Using agent-based models to understand changes in appreciation of intangible cultural heritage

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Contents

1. Introduction

Intangible cultural heritage (ICH) encompasses practices, representations, expressions, knowledge, and skills transmitted from generation to generation (UNESCO, 2003). It manifests itself through oral traditions; performing arts; social activities, rituals and festive events; knowledge and customs concerning nature and the universe; and traditional crafting (UNESCO, 2003)

Social norms and individual values influence a person's appreciation of intangible cultural heritage (Smith and Campbell, 2017). Appreciation can change over time, through a process mediated by social influence, social identity, kinship networks, technological developments, and random events, among other types of 'mediators'.

Agent-based modelling can help understand this mediating process (Flache, 2018). To do so, the interactions between 'appreciation of ICH' and the mediating factors referred to above must be formalised into logical or mathematical expressions suitable for modelling.

For three of the five mediating factors listed above – namely, social influence, social identity and kinship networks – this working paper presents possible formalisations described in the literature, and expands on some of them. Additionally, the document refers to Python code that puts these formalisations within an agent-based model framework.

Ultimately, the goal of the document is to show that agent based-modelling can be used to study the extent to which, and the reasons why, appreciation of ICH may change over time. Indeed, the evidence presented suggests that research on ICH could benefit substantially from incorporating agent-based modelling into its toolbox.

The document consists of two additional sections and one annex. For each of the three mediating factors considered, Section 2 illustrates one possible approach to agent-based modelling. Because mediating factors interact with one another in real life, Section 3 provides an example of a formalisation that integrates two of the three mediating factors considered. Hyperlinks to the online repository containing agent-based models programmed in Python are included in an annex.

2. Mediating factors

As stated above, this working paper considers three mediating factors: social influence, social identity and kinship networks. They are discussed separately, each in one subsection. The three sub-sections share the same structure, namely a definition is provided, key determinants and key literature are identified, and examples of formalisations are presented. ‘Determinants’ refers to the specific and often multiple phenomena through which a mediating factor manifests. ‘Formalisation’ refers to the logical or mathematical expressions needed to model the impact that any one determinant has on the problem being studied.

2.1 Social influence

Social influence is “the process by which individuals adapt their opinion, revise their beliefs, or change their behavior as a result of social interactions with other people” (Moussaïd et al, 2013, p. 1). Social influence has multiple determinants (Spears, 2021), including cultural assimilation (namely, the process by which individuals become more similar through interactions), social pressure, and homophily (that is, the tendency of individuals to interact with others who are similar to themselves, thus possibly adopting some of their preferences).

Agent-based models have been used to study the determinants of social influence in areas such as segregation patterns, cultural and opinion diversity, collective behaviour, and social inequality (Bianchi and Squazzoni, 2015). Building on this foundation, it is possible to formalise some of these determinants for use in an agent-based model aimed at studying people’s attitudes to ICH loss.

For example, regarding homophily at the individual level, the probability of interaction between two agents *i* and *j* is proportional to their similarity, which can be calculated as the fraction of shared traits between the agents:

$$P_{i,j} = \frac{l_{i,j}}{F}$$

where $l_{i,j}$ is the number of traits shared by agents *i* and *j*, and F is the total number of traits considered in the study.

When taking into consideration the entire community, as opposed to one individual only, the probability that an agent will switch its trait to match a neighbour's trait can be calculated as the relative number of occurrences of each trait in the agent's local neighbourhood:

$$P_{i,j}^{f} = \frac{o_i(\sigma_j^f)}{o_i\left(\sigma_i^f\right) + o_i(\sigma_j^f)}$$

where *f* represents a given trait present in the community; *O* is the occurrence of agent *j*'s trait value for feature *f* in the local neighbourhood of agent *i*; and σ is the Kronecker delta function, which is 1 if the two arguments are equal and 0 otherwise.

2.2 Social identity

Social identity is the set of elements in an individual's self-concept that derive from membership to certain social categories, and the emotional and value significance of this membership (Tajfel, 1972 ; Hornsey, 2008). Common social categories include gender, race, age, house ownership, and educational attainment, among others.

Social identity has multiple determinants (Scholz et al, 2023), including salience, comparative and normative fit, and motives. Salience refers to the extent to which a social identity is prominent at any given time, which is typically influenced by the social context and by individual readiness. Comparative fit is the perceived similarity or dissimilarity between oneself and others in relation to group membership, whereas normative fit refers to the extent to which individuals act within a group's social norms. Motives encompass psychological needs such as self-esteem, belonging, and distinctiveness.

Most agent-based modelling of social identity focuses on conflict situations, such as political polarization (Lee et al, 2022 ; Wojcieszak et al, 2022 ; Carpentras et al, 2023), protest dynamics (Kim and Hanneman, 2011 ; Petrov et al, 2023), and xenophobic anxiety (Shults et al, 2018). Other application areas include organic market conversion (Ambrosius et al, 2022), emergency responses (van der Waal et al, 2021 ; Gavidia Calderón et al, 2024), and innovation diffusion (Smaldino et al, 2017).

Lobo and colleagues (2023) formalise several aspects of social identity, including salience, and comparative and normative fit. Simplifying, they argue that an agent's identity can shift from personal (defined individual traits) to social (defined by group traits), depending on the context; the more an agent identifies with a group, the more their behaviour aligns with the norms that prevail in the group; the importance (salience) of each group is a function of fit (namely, how well the group matches the current context), and accessibility (namely, how easily the group identity can be recalled); and accessibility is updated based on past experiences and current context, making some identities easier to recall than others.

To study social identity, they introduce a 'social context', which consists of the agents that are present in a given environment, and the 'theme' in that environment. Here, 'theme' refers to the characteristics that apply to the environment in question. Examples of these characteristics are sociability (namely, how inclined an agent is to seek out and enjoy social interactions), assertiveness (that is, the degree to which an agent is confident and forceful in interactions), and competitiveness (understood as the agent's tendency to compete with others to achieve goals).

Lobo and colleagues (2023) formalise these concepts thus:

$$Ctx = (A, T)$$

$$A = \{a_1, \ldots, a_n\}$$

$$T = \{(c_1, w_1), \ldots, (c_n, w_n)\}, c \in C, w \in [0, 1], \sum_{i=1}^{n} w_i = 1$$

where Ctx is the social context; A is a finite set of agents; T is the 'theme' referred to above; a_i are individual agents; c_i are individual characteristics of the social context, such as sociability, assertiveness and competitiveness; and w_i are weighing factors.

Within this 'social context', each individual agent identifies whether there are other groups of similar agents, and how many such groups there are. Agents group themselves with others who are similar, prioritising the most important individual characteristics of the social context at any given time.

Lobo and colleagues (2023) formalise these concepts thus:

$$Cl = Clustering(Ctx, A) = \{cl_1, \ldots, cl_n\}, cl \subseteq A_{Ctx}, \bigcap_{i=1}^{n} cl_i = \emptyset$$

where cl_i are the individual clusters identified, and A_{Ctx} is the set of agents filtered by the relevant characteristics of the context.

Finally, an agent's salient social identity is formalised thus:

$$SSI = \ argmax\left(\forall_{cl \in Cl} Salience(cl)\right)$$

$$Salience(cl_i) = fit(si_i) \times acc(si_i), cl \in Cl, si \in NSG, 0 \leq Salience \leq 1$$

where

$$si_i = NormativeFit(cl_i) = \begin{cases} argmin\left(distance\left(cl_i, \forall_{sg \in NSG} sg\right)\right), \text{if } distance \ < tNormative \\ \emptyset, \text{otherwise} \end{cases};$$

Here, $tNormative$ is the threshold below which a cluster will be considered a known social group, and $distance$ is formalised thus:

$$distance\ (sg_{in}, sg_{out}) = |centroid(sg_{out}) - centroid(sg_{in})|$$

For any agent *a*, sg_i is a social group known to the agent, where $NSG_a = \{sg_1, \ldots, sg_n\}$. In this context, sg_{out} represents the out-group cluster, which includes agents that are not part of the in-group. The centroid of sg_{out} is the average of the context-filtered personal characteristics of all agents in the out-group. Conversely, sg_{in} represents the in-group cluster, which includes agents that share similar characteristics and are perceived as part of the same social group. The centroid of sg_{in} is the average of the context-filtered personal characteristics of all agents in the in-group.

2.3 Kinship networks

Lukacs (2011, p. 466) defines kinship networks thus:

> *Kinship networks are defined broadly as extended family, including biological relationships, genealogy, marriage, and other self-ascribed associations, beyond the family nucleus of parents and dependent children. Kinship is not conceptualized as a fixed meaning of natural or genealogical relationship but as a socially and culturally constructed and maintained network of individuals in constant flux. The boundaries between kinship, community, and friendship networks are increasingly blurred, thus biology, sexuality, and descendancy are no longer the sole defining factors to understand kinship.*

Multiple factors shape the way in which kinship networks influence social interactions. Key among them are cultural norms and traditions, economic conditions, geographical proximity, and network cohesion (Bamford, 2023).

The use of agent-based models to study kinship networks is recent and focuses on social care provision (Kessler et al, 2017 ; Gostoli and Silverman, 2019, 2020). An older study in social anthropology explores advanced computer methods to simulate alliance networks, which are a type of kinship network (Menezes and Roth, 2013).

Based on this limited work, the extent to which kinship networks influence an individual's appreciation of intangible cultural heritage can be formalised thus:

$$A_i = \sum_{j=1}^{N} \left(r_{ij} \cdot T_{ij} \cdot C_j \right) + \ \varepsilon_i$$

where

> A_i is the appreciation of individual i to their intangible cultural heritage;
>
> N is the total number of individuals in the kinship network;
>
> r_{ij} is the relatedness coefficient between individual i and individual j (higher relatedness typically implies stronger kinship ties);
>
> T_{ij} is the transmission coefficient, representing the strength of cultural transmission from individual j to individual i (this can be influenced by factors such as communication frequency, emotional closeness, and shared experiences);
>
> C_j is the cultural value or opinion of individual j regarding intangible cultural heritage;
>
> ε_i is a random error term accounting for individual-specific factors not captured by the model (for example, personal experiences, education, or external influences).

3. Integrating different mediators

In real life, appreciation of intangible cultural heritage is influenced by several mediators at the same time. Drawing on work by Steiglechner and colleagues (2023), this section illustrates how two mediators – social influence and social identity – can be integrated within an agent-based modelling framework. Specifically, the following example analyses two determinants of social influence (cultural assimilation and homophily) together with two determinants of social identity (salience and comparative fit).

Consider an individual who interacts with another individual – for the sake of simplicity, a 'recipient' of a message and the 'emitter' of the message. To start with, the higher the homophily, the more likely interaction is.

The extent to which the recipient will update their opinion depends on two factors: the degree of comparative fit with the emitter, and the degree of salience in the emitter's opinion. The way in which the recipient will update their opinion depends on their perception of the emitter's opinion, in that the recipient inevitably gets an incomplete or 'filtered' version of the emitter's opinion. As explained below, in some circumstances cultural assimilation will be the end result of one 'recipient' interacting with several 'emitters'.

To capture more accurately the complexity and variability of individual beliefs, the opinion of an 'emitter' is expressed as a mathematical distribution. In addition to making it possible to reflect uncertainty in an individual's beliefs, nuanced views, and temporal variability, including that caused by group interaction, a distribution facilitates Bayesian updating, which is used to revise a 'recipient's' beliefs, and modelling more generally.

The way a ‘recipient’ i perceives the opinion of an ‘emitter’ j can be formalised thus:

$$p_i(x_j) = \alpha_{in-group} \cdot x_j + (1 - \alpha_{in-group}) \cdot \mathcal{U}$$

where

$p_i(x_j)$ is the perceived opinion distribution of an ‘emitter’ i by a ‘recipient’ j;

$\alpha_{in-group}$ indicates how much the ‘recipient’ trusts the opinion of an in-group member;

x_j is the actual opinion distribution of the ‘emitter’ j;

$\mathcal{U}$ is the uniform distribution over the belief space (namely, the full range of possible beliefs or opinions that an agent can hold), representing maximum uncertainty

The opinion of the ‘recipient’ i referred to above is updated thus:

$$x_i \leftarrow x_i \cdot p_i(x_j) = \alpha_{in-group} \cdot x_i \cdot x_j + (1 - \alpha_{in-group}) \cdot x_i \cdot \mathcal{U}$$

The setting assumed above assumes homophily. When this is not the case, there will be little or no interaction between agents. The latter is known to lead to slight increases in the uncertainty associated with the opinion distributions of these agents. Such updated opinion distributions can be calculated thus:

$$\frac{\mathrm{d}}{\mathrm{d}_t} x_i(b,t) = k \cdot \frac{\mathrm{d}^2}{\mathrm{d}b^2} x_i(b,t)$$

where

$x_i(b,t)$ is the opinion distribution of agent i at time t over the belief space b;

k is a parameter determining the speed at which the opinion distribution decays during non-interaction.

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Annex: Python code

The code referenced below sets up a community of one-thousand members, where each member is considered an independent agent. Each agent is characterised through four features: gender, age bracket, location (urban, semi-urban, and rural), and level of education. For each feature, the probabilities used are those that currently apply in Hokkaido, Japan, as the code will be used in this context.

Additionally, each agent is assigned a level of attachment to intangible cultural heritage, ranging from 0 (no attachment) to 1 (high attachment). This is a two-step procedure. In the first step, a value between 0.1 and 0.6 is assigned randomly to each agent. In the second step, an extra 0.1 is added for each of the following four features: female, over 45 years of age, rural dweller, and higher education completed. Thus, in the second step an agent might add a maximum of 0.4 to their level of attachment to intangible cultural heritage. The logic behind this second step is consistent with empirical evidence from Western societies.

The model simulates one hundred successive two-by-two interactions between agents. By interacting, an agent increases (or decreases) their level of attachment to intangible cultural heritage by 0.1 if the interacting partner has a higher (or lower) level of attachment.

In these interactions, agents are paired randomly. In the following sub-sections, random pairing is replaced by criteria reflecting social influence,and kinship networks, as per the description provided in the main body of this working paper.

This basic model is available at: **https://github.com/daniel-puig/abm-ich**

Social influence

This model is an extension of the basic model introduced above. In this model, homophily – as opposed to randomness – determines the likelihood of two agents interacting.

The model considers a community of one-thousand members. Each member, or agent, interacts with other agents two-hundred and fifty times.

The model is available at: **https://github.com/daniel-puig/abm-ich**

Kinship networks

This model is a further extension of the basic model introduced above. In this model, kinship – as opposed to randomness – determines the likelihood of two agents interacting. The model also takes into account the various parameters described in the main body of this working paper, such as relatedness and transmission.

The model considers a community of one-hundred members. Each member, or agent, interacts with all other ninety-nine agents one-hundred times.

The model is available at: **https://github.com/daniel-puig/abm-ich**