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Research paper

Predicting long-term outcomes of educational interventions using the evolutionary causal matrices and Markov chain based on educational neuroscience

Hyemin Han[a,*], Kangwook Lee[b], Firat Soylu[a]

[a] Educational Psychology Program, University of Alabama, Box 870231, Tuscaloosa, AL 35487, USA
[b] School of Electrical Engineering, KAIST, 291 Daehak-ro, Yeseong-gu, Daejeon 34141, Republic of Korea

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ABSTRACT

We developed a prediction model based on the evolutionary causal matrices (ECM) and the Markov Chain to predict long-term influences of educational interventions on adolescents' development. Particularly, we created a computational model predicting longitudinal influences of different types of stories of moral exemplars on adolescents' voluntary service participation. We tested whether the developed prediction model can properly predict a long-term longitudinal trend of change in voluntary service participation rate by comparing prediction results and surveyed data. Furthermore, we examined which type of intervention would most effectively promote service engagement and what is the minimum required frequency of intervention to produce a large effect. We discussed the implications of the developed prediction model in educational interventions based on educational neuroscience.

1. Introduction

Yoda: It is the future you see.
Luke: The future? Will they die?
Yoda: Difficult to see. Always in motion is the future.
- *Star Wars: Episode V - The Empire Strikes Back*

Psychological intervention experiments in educational settings have been conducted to examine how to enhance positive youth development, such as academic adjustment and well-being, among adolescents [1]. Recently, psychologists have developed various intervention methods and tested their longitudinal influences on diverse domains, including but not limited to, adolescents' academic motivation, belongingness to school contexts and social competences to deal with bullying issues in school settings [2–5]. These intervention studies potentially contribute to the improvement of school environment and finally adolescents' development based on empirical evidence [6,7]. However, because they have tested effects of interventions in experimental settings, which are decontextualized, more restricted, controlled and involve a smaller sample compared to real school settings, it would be difficult to directly apply developed interventions to classroom contexts [8]. Thus, large-scale, long-term longitudinal studies examining diverse intervention methods adopted in school curricular and activities should be conducted to overcome this shortcoming. For instance, researchers should investigate which type of intervention can effectively promote developmental change and how often it should be conducted in classrooms in order to produce a significant and large effect. By answering these questions, educators and educational policy makers can better understand how to properly apply psychological interventions to enhance the quality of education in real school settings at the macroscopic level, such as the district level. However, it would be difficult to test the long-term effects of different types and frequencies of interventions with real adolescent populations due to limited time and resources [9].

The meta-analysis is perhaps a feasible and reliable way to examine which intervention methods can properly work in general by systematically reviewing and analyzing various methods developed in multiple studies [10]. Several scholars have conducted meta-analyses to systematically review the effectiveness of diverse educational interventions in diverse contexts [6,8,11,12]. They have identified which types of intervention programs can produce a significant effect on positive youth development [13]. However, they were not able to provide complete answers to questions that educators and policy makers may raise. For instance, although those previous meta-analyses of interventions examined the effect size of each type of interventions, they

* Corresponding author.
E-mail address: hyemin.han@ua.edu (H. Han).

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could not provide any information needed to determine the minimum frequency of interventions required to produce a significant and large effect. Moreover, the majority of previous meta-analysis studies were mainly interested in demonstrating whether or not a certain type of intervention can produce a significant effect overall [6,12], instead of more directly examining which type of intervention can be more effective than others. Thus, meta-analysis itself would not be sufficient to provide practical implications to educators and policy makers.

We intend to employ the framework of evolutionary and computational theory and develop a computational model to examine which type of intervention is effective and how often it should be conducted to produce a significant and large effect in the long term. We predict future long-term outcomes based on relatively small-scale, short-term data gathered from lab and classroom experiments. Evolutionary theory provides the present study with a theoretical scaffold to approach the current problem, that is, the long-term prediction of intervention outcomes, in a practical manner. Based on ideas in evolutionary theory, particularly the evolutionary causal matrices (ECM), we establish an evolutionary model modeling how a system consisting of adolescents will evolve over time while being influenced by interventions [14–16]. In order to implement the ECM-based longitudinal prediction model, we employed Markov Chain analysis [17]. Finally, we developed a simulation program based on the computational model to test whether the model properly predicts longitudinal outcomes.

In short, the present study aims to predict long-term outcomes of educational interventions using relatively small-scale, short-term data by applying the ideas of the ECM and Markov Chain. The developed computational model will be able to provide useful insights about how to apply intervention models to diverse educational settings to educators and policy makers. Furthermore, based on the developed computational model and prediction findings, the present study discusses their implications for future educational intervention studies in educational psychology. Particularly, we focus on how this computational approach can contribute to the improvement of interventions based on an interdisciplinary theoretical framework incorporating perspectives from neuroscience, cognitive science, and education.

1.1. Evolutionary causal matrices

The ECM that was inspired by the theory of biological evolution provide useful tools to predict the ratio of a certain type of individuals among the whole population and where the equilibrium point will be under certain selection pressures in the long term, particularly for the studies of cultural evolution [15]. ECM consist of multiple matrices describing the dynamics in certain systems. Each matrix in ECM describes the probability of the longitudinal transition between certain states [16]. For instance, we may consider a simple illustrative example of the longitudinal transition between conformers and non-conformers in cultural systems. Conformers can be defined as a group of individuals who conform to certain social norms; while, non-conformers do not observe the norms. There are two different types of systems, with different selection pressures. The first cultural system (C_1) is well organized and has plentiful resources available to individuals. In this system, conformers are more likely to have better fitness compared to non-conformers, and non-conformers are likely to follow the social norms over time. The second cultural system (C_2) does not have enough resources to support individuals and is not well organized. Non-conformers are more likely to be successful in this system. ECM describing the transition between two states from t to t+1 are presented in Table 1. We can calculate the ratio of each state in the C_1 at $t+1$ from data at t as follows:

80% of initial conformers will still be conformers while 20% of them will become non-conformers at t+1.
60% of initial non-conformers will still be non-conformers while 40% of them will become conformers at t+1.

Table 1
Sample ECM for two different hypothetical cultural systems.

		Conformers (t)	Non-conformers (t)
Cultural system 1 (Well organized, enough resources)	Conformers (t +1)	.80 (ECM [1])	.60 (ECM [1,2])
	Non-conformers (t+1)	.20 (ECM [1,2])	.40 (ECM [1,2])
Cultural system 2 (Not organized, not enough resources)	Conformers (t +1)	.30 (ECM [1,2])	.10 (ECM [1,2])
	Non-conformers (t+1)	.70 (ECM [1,2])	.90 (ECM (2,2,2])

The ratio can also be calculated in case of the C_2 similarly. In general, we can calculate the ratio of state A in the whole population at t+1 using this formula [14,15]:

$$F_A(t+1) = \frac{\sum_{i \in P} F_i(t) ECM_{iA}}{\sum_{i \in P}\left[F_i(t) \sum_{j \in p} ECM_{ij}\right]} \tag{1}$$

We can show that those two systems eventually reach a certain equilibrium in the long term using the ECM and the formula. For instance, let's say there are 50% of conformers and 50% of non-conformers in both the C_1 and C_2 at t=0. After conducting iterative calculations, both systems reach an equilibrium. On the one hand, in case of the C_1, the ratio of conformers to non-conformers converges to 75:25 at t=10. On the other hand, that ratio converges to 87.5:12.5 at t=10 in the case of the C_2.

This methodology can also be applied to predicting outcomes of interventions in groups, which can be regarded as systems. Interventions change the dynamics in a certain system and finally each state. Previous intervention studies have demonstrated that interventions altered group norms, influenced the dynamics within as well as between individuals in the group, and finally changed the individuals' behavior [18–20]. Therefore, we can create ECM based on findings from intervention experiments informing longitudinal changes between various behavioral states. One matrix is created per intervention type. In each matrix, a number in each cell is calculated by the transition rate from a certain state, which can be represented by a different type of behavior, at t to another or same state at t+1. Using the created ECM, future intervention outcomes can be predicted by iteratively calculating the ratio of each state among the whole population at a certain time point.

1.2. Markov Chain

Markov chain is a mathematical tool, which can be used to model and analyze stochastic systems [17]. It has been widely used in a wide range of fields in science and engineering. One of the most famous, recent successes of Markov chain is Google's PageRank [21]: modeling behavior of web surfers as a Markov chain, Google's PageRank efficiently ranks an enormous number of web pages on the Internet based on search metrics.

We provide a formal definition of Markov chains as follows. A Markov chain is defined with a set of states, transition matrix, and initial state distribution; in this work, we consider only discrete time Markov chains. At $t = 0$, the state of a Markov chain is in its initial, denoted by S_0, and this initial state is randomly chosen according to the initial state distribution. The transition matrix dictates how a Markov chain (randomly) evolves. When the number of states is p, the size of the transition matrix is p by p, and each row of the transition matrix defines how the Markov chain evolves from each state. More precisely,