A MARKOVIAN-BASED SIMULATION MODEL FOR THE EVOLUTION OF EMPLOYEES' EMOTIONAL STATES DURING AN ORGANIZATIONAL CHANGE

Castillo C., Fernandez V., Lordan O.[*]

Abstract: This study aims to create a simulation model with which to analyse the spread of emotional states among the employees of an organization. The model takes into account the fact that workers are influenced by their co-workers and supervisors, and simultaneously analyses these interactions. The design of the simulation model follows a standard procedure: problem definition, data collection and configuration of model parameters, conceptual model, testing of the programmed model, and analysis of the results of the simulation. The resulting simulation model makes a novel contribution to the literature by providing social sciences researchers with a simple and efficient method of analysing the evolution and propagation of emotional states during an organizational change. This kind of approach is useful for research involving the simultaneous study of interaction between a number of employees.

Key words: simulation, computational model, organizational change

Introduction

The goal of this paper is to propose a simulation model for the study and analysis of the simultaneous evolution of employees' emotional states within an organization during a process of organizational change. Our study is motivated by the difficulty involved in conducting empirical studies to understand human behaviours, particularly in relation to organizational change, which requires the use of sophisticated conceptual tools to address the non-linear character and dynamic interaction of these behaviours (Kammeyer-Muller et al., 2005). Our simulation model provides a tool that considers the characteristics of individual employees and the influence they have on others. The paper begins with a review of the literature on the use of simulation in social contexts. The development of the simulation model development, according to Law (2008)'s framework, is then presented, followed by a specific case study based on Castillo, Fernandez and

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Sallan. Finally, we discuss the results obtained from the case study, and the potential as well as the limitations of simulation modelling in the social sciences.

Literature review

The need for simulation models in research, and specifically in the social sciences context, arises out of the difficulty of performing the empirical part of the research, due to either a lack of availability (i.e., data are non-observable or difficult to measure) or the complex interaction of data (Gershenson, 2002). Despite the emergence of studies using simulation models in the social sciences (e.g., Vancouver et al., 2010), these represent only a tiny proportion of the potential offered by these models. The lack of broader acceptance of simulation models is a complex question; however, a number of indications may provide some clarity. Compared to more traditional mathematical models, the difficulty of simply and elegantly expressing a simulation model (and its software) inclines many researchers to opt for other alternatives (Troitzsch, 2009). The use of simulation models forces the researcher to make an overexertion in the abstraction of the phenomenon that is rarely simple. Many researchers also believe that the level of abstraction required for the development of a simulation model is not suitable to the drawing of conclusions relevant to professional use. From a different perspective, Axelrod (2006) states that the development of simulation models obliges researchers to define a set of initial assumptions of the phenomenon under examination, which could be interpreted by the scientific community as suggestive of transparent manipulation.

In spite of all this, the simulation model has proved its usefulness under certain circumstances, alongside other, more traditional methods. Deffuant et al. (2006) proposes that simulation models can be extremely useful to research when the purpose is to analyse the behaviours of individuals on the basis of their interaction with the elements of a social system, as well as the evolution of these behaviours over time. Taking as a premise the conclusions of Deffuant et al.'s (2006) conclusions and Law's (2008) recommendations for the construction of valid and credible simulation models, this study proposes a tool based on a simple simulation model to configure, execute, and analyse the evolution of the emotional states of individual employees, occurring simultaneously within an organization, taking into account various levels of interaction. A social network approach was adopted to represent the interactions between the individuals taking part in the simulation model.

As previously mentioned, the simulation model contemplates the interactions of individual employees within organizations. Despite the various possible abstraction options, the most common is the formal and informal structure of the organization (e.g., Sykes et al., 2014). Mintzberg (1979) defines formal structure (or formal organization chart) as the rational, conscious and institutionalized disposition of the division of work, which is the bureaucratized image of the organization (Weber, 2014). From the social network analysis (SNA) point of view, the formal structure

defines the internal relationships within the organization and is stipulated by the management team. Molina (1995), on the other hand, defines the informal structure (or informal organization chart) as existing relationships within the organization that have not been formalized, thus differentiating two levels of informal relationship: (1) friendship, and (2) advice networks. Relationships established through the organization's formal and informal structures are a key element since they enable the channels of influence to which each individual is subjected to be identified. The explanation of the structure of formal relations is relatively simple, since it is defined by the organization itself. The workers themselves, however, are often unaware of the social groups they belong to within their organization (Bastin & Delgado, 1966).

Workers' perceptions of their social relationships at work affect the way they respond to or exhibit commitment to change (Bouckenooghe et al., 2014). These relationships are also determined by the individuals' personality traits. Kassin (2003) defines personality traits as the psychological system of viable organization that determines people's characteristic patterns of feeling, thinking and behaving. Personality traits also determine their behaviour – their cognitive and affective responses – to organizational change (Smollan et al., 2010). On the basis of these contributions and the findings of Castillo et al. (2018), the present paper considers that an individual's emotional state will affect the other individuals with whom they interact at work, and that this interaction will cause them to move between different emotional states. The proposed simulation model therefore uses one network for the formal structure, and a second network for the informal structure, to represent the interactions and influences that occur between the individuals in an organization over time. The combined characteristics of the two networks represent the structure of the organization, hence the simulation model allows for simulations of completely different organizations at a much lower resource cost (e.g., time) than other more traditional research approaches. From our review of the literature presented, the research question we proposed to achieve our objective was clear. Is it possible to design a simple model for social science researchers to simulate emotional evolution during an organizational change?

Methodology

Our method follows Law's (2008) proposal for the development of simulation models, which consists of presenting a set of recommendations for the development of valid and credible models. As already stated, the purpose of the simulation model is to be able to analyse the propagation and evolution of several individuals through a set of states (e.g., mood states), based on different interaction networks simultaneously. The simulation model consists of a set of individuals $\{A, B, C...\}$, each of whom are experiencing n different states at time t (e.g., $A_t \in \{A_1, A_2... A_n\}$. The evolution of an individual through the n states is modelled as a first-order Markovian process, that is, the future state is determined only by the current state of the individual. In addition to the current state of an individual, the

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probabilities of a transition from one state to another are also determined by their environment (Sykes et al., 2014) and, more specifically, by the individuals with direct connections to them (direct connectivity), and by the emotional state of these individuals. In this case, the effect of the individual on the rest is also modelled through a Markovian process of the first order. Finally, a principle of additivity is applied to the combined effect of individuals on the rest. The additivity principle is based on Castillo et al.'s (2018) definition of change in relation to emotional states, according to which the individual can only be in one state at a time.

Having defined the problem and the main focus of the modelling effort, the next step is to determine the range of possible emotional states. This requires a review of the literature, and also possibly an inductive study to describe and define the social phenomenon under examination (Bonilla-Castro & Sehk, 2005). After identifying the emotional states, we proceeded to determine the probability of an individual beginning in each of the given states. Thus, if n is the number of possible states of an individual, E_i is the set of possible states of an individual, and $p_i^{(0)}$ is the probability that the individual will begin in an E_i state, the model considers that the sum of their probabilities will be equal to one. In the same way, if $p_j^{(1)}$ is the probability that an individual has of reaching an E_j state after a single transition, Bayes' theorem enables a calculation based on the previous state:

$$\sum_{i=1}^{n} p_i^{(0)} = 1 \quad and \quad p_j^{(1)} = \sum_{i=1}^{n} p_i^{(0)} p_{ij} = 1 \tag{1}$$

These probabilities can be represented by an array, where $p^{(0)}$ represents the probability that an individual will be in some of the possible states at the beginning of the process, and $p^{(1)}$ represents the probability that an individual will be in one of the available states, having undergone a transition since the beginning of the process:

$$p^{(0)} = \left(p_1^{(0)}, \dots, p_n^{(0)}\right) \quad p^{(1)} = \left(p_1^{(1)}, \dots, p_n^{(1)}\right) \tag{2}$$

To conclude, the probabilities of an individual being in a given state as a function of their previous state can be showed in matrix form:

$$p^{(1)} = \left[p_j^{(1)}\right] = \left[\sum_{i=1}^{n} p_i^{(0)} p_{ij}\right] = p^{(0)} M_T \tag{3}$$

Where M_T is the first order state transition matrix for an individual:

$$M_T = \left[p_{ij}\right] = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2n} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & p_{n3} & \cdots & p_{nn} \end{bmatrix} \tag{4}$$

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The p_{ij} elements of the matrix M_T represent the probability that an individual will change from state i to state j after a transition, therefore there will be $i \cdot j$ transition probabilities:

$$p_{ij} = P(X_n = j \mid X_{n-1} = i)$$

(5)

With the initial probability vector $p_i^{(0)}$ representing the starting point of the process, and the first-order transition (M_T) probability matrix representing the evolution of individual states, the following step is to define and include the influence of the rest of the individuals in the simulation model. Similar to the state transition matrix, it is proposed to create an influence matrix of the social environment on the individual (M_I), which increases and decreases the parameters of the transition matrix (M_T). The ability of one individual to influence another depends on three elements: the existence of a direct relationship between them, and the current states of both the influenced and the influential individual. The current state of the individual, whether influenced or influential, is related to their personality traits (Mayer, 2017). Day-to-day situations require people to deal with emotions; personality, therefore, is characterized by the way in which an individual deals with the world emotionally. The present study considers that the personality of individuals is a predictor of their emotional state, used to explain how individuals deal with situations (Bolger, 1990). Hence we also consider that, by focusing on the individuals' current emotional state, it is possible to contemplate their personality and how they are influenced by other individuals. Therefore, the influence matrix is formed by parameters of influence p'_{ijk} where i represents the current state of the influenced individual, j represents the current state of the influential individual, and k represents the future state of the influenced individual.

In order to operate the influence matrix more easily, it is possible to define an influence matrix for each current state of the influenced individual. The influence matrix for state Ei would therefore have the following structure:

$$M_{Ii} = \begin{bmatrix} p'_{i11} & p'_{i12} & p'_{i13} & \cdots & p'_{i1n} \\ p'_{i21} & p'_{i22} & p'_{i23} & \cdots & p'_{i2n} \\ p'_{i31} & p'_{i32} & p'_{i33} & \cdots & p'_{i3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p'_{in1} & p'_{in2} & p'_{in3} & \cdots & p'_{inn} \end{bmatrix} \begin{matrix} = 0 \\ = 0 \\ = 0 \\ = 0 \\ = 0 \end{matrix}$$

(6)

As the influence matrix (M_I) is additive to the transition matrix (M_T), the model should ensure that the condition continues to be met so that the sum of probabilities of the transition matrix for the current state is equal to one. The sum of parameters of influence for the current state of the influence matrix must therefore be equal to zero. Parameters of influence p'_{ijk} can take positive and negative values depending on the phenomenon studied. For example, if the current state of the individual influenced is E_i, and the current state of the only influential individual is E_j, the probabilities of ending up in another state are:

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$$[p_{i1} + p'_{ij1} \quad p_{i2} + p'_{ij2} \quad ... \quad p_{in} + p'_{ijn}] \tag{7}$$

In situations with more than one influential individual, the model works in an analogous way. For example, if the current state of the influenced individual is E_i, and the current states of the only two influential individuals are E_j and E_m, the probabilities of the influenced individual transitioning to another state are as follows:

$$[p_{i1} + p'_{ij1} + p'_{im1} \quad p_{i2} + p'_{ij2} + p'_{im2} \quad ... \quad p_{in} + p'_{ijn} + p'_{imn}] \tag{8}$$

In situations where any element of M_{TI} is greater than one or smaller than zero, it will be necessary to begin with data collected from a previous study, since the properties of the Markovian matrix transition are (1) the sum of the probabilities of the states must be equal to 1, (2) the transition matrix must be square, and (3) the transition probabilities must be between 0 and 1 (Chung, 1960).

Finally, we proposed the use of an absorbing state, at least in the simulation model, which represents the state or final state that can be reached by an individual. The final states in the simulation model are either deserting or acceptance (Castillo et al., 2018). Since it is not possible for the individual to move from these states to another state, these are considered final states. The final state in the Markov chains will therefore be considered an absorbing state (Dynkin, 2012), and in the transition probability matrix (M_T), it must be satisfied that the absorbing state (E_i) is as follows:

$$p_{ii} = 1 \qquad p_{ij} = 0 \ (i \neq j, j = 1, ..., n) \tag{9}$$

Once the necessary parameters for the construction of the simulation model have been defined, the next step is the development of a computational engine able to simulate the evolution of the model over time. For this, the following heuristic is proposed, wherein the term node is used as representative of the individuals in an organization. Finally, it is necessary to verify that the heuristic behaves as described in the definition of the problem through a simple example.

Initial data

1. Table $\left\{p_i^{(0)}\right\}$: Probability table representing the probability of an individual beginning in state *Ei*.
2. Table M_T: Transition matrix for the individual, without social environment influence.
3. Table M_I: Matrix of parameters of influence of the individual's social environment.
4. Table M_{TI}: Transition matrix for the individual, with probabilities modified by social influence.

Constants

(1) *SN:* Size of the network (number of nodes). (2) *SS:* Sample size (number of simulations). (3) MN: Identify the different types of relationship the individual may have in the network, and specify the maximum number of relationships that can exist. For example, M1 (maximum number of relationships with other individuals of type 1), M2 (maximum number of relationships with other individuals of type 2), MN-1 (maximum number of relationships with other individuals of type N-1) and MN (maximum number of relationships with other individuals of type N).

Variables

RES_n [i, j]: State of the individual [*i*] (1÷SS) at time [*j*] [0÷∞] of the simulation *n* [1÷SS].

Pre-processing

Define the rules of creation for each of the networks of interaction between the individual and their social environment *MN* (M1÷MN).

Process

1. Start the simulation counter at n=1 (Label = simulation).
2. Create each of the networks related to the individual (*MN*) according to the rules established in the pre-process.
3. Start the state of the individuals in the sample (*SN*) according to the probabilities of the table $\left\{p_i^{(0)}\right\}$.
4. Save the initial state of each individual in the network in the corresponding box. The total number of individuals will be the equivalent of the sample (SN): RES_n [1,0] + RES_n[2,0] + ... + RES_n[SN-1,0] + RES_n[SN, 0].
5. Start the timer at t = 1 (Label = time).
6. For each individual in the network, calculate the probabilities of transition between states of the system:
   6.1. Select the transition probabilities of the individual based on the *MT* table according to their state at t = 1.
   6.2. Calculate the relationships the individual has with other individuals in the network (*MN*), differentiating these by their current state.
   6.3. Update the value of the transition probability between states for the individual (*MTI*), taking into account the influence table (*MI*) of each of the individuals to whom they are related in the defined network.
   6.4. Calculate the transition of the analysed individual and save it in the corresponding table: RES_n[1,1] + RES_n[2,1] + ... + RES_n[SN-1,1] + RES_n[SN, 1].
7. Check whether the individuals in the network are in any of the absorbing states of the system at t = 1.
   7.1. If the individuals are not in absorbing states, advance the timer to t=t+1; (Label = time).

7.2. If the individuals are in an absorbing state, check whether all the predicted simulations have been performed (SS == n):
   a) in the case that none of the simulations have been performed, advance the simulator counter to n = n + 1 (Label = simulation);
   b) in the case that all the simulations have been performed, END.
   c)

Development and results for the simulation model of emotional states during an organizational change

The first step, as described above, is to perform a review of the literature in order to define the problem and the most suitable simulation model. In line with Castillo et al. (2018), this study develops a theoretical model for describing the evolution of employees' emotional states during a negatively perceived organizational change, and explains the evolution of their behavioural patterns, taking into account their social environment. The model comprises six emotional states: denial and anger (E_1), bargaining (E_2), depression (E_3), revising (E_4), deserting (E_5) and acceptance (E_6). Their results show that individuals begin by moving freely between the first four states, while deserting and acceptance states are the final states of the process. Castillo et al. (2018) also identify that sources of social influence (e.g., family, friends, and co-workers) have different effects according to the current state of the individual undergoing the organizational change. Experiencing these emotional states influences relationships between individuals and their social environment. For instance, relationships with supervisors deteriorate during denial, anger, and depression, but remain stable during bargaining. On the basis of these findings, a simulation model is proposed.

The proposed simulation model consists of six states, where the probability that an individual is initially in the E_i state is defined by the vector $p_i^{(0)}$. These probabilities (see equations 10 and 11) are based on Castillo et al. (2018)'s results.

$$\sum_{i=1}^{n} p_i^{(0)} = E_1 + E_2 + E_3 + E_4 + E_5 + E_6 = 1 \tag{10}$$

$$\sum_{i=1}^{n} p_i^{(0)} = 0.5070 + 0.2254 + 0.1127 + 0.0704 + 0.0282 + 0.0563 = 1 \tag{11}$$

The next step is to model the behaviour of an individual through a first-order transition (M_T) probability matrix. In line with Castillo et al. (2018), a transition matrix is developed (12). This transition matrix does not take into account the influence of the employees' social environment within the organization. The relationship between probability states and emotional states is as follows: E1 (denial and anger), E2 (bargaining), E3 (depression), E4 (revising), E5 (deserting), and E6 (acceptance). For instance, the transition matrix (12) shows that the probability that the employee remains in the state of denial and anger (first state,

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E1) is 0.56; however, the probability of moving to the bargaining (second state, E2) is 0.24. In this way, all the transition probabilities are reflected.

$$
M_T = \begin{array}{c} \\ E1 \\ E2 \\ E3 \\ E4 \\ E5 \\ E6 \end{array} \begin{bmatrix} E1 & E2 & E3 & E4 & E5 & E6 \\ 0.56 & 0.24 & 0.12 & 0.08 & 0 & 0 \\ 0.24 & 0.62 & 0.07 & 0.03 & 0 & 0.04 \\ 0.12 & 0.07 & 0.36 & 0.36 & 0 & 0.09 \\ 0.08 & 0.03 & 0.36 & 0.24 & 0.29 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{array}{c} = 1 \\ = 1 \\ = 1 \\ = 1 \\ = 1 \\ = 1 \end{array} \tag{12}
$$

The next element of the simulation model is the probability matrix representing the influence of the social environment (M_I). Castillo et al.'s (2018) theoretical model suggests two types of influences exerted by individuals directly connected through formal ("Workflow") networks, and informal ("Friendship") networks. Each of these sources of influence exerts different effects according to the current state of the individual. Two influence matrices must therefore be produced (M_{IFn} for the formal network, and M_{IWn} for the informal), through which the increments and decrements for each of the individual's emotional states during an organizational change are obtained. In order to be able to visualize and work more easily with the influence tables (formed by three dimensions), each matrix is transformed into six sub-matrices: one for each current state of the influenced individual. In the tables of increments developed for this study, it must be taken into account that, when the influenced individual's current state coincides with that of the influential individual in their Friendship relationship, the increase that occurs in the individual probability is 0.04 in favour of the shared state, whereas in the Workflow relationship, the probability is 0.02. Where the current states of the individuals do not coincide, the model considers an increase in the individual probability of 0.02 and 0.01 in favour of the influential individual's state in their Friendship and Workflow relationships, respectively. For the remaining states, the model considers r a decrease proportional to the increase produced in the state in which the relationship is located: Friendship and/or Workflow. In the event that either relationship has left the organization (E5, deserting), the increase will be considered in the status of revising (E4). There is also an influence matrix for individuals who begin in the E_1 state (denial and anger). The remaining influence matrices can be found in Appendix I.

$$
M_{IFE_1} = \begin{bmatrix} 0.04 & -0.013 & -0.013 & -0.013 & 0 & 0 \\ -0.0067 & 0.02 & -0.0067 & -0.0067 & 0 & 0 \\ -0.0067 & -0.0067 & 0.02 & -0.0067 & 0 & 0 \\ -0.0067 & -0.0067 & -0.0067 & 0.02 & 0 & 0 \\ -0.0067 & -0.0067 & -0.0067 & 0.02 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{array}{c} = 0 \\ = 0 \\ = 0 \\ = 0 \\ = 0 \\ = 0 \end{array} \tag{13}
$$

It is important to note that increment and decrement values must be selected in line with the literature. Their accuracy does not affect the simulation model, but they do

have to reflect the trend of influence. For example, a high-influence relationship should add more than a reduced influence.

Having defined the states, the transition probabilities matrix (M_T), and the influence parameter matrices (M_{IFn} and M_{IWn}), the next step is to define the number of individuals that are part of the simulation model and the direct relationships that exist between them. A proposal with ten individuals and two networks (representing the relationships originating in the formal and informal structures) has been selected as an example. Figure 1a shows the formal network defined for the simulation model. In this case, the first network is shown in tree form, though another form could be used. Figure 1b shows the informal network. In this case, a random network is proposed.
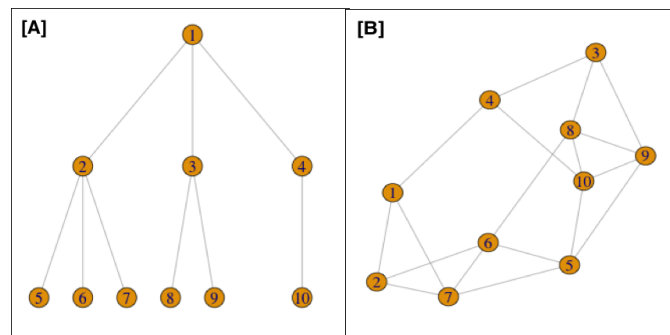

Figure 1: Formal network of the example. (A) / Informal network of the example.(B)

Once all the parameters of the simulation model have been defined, the next step is to establish the parameters of the simulation, in other words, the initial conditions and the number of simulations to be performed. In this example, we propose to define 100 initial situations of the system according to the probabilities $p_i^{(0)}$. For each of these, 100 simulations are performed using the simulation engine (the heuristic proposed above). The final result is equivalent to 10,000 simulations of the proposed problem. The first results obtained from the experiment are the number of iterations that have been necessary to reach a stable situation in each of the simulations and the number of individuals that have finished in each of the final states. Table 1 shows the simulation results.

Table 1. Number of iterations necessary to reach a stable situation and number of individuals that finish in each final state.

#Simulation	Iterations	Nº Individuals	
		State E_5	State E_6
1	19	5	5
2	59	4	6
3	27	6	4
...	...	...	...

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The number of iterations to reach a stable situation in the system enables us to evaluate the process of cognitive and emotional adaptation to which the individual has been subjected (Huy, 2001). In other words, the greater the number of iterations performed, the greater the adaptation effort of the individual, since this is usually linked to a greater number of transitions between possible emotional states. The difficulty of the adaptation translates into resistance to change, which can result in unwanted or counterproductive work behaviours (Bowling & Eschleman, 2010). Knowing the initial state of each individual and the number of iterations necessary to arrive at a stable situation enables change managers to focus actions that counter this resistance.

Although the results in Table 1 are interesting, the representation of each of the separate simulations is not efficient for analysis. One way to condense such information is through histograms. Figure 2 shows an example of two histograms to represent the number of individuals ending in states E_5 and E_6, the 10,000 simulations having been performed. Similarly, a histogram could be performed for the number of iterations for the 10,000 simulations.
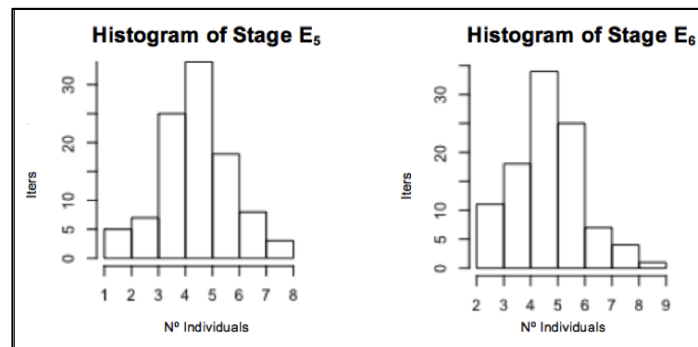

Figure 2: Histograms of the meanings of iterations and the number of individuals in states E5 and E6.

The representation of a simulation, more specifically the evolution of each individual over time for a specific simulation, can also be considered of interest in the analysis of the problem. Figure 3 shows how organizational changes are nonlinear, dynamic processes (Scheck & Kinicki, 2000), as each individual experiences a different transition before arriving at one of the two absorbing states. During this process, the representations show how some individuals have oscillated repeatedly between different states, which can be interpreted as emotional instability and difficulty in accepting change (Castillo et al., 2018).
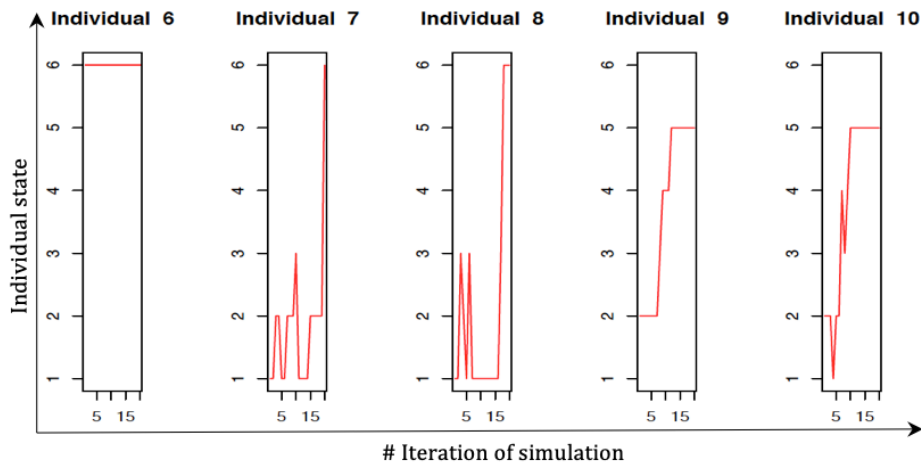
Figure 3: Example of evolution states of individuals (6 to 10) during the course of the simulation.

Individual 7, for example, begins the simulation in the denial and anger state and ends in the state of acceptance, crossing several times between denial and anger, bargaining and depression. Some individuals (e.g., 6), on the other hand, transition directly into the acceptance state. It is possible to conclude that the transition does not produce a complicated emotional situation for them, as it does for Individual 7. Finally, it is also possible to make a visual representation that shows the results of several simulations simultaneously. Figure 4 shows the mean number of individuals found in each of the six states over time, as well as their confidence intervals with a margin of error of 99.5%. This representation allows us to observe in detail the transient state and how it evolves, according to our simulation model.
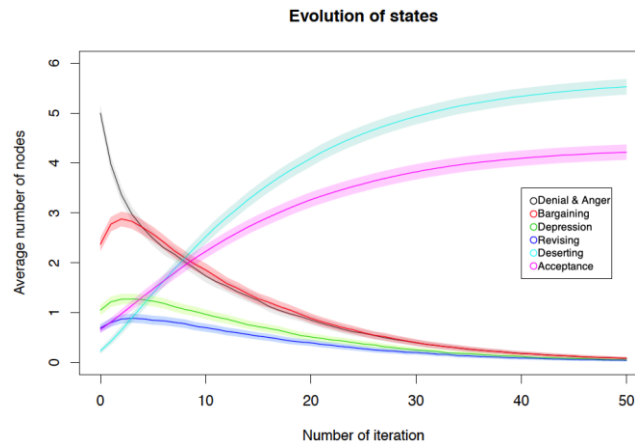

Figure 4: Evolution of states and average number of individuals in each state during the course of the simulation.

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Figure 4 shows that 50% of the individuals begin the process in the denial and anger state, the state in which they experience greater confrontation and rejection of the lived situation (Castillo et al., 2018). However, at the end of the simulation, 40% of the individuals have arrived at the acceptance state, while the remaining 60% finish in the deserting state. Both states are absorbent and are therefore considered the two final states of change. Drawing on these results, two strategies can be implemented to improve management of an organizational change: (1) establish an initial favourable process situation, which would affect the initial probabilities of the simulation model, and (2) create formal and informal structures that promote better results, which would affect the effective transition probabilities of individuals. The rest of the parameters and variables of the simulation model remain constant to strategies implemented by managers or the organization as a whole.

From this point, there are two other strategies for analysis of the simulation: focusing on only the results in the first iterations, what could be termed the first transient state; and focusing on only a sample of the simulations. It is also possible to combine both strategies to represent the results. This representation is one example of the possible ways of representing the data obtained, and the multitude of possibilities offered by the proposed simulation model.

Study results discussion

The results show that our model provides researchers with a tool with which to simulate the different emotional states experienced by employees in the course of an organizational change, taking into account the influence exerted on them by their co-workers and supervisors, following the contribution of Castillo et al. (2018). Our results also show how the simulation model allows us to explain a complex social phenomenon such as organizational change and analyse its behaviour over a long period of time that, in an empirical study, would be extremely difficult to carry out. This concurs with other contributions to the literature (e.g., Vancouver et al., 2010; Vancouver & Weinhardt, 2012). The time aspect is particularly important, since our results show that, using the proposed simulation model, studies of the emotional evolution of individuals during an organizational change can be performed with any organizational structure, and for as long as desired. The simulation conditions can be determined by the researcher, and all the possible cases can be tested to analyse the differences between scenarios, something that would take years to carry out in an empirical investigation. This is also consistent with previous studies, such as Deffuant et al. (2006).

Conclusions

The paper presents a simple and powerful simulation model for studying and analysing how individual states (such as emotional states and organizational behaviours) evolve during an organizational change. The model contemplates the individual's personal characteristics, as well as the influence exerted by their environment.

Our results show the practicality of the simulation model for predicting different organizational scenarios in terms of the emotional states likely to be experienced by individual employees. This information can help organizations to anticipate the negative effects of the changes they implement, and encourage practices that minimize them. Furthermore, the different possibilities offered by our model has practical implications for future research. For example, future studies could add new analysis metrics to our simulation model as centrality metrics for exploring social network effects (e.g., Zhou et al., 2018; Fronzetti & Naldi, 2020). Similarly, another hypothesis for validation by a future study, based on Castillo et al. (2018), could be that individuals with a higher betweenness metric could exert more influence over others, and that individuals who are part of a more cohesive network (measured as a clustering metric) could also influence each other more strongly, or remain in their original states for longer. This would only be possible using a simulation model such as the one proposed in this paper.

As with any simulation model, researchers should be aware of its limitations. The parameters of the simulation model (e.g., initial probabilities, transition probabilities, and parameters of influence) must be established from a preliminary study. In many cases, detailed information on the organizational phenomenon will be needed in order to be able to represent and interpret in greater detail the results obtained from the simulation (Law, 2008). A further limitation is that the model only contemplates the influences of individuals directly connected through the formal and informal network. Other influences that may exist are not taken into account (e.g., groups of people). This representation allows detailed study of the transient phase and how it evolves according to the established model. To date, no studies have used our proposed simulation model (beyond our organizational change application), but it could be applied in the following contexts: organizational learning (e.g., Carley & Hill, 2001), motivation (e.g., Lord et al., 2003), and propensity to information search (e.g., Vancouver et al., 2010).

Finally, we wish to emphasize that the system has been modelled as a Markovian process of the first order, that is, that the future state of an individual is determined only by their current state. This implies that the simulation model has little historical memory about the evolution of the process. All these limitations are what allow any social science researcher to carry out simulation of social phenomena without the need to be an expert in operational programming or research. Thus, we can confirm that we have fulfilled our aims and answered our research question,

since we have been able to present a simple and easily applicable simulation model for future research on organizational change.

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MODEL SYMULACYJNY W OPARCIU O MODEL MARKOVIANA, EWOLUCJI STANÓW EMOCJONALNYCH PRACOWNIKÓW PODCZAS ZMIANY ORGANIZACYJNEJ

Streszczenie: Niniejsze badanie ma na celu stworzenie modelu symulacyjnego do analizy rozprzestrzeniania się stanów emocjonalnych wśród pracowników organizacji. Model uwzględnia fakt, że na pracowników wpływają ich współpracownicy i przełożeni, jednocześnie analizując te interakcje. Projektowanie modelu symulacyjnego odbywa się według standardowej procedury: definiowanie problemu, zbieranie danych i konfiguracja parametrów modelu, model koncepcyjny, testowanie zaprogramowanego modelu oraz analiza wyników symulacji. Powstały model symulacyjny wnosi nowatorski wkład do literatury, zapewniając badaczom nauk społecznych prostą i skuteczną metodę analizy ewolucji i propagacji stanów emocjonalnych podczas zmiany organizacyjnej. Takie podejście jest przydatne w badaniach polegających na jednoczesnym badaniu interakcji między wieloma pracownikami.

Słowa kluczowe: symulacja, model obliczeniowy, zmiana organizacyjna

基于马尔科夫的组织变革过程中员工情绪状态演变的仿真模型

摘要:本研究旨在创建一个模拟模型,用于分析组织员工之间情绪状态的扩散。该模型考虑了工人受其同事和主管影响的事实,并同时分析了这些交互作用。仿真模型的设计遵循标准程序:问题定义,模型参数的数据收集和配置,概念模型,编程模型的测试以及仿真结果的分析。由此产生的模拟模型通过为社会科学研究者提供一种简单有效的方法来分析组织变革过程中情绪状态的演变和传播,为文献做出了新的贡献。这种方法对于涉及同时研究多个员工之间的交互作用的研究很有用。

关键词:模拟, 计算模型, 组织变革