intradisciplinary sensitivity.

In summary, it is assumed that as design agents interact with each other, they exert influence on each other, which has the potential to change their design values. The likelihood for the change to occur is contingent on how influential the interacting agents are, what is the status difference between the interacting agents, and how much contributions these influences have on a design agent's change in value. The emergent design practice including the knowledge and social dimensions of the design agents and concepts are presented graphically. For simulation cases where the agents' values change during the simulations, the forces of influence change over time.

3.1 Experiment Design and Simulation Scenarios

The simulation model and the parameters listed in Table 2 are used to conduct what-if comparisons across two different simulation scenarios, Table 3. The first set of simulations is conducted to assess the effects of T^i, the threshold status gap needed for agents to influence each other. Three different values for T^i are used, which are 1.2, 1.8 and 2.4. These values are used to conduct comparisons, with the expectation that observable effects of the threshold T^i can be found to understand its role in convergence of design values. Conceptually this parameter compares scenarios where design agents of similar social status influence each other's

Table 3 Research questions, simulation matrix and scenarios

Research questions (what if studies)	Comparative simulation scenarios
Q1: If the status difference determines the change in design values, what is its effect on the emergent design practice?	With three different values of T^i
Q2: How does the design practice vary as a function of the relative contributions of social influence?	With two weight distributions i.e., W_O:W_S:W_T ratio

design values to those scenarios where design agents only change their design values looking up to design agents who are much higher than they are in their social status.

The second set of simulations is conducted to assess the effects of the weight distribution ratio, W_O:W_S:W_T, Table 2. Two different values for W_O:W_S:W_T are used, which are 0.50:0.25:0.25 and 0.8:0.1:0.1. Conceptually, in the first case the agents are more receptive to design values of agents from other disciplines than in the second case.

At the commencement of the simulation, i.e., at $t = 0$, all the design agents and concepts in the simulation environment start with a pre-defined position on the two dimensional space, defined by their social and knowledge axes.

4 Simulation Results

A summary of the results from these simulation cases is presented in Fig. 1. For each case the results are based on an average of 50 simulations. Each graph in Fig. 1 presents time series plots of agents' movements along the social axis, averaged over all agents from the same discipline. For example, graph A, presents the results from a simulation case where the parameter values are W_O:W_S:$W_T = 0.50$:0.25:0.25 and $T^i = 1.2$.

In all the simulations agents from each discipline showed bimodal behaviour, such that a majority of agents could be aggregated together into one trend while a minority aggregated to show a different trend in their movement along the social axis. Treating all agents as a single aggregation resulted in a high standard deviation in their behaviour, which was reduced when the agents were divided into two groupings. For each simulation case the results are split and plotted as two graphs, as shown in the label using the mode values, indicated either as M (majority) or NM (non-majority). For example, graphs **A** and **A′** correspond to the same simulation case, but A shows the trend observed with majority mode while **A′** shows the trends observed with the non-majority of the agents from each discipline.

The graphs show a power-like trend-line that approximates the observed patterns. The different starting points of the regression lines is an artifact of their calculation, even though all the simulations have the same starting condition, and with nearly all agents are close to each other at the start of the simulation, i.e., at time $t = 0$.

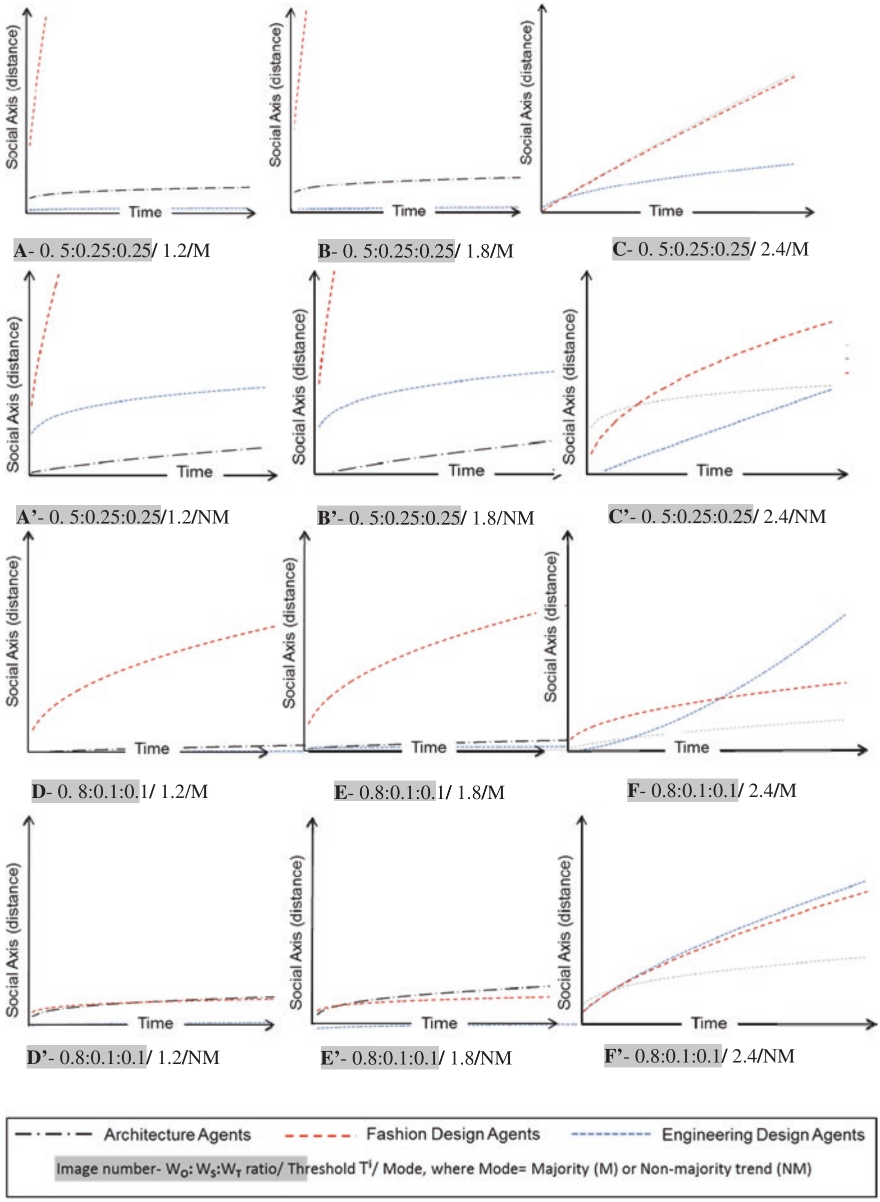

Fig. 1 Average movement of agents along the social axis across different cases

The consistent bimodal trend (comparing any graph X with its counterpart X′) in almost all the cases was an unexpected finding as it was anticipated that typically the differences across the cases would be the slope of the graphs and not necessarily their order. It was expected because of the underlying force assumptions that the graphs corresponding to the fashion agents would have the greatest slope, followed by architecture agents and then the engineering agents. This can be observed in graph **A**. In many cases this expected trend was not observed. A plausible reason for this unexpected result could be the starting positions of the agents at time t = 0. Each agent's starting position was randomly chosen within limits, but once the starting positions were chosen for the first simulation, the positions were retained in all the simulations. Therefore, many of the agents may have been too close to each other (i.e. less than the threshold T^i) in their social dimension, and hence, the social influence was not experienced by them. Even though the initial positions of the agents were not considered as a simulation parameter, it may have been a critical factor in determining the emergent trend.

The effects of gap threshold, T^i (Question Q1, Table 3), can be compared across each row by comparing the trends in A, B and C, with T^i values as 1.2, 1.8 and 2.4 respectively. At lower gap thresholds (Cases A and B), this is where agents are also influenced by their comparable peers, the results are more consistent with the expected order of social growth. When the gap thresholds are much higher (Case C), the convergence is slightly higher, i.e., the slopes are relatively closer than the first two cases. This is likely because of the fact that only fewer agents are able to exert attraction forces on the other agents such that the knower effects are lesser on fashion design and architecture agents, bringing their social growth closer to the engineering agents. This explanation is partly supported by the observed trends in cases D, E and F as well, where the social growth order is skewed towards engineering agents compared to the architecture agents when the gap thresholds are increased. The results also indicate that in the initial starting conditions, there may have been more engineering agents at farther distance to begin with, and hence, when the interdisciplinary exchange (Case F with ratio 0.8:0.1:0.1) were reduced it is the engineering agents that had comparatively higher social growth, unlike the expected trends. These patterns reiterate the conclusion that the initial starting condition of the agents may be an important factor.

The effects of weight distribution ratio, W_O:W_S:W_T (Question Q2, Table 3), can be analyzed by comparing graphs in row 1 (A, B, C) with corresponding graphs in row 3 (D, E, F). While the two sets of results for different weight distribution ratio show that when the interdisciplinary exchange (row 1, with ratio 0.5:0.25:0.25) was greater, the slopes across the three disciplines were more demarcated, and yet the architecture agents moved up the social axis with time. When the gap threshold was increased across the two distributions it showed that weight distributions across disciplinary boundaries had an effect. As noted earlier, the starting conditions may have affected the results.

5 Discussion and Future Work

These preliminary simulation results indicate that more research on the effect of initial conditions of an existing society is needed to determine its significance for how the collective patterns of design trends emerge. In particular, the results indicate that contingent on the initial distribution of agents across their social positions, it is likely that multi-modal patterns will emerge in a society even if all agents have the same mechanisms of value change. Uniformity and collective convergence through a uniform mechanism of exchange may not be supported by the evidence from agent-based simulations. Though the results corresponding to the roles of gap threshold and weight distribution ratio are not conclusive, the results do indicate that gap threshold and weight distribution ratio are interesting parameters to investigate further. For example, as reinforced in the simulation results, lower gap thresholds might increase peer influence along design disciplines with greater knower influence, while higher gap thresholds might lead to skewed trends towards those disciplines that have established leaders or icons that are way ahead of the pack.

Methodologically, these simulations use a simple model with only two parameters, and yet show unexpected results and trends. The results demonstrate the usefulness as well the challenges in using agent-based models to study collective social behaviour. While the observed bi-modal trends appear explicable after post-simulation rationalization, it was not predicted when all agents had similar mechanisms of value change. These results indicate that simpler relationships defined at local levels might have unexpected, emergent outcomes that are difficult to predict. These models can be used to identify such potential behaviour. These models are developed to observe aggregate trends rather than trends at the individual level, and though the actual values of the parameters are not critical, the choice of the values should allow noticeable behavioural change at the global levels. From that viewpoint, the lack of conclusive trends for the two main research questions raises questions such as: What if the gap threshold values that were chosen at 1.2, 1.8 and 2.4 were instead chosen to be 1.2, 2.4 and 4.8? Would that lead to more conclusive comparisons? The experience of developing and using these models indicate that 'calibrating the model' to get useful results is a critical step in social simulations using agent-based models, especially in the context of 'what if' studies of social phenomena that are not well-understood even at the levels of local interactions. The meanings of these values need to be explored.

The next steps in this research are to further calibrate the model and conduct additional simulations. The researchers plan to use initial starting condition as another parameter to investigate how that influences emergent trends. In future, the model will be extended to include other parameters once the roles of the current parameters are better understood.

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