Conceptualizing Higher Education Institutions: An Agent-Based Modelling Approach

Simulation for Enterprise-Scale Systems - Final Research Project
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December 2020

Notes to the Reader

All aspects of the agent-based model simulation implementation can be found by accessing the project repository via the associated labeled link found below. The repository's README.md file gives a brief technical introduction as well as an explanation of repository contents and suggested usage for running the simulation locally. Notably, the file nb.ipynb, found within the root directory of the project repository, contains analysis and modelling of the data produced by the different experiments, including widgets to produce visualizations for any of the over 8000 experiments. Furthermore, for ease of access and avoidance of dependency issues, nb.ipynb is also cloud hosted, allowing any user to examine and manipulate the notebook through their browser. The link to the cloud-hosted notebook can be found below. The cloud-hosted notebook is best for viewing the saved, run state of the author's local notebook. However the service does not provide enough RAM to properly load all experimental data and interact with the resulting visualizations. Please follow the usage instructions on the README.md to properly interact with all features of the project notebook.

| Project Repository | Virtual Project Notebook |

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1 Motivation and Introduction

When first tasked with creating an open-ended project that applies simulation paradigms, broad research across numerous simulation methodologies and applications was conducted. Governing this research process was the desire to combine disparate interests together resulting in systems abstractions of manageable complexity to serve as robust models for experimentation. There was a hope to not only learn more concerning the underlying dynamics of a system through the abstraction process, but also — through simulation experimentation — gain an analytical understanding of the relationships found amongst the system's components. The amalgamation of these hopes and desires served to narrow my research process.

Having a personal interest in the development and transformation of interpersonal social dynamics, coupled with a modest history in studying leadership and organizational behavior, it was determined that the project's focus would be on some sort of social system with an abstraction realized through organizational behavior theories. Among the different major simulation methodologies (namely discrete-events, system-dynamics, and agent-based) agent-based modelling (ABM) techniques seemed to be the most compelling in both theory and practice. By offering a bottom-up perspective, ABMs can facilitate deep understandings of how systems develop over time from the combinations of interactions among individuals that interact within it [10, 16, 9, 15].

Next, particular domains for the application of ABM were considered. Throughout the research concerning organizational behavior the concepts of organizational ambidexterity and organizational co-evolution arose on numerous occasions. [3, 4, 11, 19, 18, 5, 2, 1]. Several papers utilize these concepts in ABM simulations with varying granularities and applicative domains.

The notion of an organization is quite abstract, however throughout most of the researched models, a clear feedback relay can be established by considering the varying levels of encapsulation and information exchange. One key observation made across the reviewed literature is that it seems in practice an organization requires a rigorously defined in-group and out-group. In this case, the in-group — with possible sub-groupings — can be considered as every individual whom is contained within the organization. The organization's routines can be viewed as a negotiated compromise among the different organization members, scaled by the member's relative importance and personal opinion formulation. The out-group consists of all external stakeholders, e.g. customers, who can provide feedback to members of the organization. This feedback is of a unique circumstance because it is informed by organizational output, which is governed by macro-level organizational routines, however is communicated through micro-level interactions with organizational members. This is an important distinction because it avoids issues of informational feedback loops among other issues. It was determined that considering how to apply ABM to a class of systems where members of the class could be considered as organizations albeit have unique, differentiated architectures found commonly across the class could prove to be an interesting research endeavor.

One particular system that came to mind was that of the higher education institution (HEI). Not only has there been ample personal exposure both from within and outside of HEIs, but HEIs seem to present a quite unique system architecture, in addition to their broader social, political, and scientific importance. As opposed to the generalized organizational model, there is not a clear in-group and out-group, there are numerous loops of feedback in information transfer, stakeholders can be found within and outside of the institution, and these stakeholders each have a rather unique set of goals, accompanying actions, and associated metrics. This makes the problem of trying to create a generalized HEI behavioral model quite compelling.

First, a validated organizational behavior model and simulation from related literature is detailed and implemented. This more easily establishes the concepts aimed to be applied to HEIs and creates a logical starting point for further adaptation and modification. Next, conceptual differences between the establishes organizational behavior model and HEIs are discussed and ideas for changing the model accordingly are presented. From there, the full model created for this project is detailed in its entirety and an explanation is given regarding its implementation. Next, the experiments performed on the model are summarized. Furthermore, experimental data analysis and modelling is presented. The paper concludes with a discourse on the scope and limitations of the included findings as well as ideas for future work.

2 Establishing a Starting Point

To better conceptualize the HEI modelling case, a validated organizational behavior model is replicated. Breslin [2014] creates a simulation of management organizational co-evolution [3]. The particular model also includes the notions of multi-level hierarchical interactions within the organization governed by variation-selection-retention mechanisms within environments necessitating ambidexterity. Using his model, Breslin seeks to explore two hypotheses. First, how higher levels of management control, lower levels of employee adaptability, and lower customer proximity affect the exploitation of knowledge and experiential learning of the organization during periods of stable customer demand. Second, how lower levels of management control, higher levels of employee adaptability, and higher customer proximity affect organizational adaptability during periods of unstable customer demand and knowledge exploration. To explore these hypotheses, Breslin constructs and uses a model to be used in ABM simulation. Figure 1 offers a flowchart summary of the model.

A good starting point is considering how customers provide feedback in this model. This feedback, $f(t)$, is given by a customer fitness curve between the organizational routine, R_O, and target customer value , R_D as defined by:

$$f(t) = \begin{cases} 1.0 & \forall\, R_O(t) = R_D \pm 2 \\ 0.5 & \forall\, R_O(t) = R_D \pm 10 \\ 0.25 & \forall\, R_O(t) = R_D \pm 20 \\ 0.1 & \forall\, R_O(t) = R_D \pm 30 \\ 0.05 & \text{else} \end{cases} \tag{1}$$

Furthermore, this feedback is then scaled by the customer proximity, C_{prox_i}, of each individual i:

$$f(t)_i = 1.0 + (C_{prox_i} \times (f(t) - 1)) \tag{2}$$

Next, the capability of a certain individual to change their opinion from one period to the next, $\pm\delta R_{G,i}$ is modelled by scaling $f(t)_i$ by a capacity to change factor, $\Delta R_{G,i}$:

$$\pm\delta R_{G,i}(t) = \pm - \Delta R_{G,i} \times (1 - f(t)_i) \text{ with } \pm \text{ same as: } R_O - R_D \tag{3}$$

A brief note here: determining the sign of the change capability based off of the sign of the difference in organizational routine and target customer value was not clear in Breslin's paper. However, correspondence was established with Dr. Breslin and confirmation of this determination was made. Further, Dr. Breslin commented on the difficulty in abstraction regarding HEIs through an organizational lens and most likely high resultant model complexity.

This change capability is then scaled for inertial effects in opinion change:

$$\delta R_{G,i}(t) = \frac{\delta R_{G,i}(t)}{In_i(t) \times C_i} \tag{4}$$

where $In_i(t)$ is an intertial clock that keeps track of a how many time periods since a change above a threshold value and C_i is an intertial constant

This change capability is then combined with an individual's routine opinion from the last time step, $R_{A,i}(t-1)$ to form the current time step opinion, $R_{A,i}(t)$:

$$R_{A,i}(t) = R_{A,i}(t-1) + \delta R_{G,i}(t) \tag{5}$$

Overall group routines, e.g. $R_A(t)$ for group A in time period t, are determined by taking averages across group member's opinions weighted by those group member's relative influence, P_i:

$$R_A(t) = \sum_{i=1}^{n} (R_{A,i} \times P_i) \text{ where } n \text{ is the number of group members} \tag{6}$$

Following, the overall organizational routine, R_O, is found through an average of the group routines weighted by the relative group influences, e.g. P_A for group A:

$$R_O(t) = \sum_{i \in G} (R_i(t) \times P_i) \text{ where } G \text{ is the set of groups} \tag{7}$$

3 Conceptualizing Higher Education Institutions

One significant difference between Breslin's model and HEIs is that the relationship between the types of stakeholders in an HEI is not as clear. In Breslin's model, there is a definite distinction between producers and consumers — producers are all individuals who are contained within the organization and work to generate the organizational output with consumers being external to the organization. However, in an HEI, there are students, faculty, administration, staff, and other stakeholders who all impact the overall set of organizational routines and to a point both produce and consume. Simply, these different stakeholders have different sets of routines, goals, and associated metrics however all coexist within the same institution. A consideration of information flow can be found in Figure 2.

In Breslin's model, routine is a unitless value between 1 and 100, but this needs to become more nuanced in order to fully abstract HEI routines. Stakeholders each have, from their perspective, an ideal portfolio of different institutional routines to maximize their own particular benefit, however the final overall policy ends up being a balance of these portfolios. One modelling possibility for this is considering routines as vectors where each element is the balance of the portfolio aligned with the corresponding stakeholder as:

$$\vec{R}(t) := [r_1, r_2, \cdots, r_n]^T \text{where n is the number of stakeholders} \tag{8}$$

which necessitates:

$$0 \leq r_i \leq 1 \, \forall \, i \in \{1, \cdots, n\} \tag{9}$$

$$\sum_{i=1}^{n} r_i = 1 \text{ where } n \text{ is the number of stakeholders} \tag{10}$$

Since stakeholders are influenced by other stakeholders and outside influences, the feedback mechanism of Breslin's model needs to be changed. Each time step, a stakeholder will adjust their opinion based on outside influence. This adjustment can be derived by first aggregating external influence weighted by the relative receptivity of the stakeholder to a certain type of influence. First, a matrix of influences, is produced using the last time period's group routine as a proxy for that type of stakeholders influence and including that stakeholders external influence, $\vec{e_i}$ into consideration:

$$I_{i,j}(t) = [\vec{e_{i,j}}(t), \vec{R_1}(t), \vec{R_2}(t), \cdots, \vec{R_n}(t)] \tag{11}$$

Now, this matrix can be consolidated into a single influence vector by scaling via a dot product with that individual's receptivity vector, $\vec{c}$:

$$\vec{A_{i,j}}(t) = I_{i,j}(t) \cdot \vec{c} \tag{12}$$

where $\vec{c}$ is composed of the proportion of external influence receptivity combined with the proportions that each stakeholder influences the individual, with the requirements of a routine, Equation 9 and Equation 10.

To ensure the result is a routine, $\vec{A_{i,j}}$ satisfies Equation 10, it is then normalized by dividing each element by $\|\vec{A_{i,j}}\|_1$, which preserves relative scale.

To combine this external influence into a stakeholder's opinion, first a metric for comparing two routines must be defined. Total Variation Distance (TVD) is the suggested metric and is defined as:

$$\mathrm{TVD}(\vec{R_1}(t), \vec{R_2}(t)) = \frac{\|\vec{R_1}(t) - \vec{R_2}(t)\|_1}{2} \tag{13}$$

Now, the total difference in opinion, $D_{i,j}(t)$, from the external influence to group i, member j's last period's ideal routine, $\vec{R_{i,j}}(t-1)$ can be computed as:

$$D_{i,j}(t) = \mathrm{TVD}(\vec{R_{i,j}}(t-1), \vec{A_{i_j}}(t)) \tag{14}$$

However, individuals will only have a certain degree of opinion flexibility, $f_{i,j}$. In other words individuals will compare their own opinion to that of their influences with a certain proportion. Furthermore, individuals who have changed little over the previous time steps will exhibit inertia, $v_{i,j}$, further reducing their willingness to change. This inertia builds up each time an individual does not change more than a certain tolerance, $b_{i,j}$, and is scaled by an inertial constant, $c_{i.j}$. Thus:

$$v_{i,j}(t) = \frac{1}{\frac{s(t)}{s(t)-c_{i,j}}} \text{ where } s(t) \text{ is the number of time periods since last change} \geq b_{i,j} \tag{15}$$

By multiplying by opinion flexibility as well as inertia, the distance in opinion able to be traveled in time period t, $Z_{i,j}(t)$, is:

$$Z_{i,j}(t) = D_{i,j}(t) \times f_{i,j} \times v_{i,j}(t) \tag{16}$$

Now, a search can be conducted to find $\vec{R_{i,j}}(t)$, a routine $Z_{i,j}(t)$ away from the individual's last routine in the direction of influence, $\vec{A_{i,j}}(t)$. Many possibilities for conducting this search exist, however a binary search of sorts has been implemented. First, a guess is made that is the mean of the individual's last routine and their current influence and normalized. Next, the distance between the guess and the original routine is found. If this distance is larger than the ability to change, then a new guess is made using the mean of the last guess and the last routine. However, if the distance is smaller than the ability to change, then a new guess is made using the mean of the last guess and the current influence.

Similarly to Breslin's model, negotiations weighted by intra-group influences are conducted to determine group-routines. Each individuals routine is added as a vector column to a matrix, $\boldsymbol{R_i}$, and then each individual's intra-group influence is compiled into a vector $\vec{U_i}$:

$$\vec{R_i}(t) = \boldsymbol{R_i}(t) \cdot \vec{U_i} \tag{17}$$

Once again, to ensure the result is a routine, $\vec{R_i}$ satisfies Equation 10, it is then normalized by dividing each element by $\|\vec{R_i}\|_1$, which preserves relative scale.

This same process is repeated to determine the organizational routine, $\vec{R_O}(t)$, but applied to group-routines scaled by inter-group influences.

4 Model Experimentation

The model inputs are:

1. Model Stakeholders
2. Number of agents of each class
3. Inter-group influences for the institution
4. Frequency of negotiations
5. Agent-Specific Inputs
    (a) Stakeholder type
    (b) Intra-group influence
    (c) Renewal of Opinion Frequency
    (d) Opinion Flexibility
    (e) Initial Routine
    (f) External Influence
    (g) Influence Proportions

For the purposes of experimentation, 4-year United States degree-granting post-secondary institutions are considered. Within these institutions, students, faculty, managers, and other staff are considered to be the stakeholders (input, item 1). The National Center for Education Statistics (NCES) details that among these type of institutions during Fall 2018, there were 13,900,710 students and 3,326,613 total staff members consisting of 1,216,524 faculty, 227,856 managers, and 1,882,233 other [6, 7]. Furthermore, the NCES also shares that there are 3,167 institutions of the considered type [8]. By dividing the associated values of different stakeholder classes by the number of institutions and rounding to the nearest integer, a rough estimator for the average is obtained. This produces 4,390 students, 384 faculty members, 72 managers, and 594 other staff members.

Here we consider the set representing stakeholder counts as: $\{4{,}390, 384, 72, 594\}$. Scaling by the smallest set member produces the set: $\{61, 5, 1, 8\}$. This set establishes the number of agents per single manager agent. When considering the number of agents to use a balance has to be struck between statistical validity and computing resources. To account for enabling the experiments to model intra-group negotiation well for all stakeholder classes, the preceding set is scaled by a factor of 5 and used for producing the number of agents per stakeholder class. This results in 305 student agents, 25 faculty agents, 5 manager agents, and 40 other agents for a total of 375 agents (input, item 2).

Inter-group influences signify the relative weight of a certain stakeholder group's opinion when negotiating an organizational routine. Three cases are considered: high manager control with equal remaining class balances, control based on relative agent-number, and high manager control with a focus on students and faculty and represented by $\{0.2, 0.2, 0.4, 0.2\}$, $\{0.813, 0.067, 0.013, 0.107\}$, $\{0.25, 0.25, 0.4, 0.1\}$ respectively (input, item 3).

Negotiations will occur either each time step or every 5 time steps for these experiments (input, item 4).

A certain agent's intra-group influence will be a random variable sampled from an exponential distribution with a rate parameter of 1 (input item 5b). An exponential distribution is used in order to model how within a group there will be a large proportion with little influence, and a small proportion with larger influence. To ensure that the collection of the intra-group influence of all agents of a certain stakeholder class is composed of proportions, each item of the collection is normalized as previously described.

Renewal frequency of individual agents can be either 1, 3, or 5 time periods (input, item 5c).

Further, a grid of opinion flexibilities is considered where each stakeholder could have 0.25, 0.5, or 0.75 flexibility (input, item 5d).

To initialize agent routines, routines are designed with the corresponding stakeholder's element uniformly picked between 0.25 and 1 and remaining proportion shared between the other interests within the routine are assigned.

External influence on a particular agent is twice weighted towards that agents class. For example, a student's external influence would be: {0.4, 0.2, 0.2, 0.2}

The relative influence of stakeholder classes towards a particular stakeholder is defined in two ways: equal influence and influence based on relative agent numbers with external influences of 0.25, 0.5, or 0.75 item 5g).

Combining all possible sets of these parameter options produces 8,748 unique experiments. These experiments were then carried out over 100 time steps producing 883,548 data points.

5 Model Implementation and Data Operations Notes

This model was implemented from scratch in Python. An object-oriented paradigm was utilized and three classes were created: Agent, Environment, and Model. The logic used here is that a model contains experiments which apply starting parameters to an environment which initializes and contains groups of agents. Project Mesa, an ABM modeling Python framework, was referenced for validation of implementation logic [17].

The model class contains necessary methods to instantiate, formalize and experiment on a particular model. Once an empty model is created, a method, generate_experiment_parameter_set, can be run resulting in the addition of a model parameter containing a list of all experimental parameters to be tested. Utilizing these parameters an environment can then be added to model through the set_environment method. An experiment can then be run on the resultant environment for a given number of time steps.

The environment class contains necessary methods to create a new environment with certain agents generated within it. The environment class also serves an important role since it gives access to all agents contained within it. Utilizing this access, the associated methods for intra-group and inter-group interactions are able to be created. Thus, the environment of this programmatic model serves to parallel the notion of the institution, and both tracks and manipulates the organizational routine variable. Between the model and environment classes, actions spanning from experimentation given certain starting parameters, and inter/intra group negotiating are enabled.

However, to aptly model micro-level interactions among agents the generation of an agent class is needed. Members of this class belong to a certain environment and have starting parameters passed from the environment, which are generated from the model. Within the Agent class, there are methods needed in order for an agent to vary their opinion. Binary search is conducted within these methods through a recursive means with a maximum depth of 900.

The simulation can be run by utilizing the main script (src/main.py) with the aforementioned parameters as specified inside the environment class. Each experiment is saved into a directory (./data/raw/) as a .json file. This file type is utilized because it offers easy Python dictionary serializing and keep simulation data compact.

In order to not have enormous sets of inputs persist throughout the data, experiment 1 is first processed including all inputs. This file is then saved to .csv (data/processed/experiment_1) and uploaded to Dropbox for further retrieval. Next, all experiments within the directory are compiled, columns subsetted (to remove random variable inputs), exploded (turning columns of lists into multiple columns), then saved to .csv (data/processed/all_data) and uploaded to Dropbox for further retrieval. The author's computer seemed to stall when processing and producing the whole dataset. To remedy this, Apache Spark was utilized for distributed data processing resulting in large speed upgrades.

Next, within a Jupyter Notebook Environment, the datasets are requested from Dropbox using each file's unique link. Due to the large number of experiments, Jupyter widgets are utilized such that plots can be generated for any experiment inputted. After summarizing and creating visualization of the data, modelling is conducted utilizing the scikit-learn library.

A train-test split is created in the overall dataset such that model accuracy may be validated later on. Next, the predictors (simulation inputs) are standardized using the training set predictors. Using these standardized predictors, a multi-output multiple linear regression model is applied. The accuracy (measured as explained variance score, root mean square error (RMSE), and R^2 score) of the trained model is then established using the test set. Further, this regressor is utilized in the application of permutation importance testing.

Next, a multi-output Random Forest model is applied to the non-standardized training set. Similarly to the linear regression model, accuracy scores are computed and the regressor is used in permutation importance testing. Random Forest feature importance scores are also queried from the model.

From evaluation of modelling outputs so far, a subset of features is chosen to establish more accurate feature importance scores. As the feature importance scores from the Random Forest model seemed to agree for the most part with the magnitude of linear regression model coefficients, the feature subset was chosen based off of features where the Random Forest importance score was over 1×10^{-6}. Using this subset of features, all the above modelling is repeated.

Finally, SHAP (SHapley Additive exPlanations) is applied to a subset of training data [12, 13, 14]. SHAP is difficult to calculate for a large sample, thus around 3% of the training data is randomly sampled. This subset is then modelled using a Random Forest. Accuracy scores are calculated to ensure the sample. Further, this regressor is then utilized with the SHAP algorithm to produce interactive plots concerning variable importance to the overall model predictions.

6 Experimental Results

Figure 3 depicts the distribution of agent's initial considerations for their own proportion of the routine for experiment 1. Figure 4 shows the distributions of intra-group influences across different stakeholder classes for experiment 1 as well. As could be expected from the Law of Large Numbers, the distributions become less similar to the distributions there were sampled from as the number of agents of a certain class decreases.

Figure 5 shows the change in routine values across 100 time steps in experiment 1. Furthermore, Figure 6 zooms in on the first 10 time steps. The former indicates that all routines seem to stabilize after about 30 time steps. The latter allows for better delineation between unique routines. The four downward sloping lines represent a stakeholders opinion of their own class proportion with extremity of line indicated by number of agents within the class. The four lines in the middle represent the organizational routines and seem complimentary to the two sets of routines above and below. Plots of these factors for the other experiments can be found by utilizing the associated widgets within the notebook.

Figure 7 portrays the convergence proportions of a given stakeholder class across time with Figure 8 being zoomed in on the first 10 time steps. This value represents the proportion of the class where the binary search algorithm terminated with an error less than the tolerance. It can be seen that all classes convergence proportions stabilize after 5 time steps. Similarily, plots of these factors for the other experiments can be found by utilizing the associated widgets within the notebook.

Figure 9 and Figure 10 show the change in group decisions over 100 and 10 time steps for experiment 1 respectively. For experiment 1, group decisions stabilize after 8 time steps, however this is constant across all experiments. Some, for example experiment 7777, show a more punctuated change where group decisions periodically change with smaller magnitudes as time progresses.

The multi-output multiple linear regression scored an average 0.773 explained variance score, 0.013 average root mean square error (RMSE) score, and 0.773 average R^2 score across the four outputs. Upon analysis of model coefficients it appears that opinion flexibilites and external influences both had relatively little impact on the model (coefficients near 0 for all four outputs for all four types). Permutation importance scores indicate that renewal frequencies (all), relative influences (external and student), and inter-group influences (all) have the highest importance scoring with mean values on the order of 10^7 or higher.

The multi-output Random Forest completely fit the testing set with average scores of 1, 0, and 1 for explained variance score, RMSE, and R^2 respectively. Further, the model indicated that relative influences, inter-group influences, negotiation frequency and time were the only variables of importance with faculty relative influence (0.31517), faculty inter-group influence (0.16894), and manager inter-group influence (0.16737) scoring at least an order of magnitude higher than other features. Permutation importance scores corroborate these findings with features of relative influences, inter-group influences, negotiation frequency, and time scoring at least 10 orders of magnitude higher than other features. These scores did not have as much variability between them as the Random Forest importance scores however. They do indicate that faculty relative influence, time, faculty inter-group influence, and manager inter-group influence are of higher importance, with scores an order of magnitude higher than other significant scores.

Using the important features from the Random Forest model as a subset of model features for another multi-output multiple linear regression model derived exactly the same accuracy scores as the original linear regression model. However, analysis of model coefficients indicates that inter-group influence is the most important to the model with all features of that class having coefficients on the order of 10^{10} or higher. Faculty and other group have negative coefficient values, with student and manager groups having positive values. External and student relative influences are next most influential being on the order of 10^8, external with negative sign and student with positive. Furthermore, faculty and other relative influences are next most influential wtih a single order of magnitude. Manager relative influence is next most influential on the order of 10^{-1} with time (negative sign) and negotiation frequency (positive sign) following on the order of 10^{-3}. However, permutation importance scores for this regressor revealed that inter-group influences were most important (order of 10^{10}) followed by student and external relative influences (order of 10^8), followed by faculty relative influence (single order), followed by other and manager relative influence (order of 10^{-1}), followed by time (order of 10^{-3}), and lastly negotiation frequency (order of 10^{-4}).

The Random Forest fit to the subset of features chosen also repeated its accuracy scores across all three metrics. Among the model's feature importance scores, faculty relative influence scored the highest (0.32), followed by manager inter-group influence (0.17), time (0.168), and faculty inter-group influence (0.16). Manager relative influence, other relative influence, and negotiation frequency follow with scores on the order of 10^{-2}. Student relative influences, external relative influences, other inter-group influences, and student inter-group influences follow on the order of 10^{-3}. Permutation importance scores seem to corroborate these findings.

Figure 11, Figure 12, Figure 13, and Figure 14 show SHapley Additive exPlanation force plots for the first prediction of the corresponding proportion of organizational routine as determined by the SHAP algorithm. The Random Forest fit to this subset persisted its perfect accuracy of test set predictions. For the student proportion, relative faculty influence, manager inter-group influence and faculty inter-group influence are most influential to push the expected value, 0.25 (as shown in the JavaScript output within nb.ipynb), lower with no features pushing it higher. Whereas, for the faculty proportion, faculty relative influence, manager inter-group influence, faculty inter-group influence, manager relative influence, other group relative influence, and time serve are most influential in pushing the expected value, 0.25, higher with several features pushing it lower. For the manager proportion, faculty relative influence, manager inter-group influence, faculty inter-group influence, student relative influence, and external relative influence are most influential in pushing the expected value, 0.26, higher with no features pushing it lower. Finally, for the other group proportion many more factors serve to push the expected value, 0.24, higher (so many that they overlap and make analysis difficult) and a modicum of features pushing it lower. SHAP plots across multiple predictions are given in the notebook within JavaScript interactive cells. Figure 15 depicts a summary of variable importances as determined by SHAP for each outcome. Figure 16, Figure 17, Figure 18, and Figure 19 show the variable dependence plots between the highest scoring in terms of importance feature, faculty relative influence, and the different inter-group influences in terms of SHAP value.

7 Results Discussion

From the modelling results, it is apparent that external influences, opinion flexibilities, and renewal frequencies had little to no impact on the organizational routine compared to the other inputs. Of the other inputs, relative influences seem to be most important, followed by inter-group influences, time and negotiation frequency. Time and negotiation frequency are important since they play a factor in defining the space between punctuated changes in group and organizational decisions. Relative influences help to define the variation of each agent which is then realized and scaled through the inter-group influences.

However, the low importance of external influences, opinion flexibilities and renewal frequencies brings the validity of the underlying model's variation consideration into suspicion. Intuitively it would seem that these factors should play a large role in determination of the organizational routine, however the experimental data does not echo this sentiment. The data seems to demonstrate that regardless of how often agent opinions are reconsidered, the organizational routine is dependent only on how much a certain class of stakeholder influences another and how much each class affects the overall decision.

8 Considerations for Future Work

This project's main focus was to conceptualize how a co-evolutionary multi-level organizational behavior model could be applied to the specific case of an HEI and furthermore to understand which factors of the model had the most overall impact. As such, the realized model and experiments succeeded in this goal, however there is ample material for further work found throughout this project.

Validation of the underlying model can be achieved through the creation of experimental parameters that are empirically derived from HEIs and outcomes can be verified through empirical HEI data as well. This would help to determine if the model's abstractions are accurate and useful. Without this step, the model is purely conceptual and results cannot necessarily be applied in the real world. Considering the outcome of the Random Forest models, it is suspected that the model needs to be re-conceptualized. Additionally, the inclusion of a greater number of agents would serve to allow the model to evolve more in line with conceptualizations of the model.

For reproducibility, each experiment's random components were initialized using a random seed. However, this does not take into consideration intra-experiment variability created by this choice of random seed. It would be beneficial to run each experiment over a list of random seeds in order to better understand this variability.

It proved difficult to analyze each experiment, although it can be done using the current analysis. Thus, it would be helpful to create a set of metrics to evaluate important changes within each experiment over the course of its development. This could include the creation of boundary conditions for certain system changes, which the fulfillment, or lack thereof, could be measured across all experiments. This would allow outlier experiments to be identified more rapidly and further analysis can be conducted on these experiments.

9 Appendix

9.1 Model Flowcharts

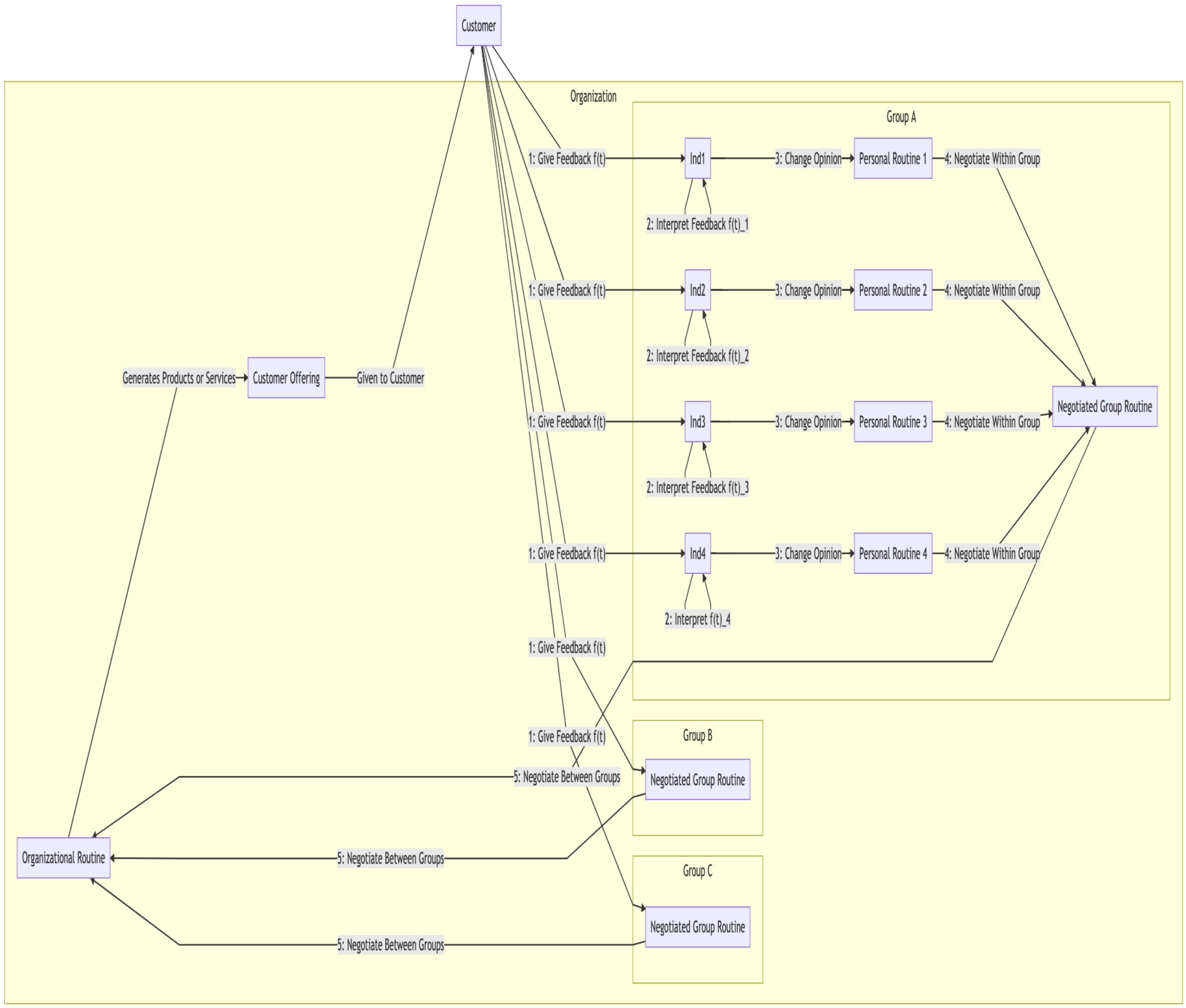

Figure 1: A Rendition of Breslin's Model

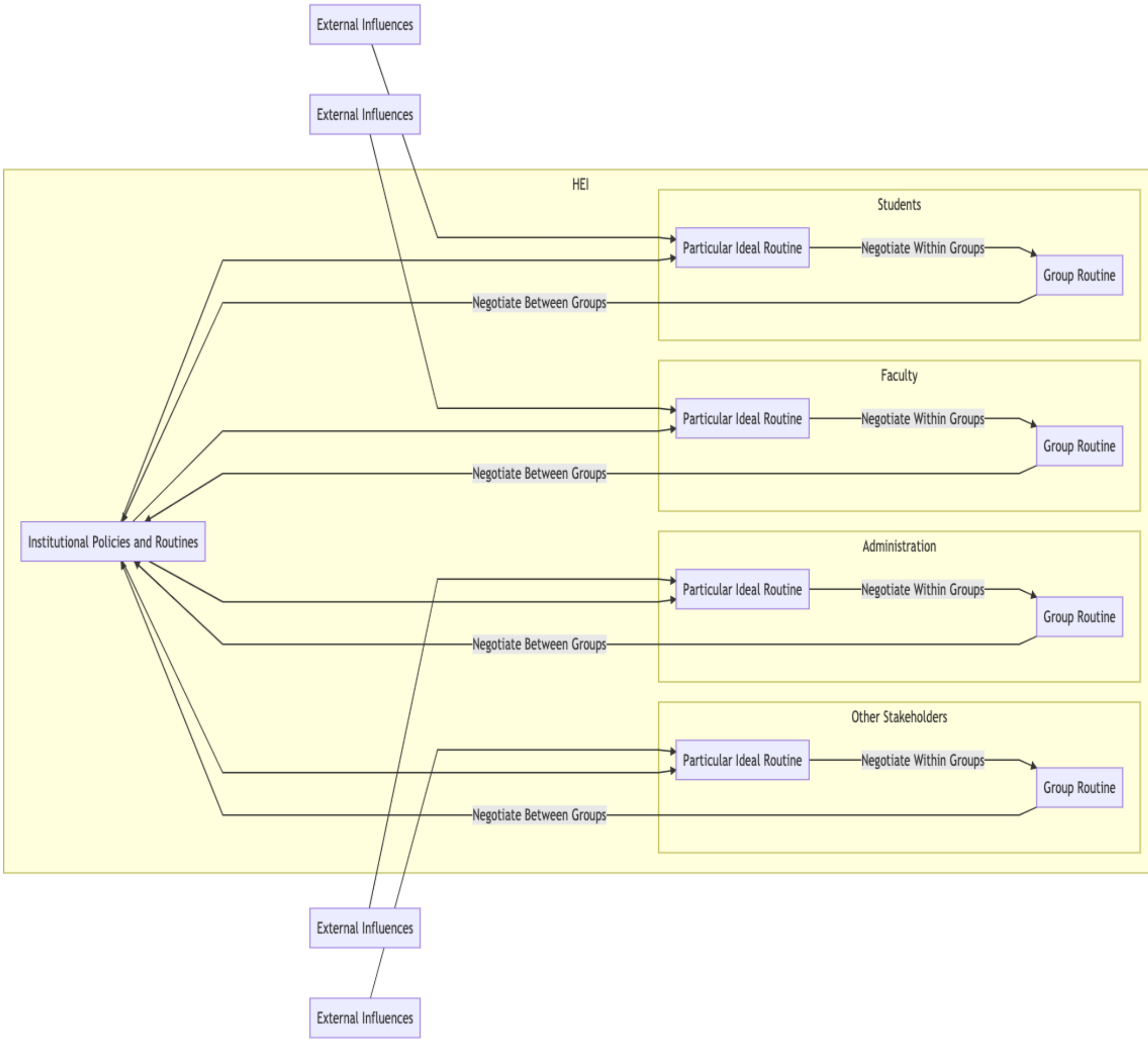

Figure 2: HEI Model Overview

9.2 Experimental Results

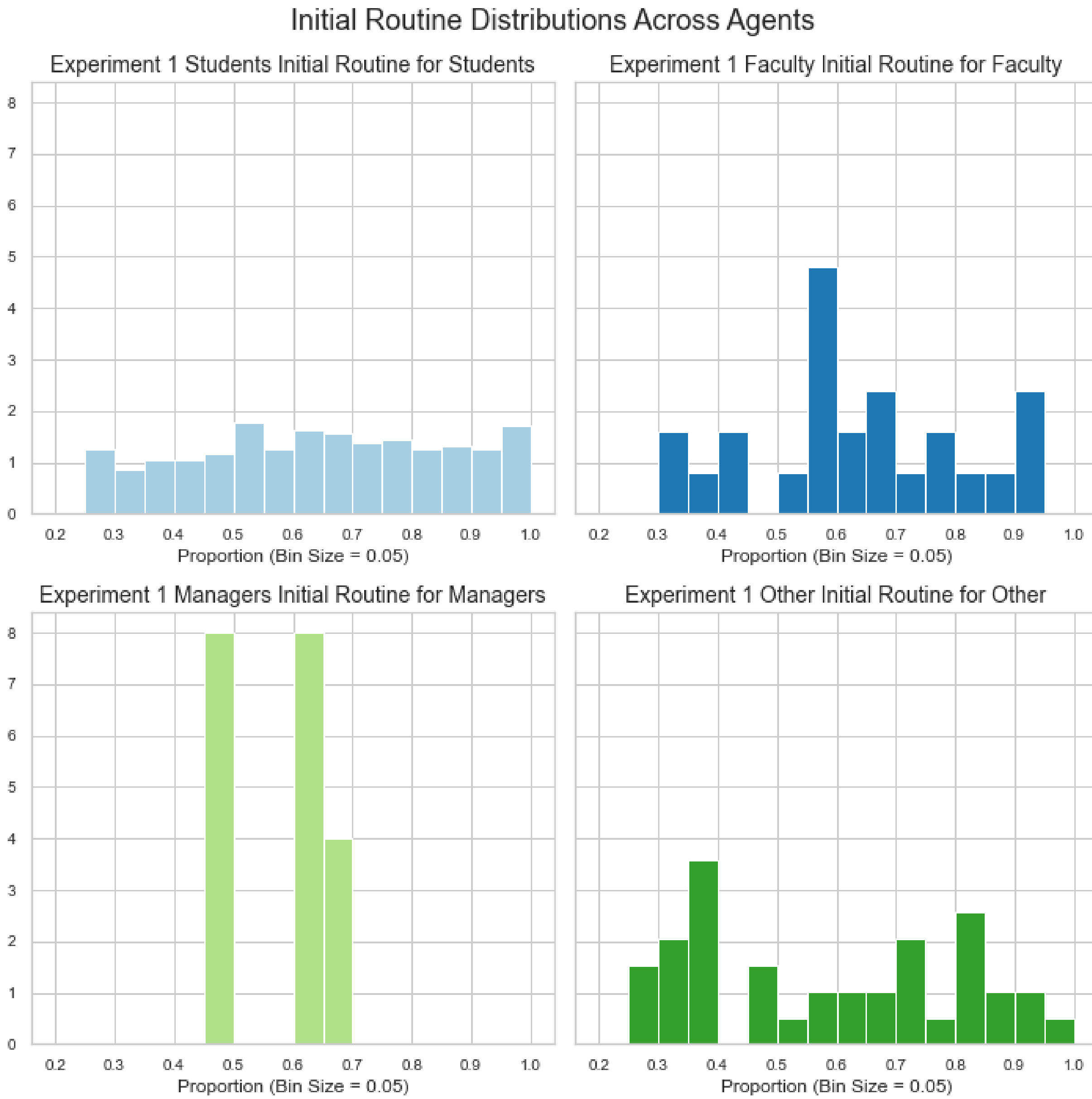

Figure 3: Initial Routine (self-favoring) Distributions Across Agents

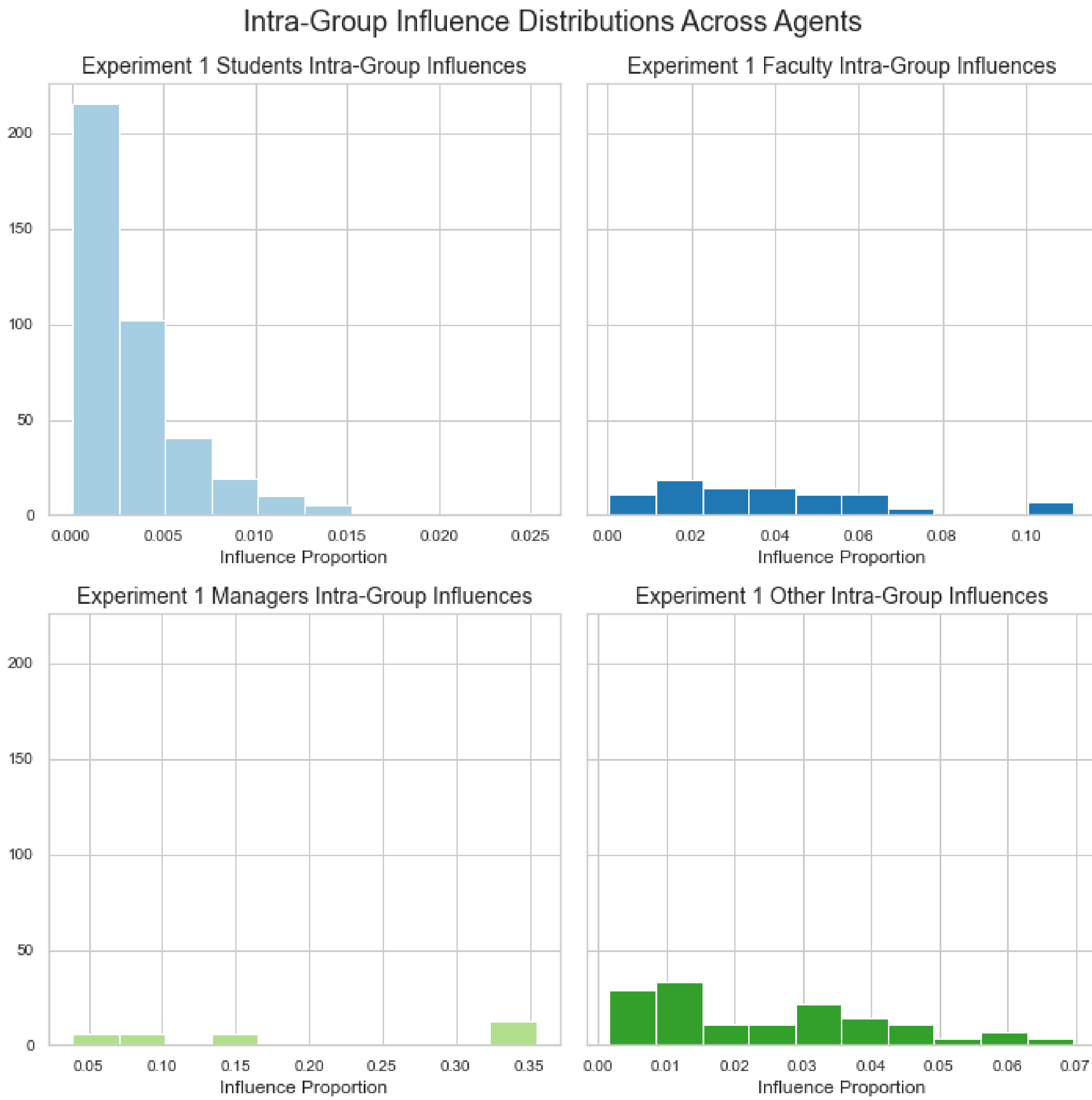

Figure 4: Intra-Group Influence Distributions Across Agents

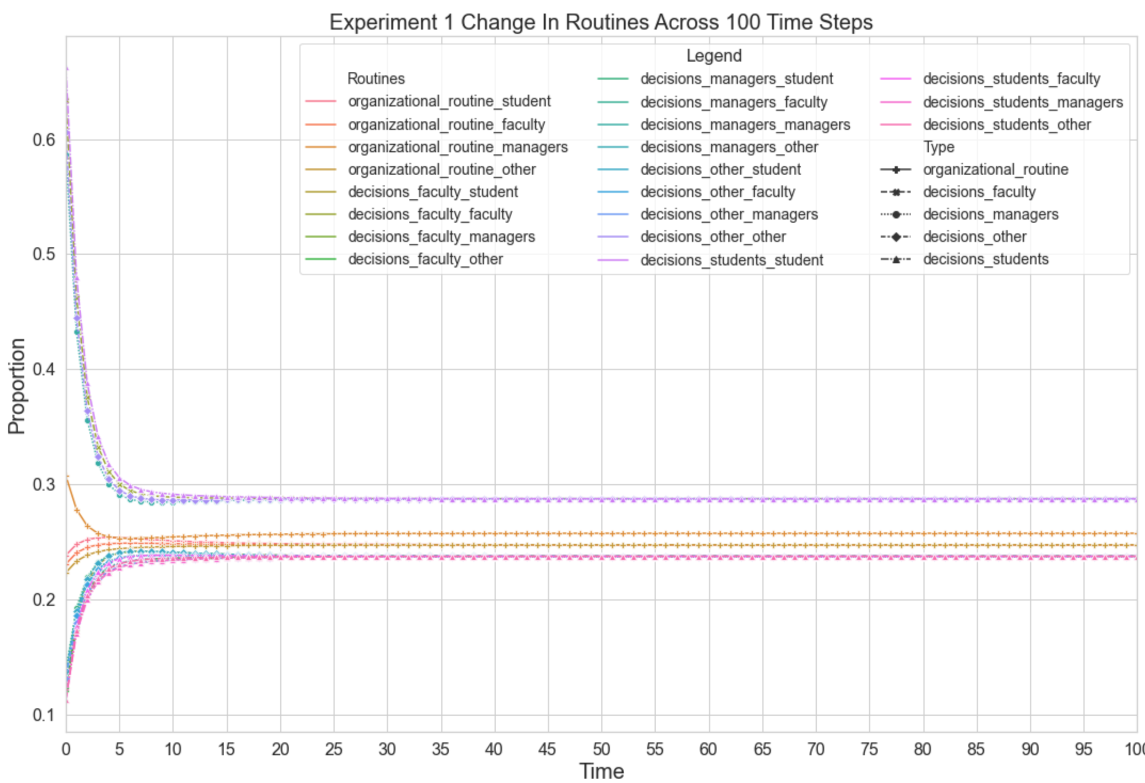

Figure 5: Experiment 1 Change in Routines Across 100 Time Steps

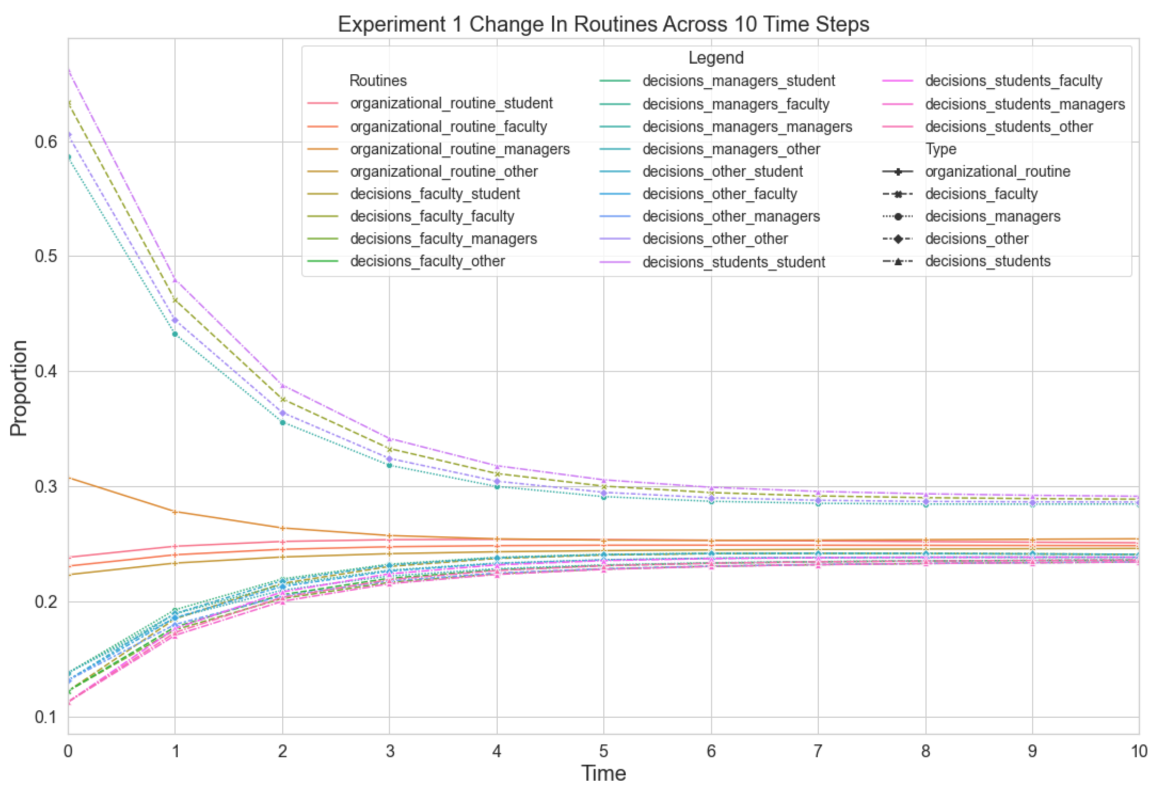

Figure 6: Experiment 1 Change in Routines Across 10 Time Steps

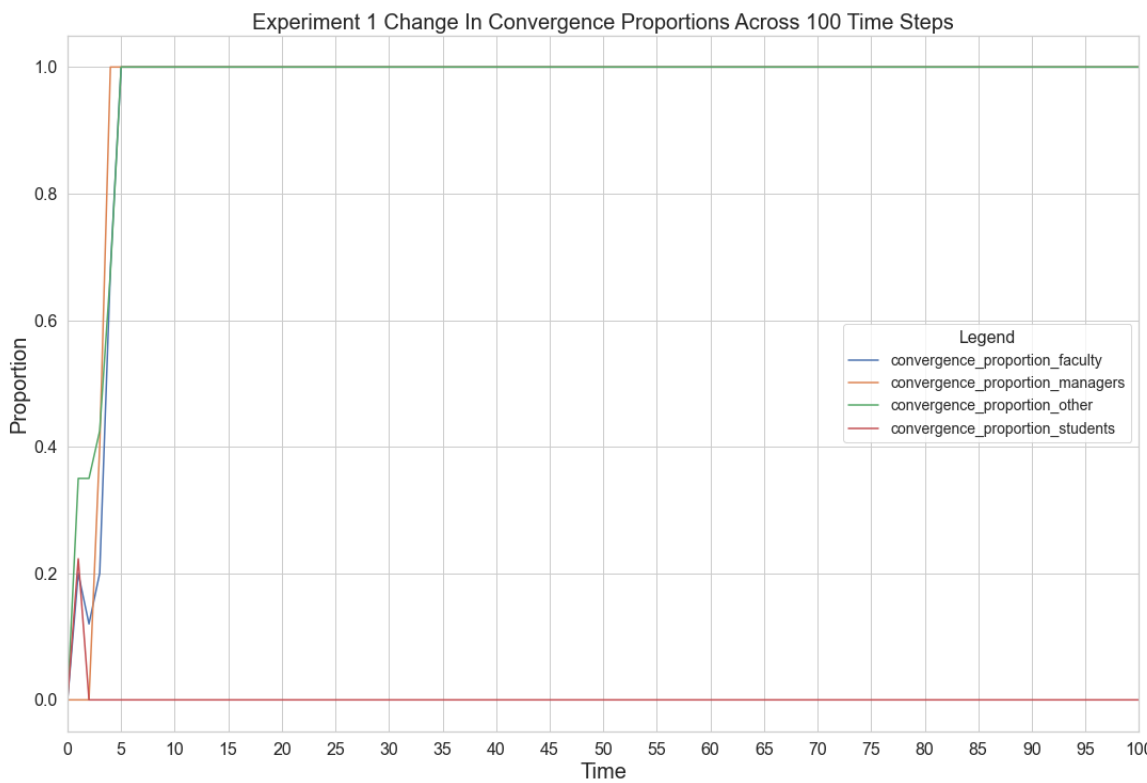

Figure 7: Experiment 1 Convergence Proportion Across 100 Time Steps

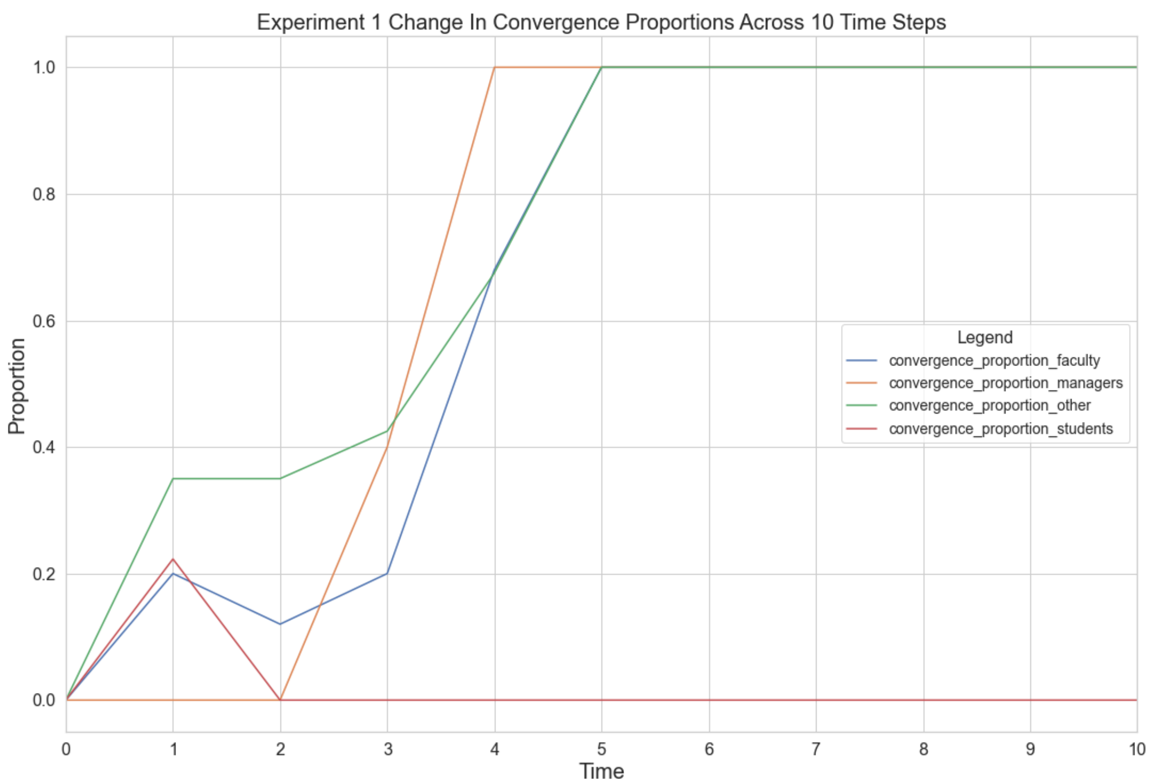

Figure 8: Experiment 1 Convergence Proportion Across 10 Time Steps

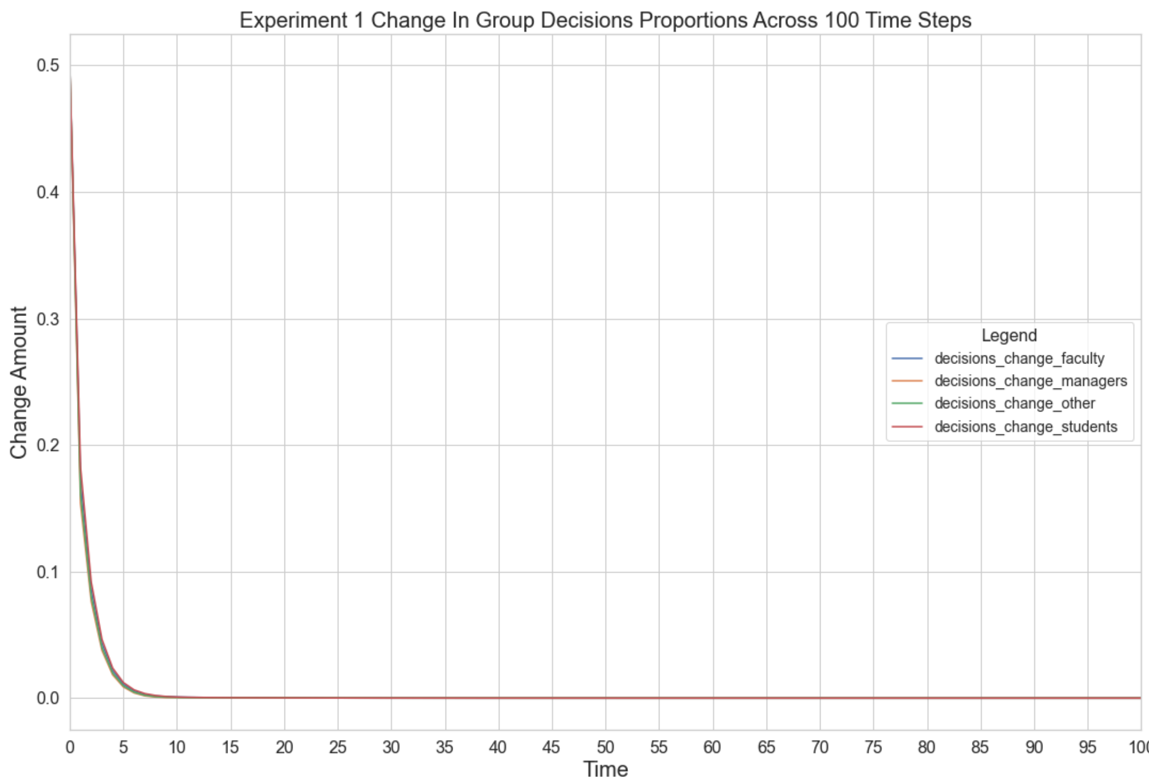

Figure 9: Experiment 1 Change in Group Decisions Across 10 Time Steps

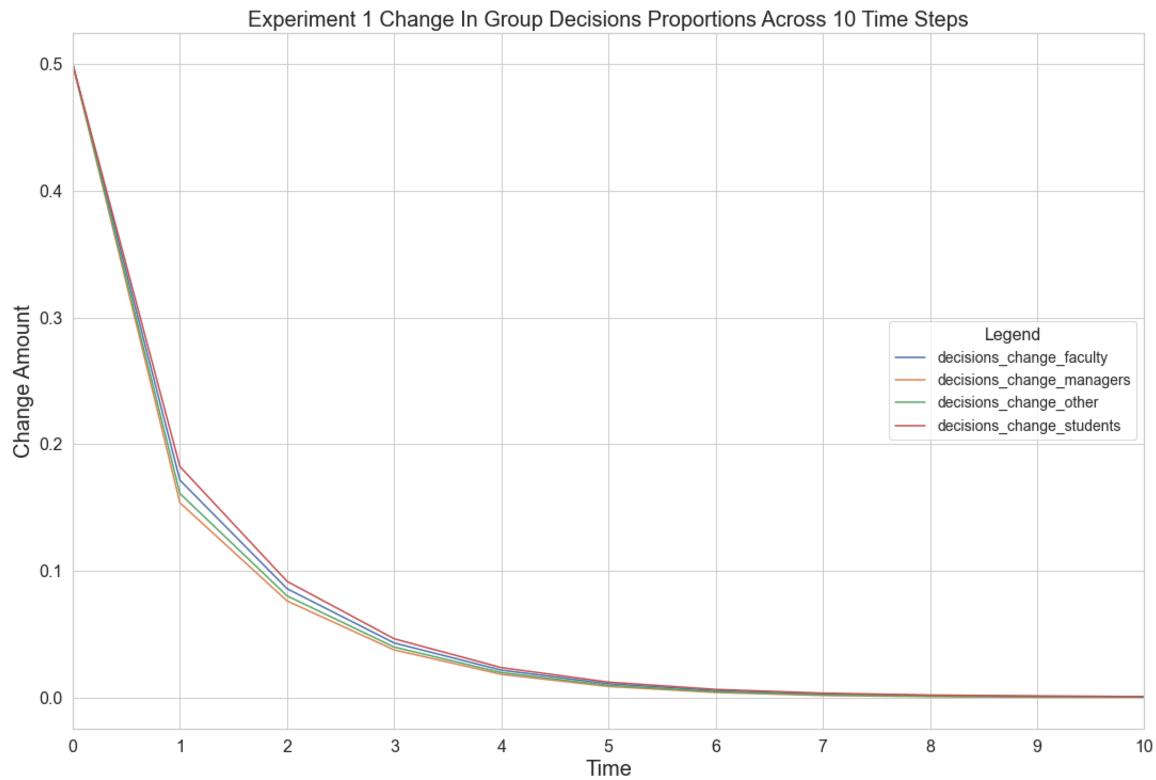

Figure 10: Experiment 1 Change in Group Decisions Across 10 Time Steps

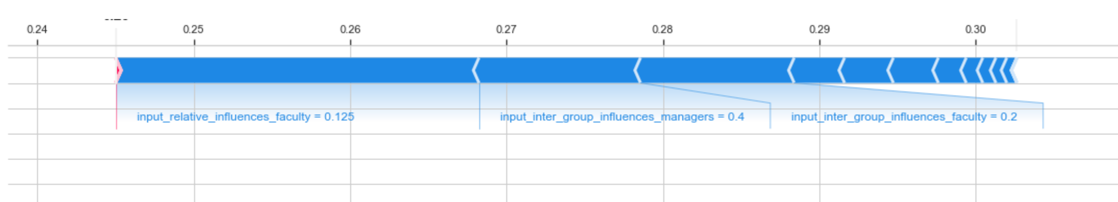

Figure 11: SHAP Variable Importance for Organizational Routine, Student Proportion

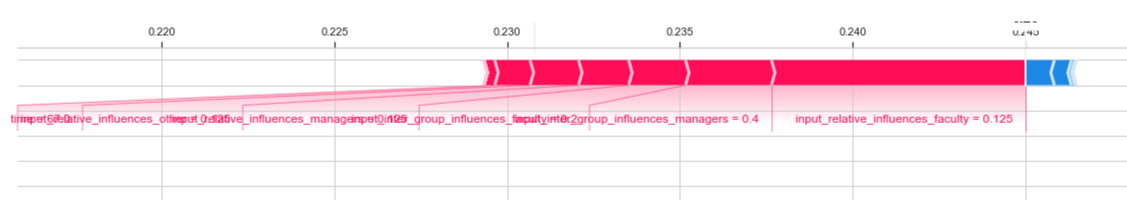

Figure 12: SHAP Variable Importance for Organizational Routine, Faculty Proportion

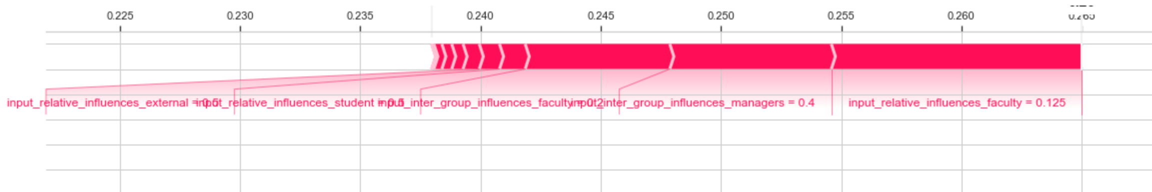

Figure 13: SHAP Variable Importance for Organizational Routine, Manager's Proportion

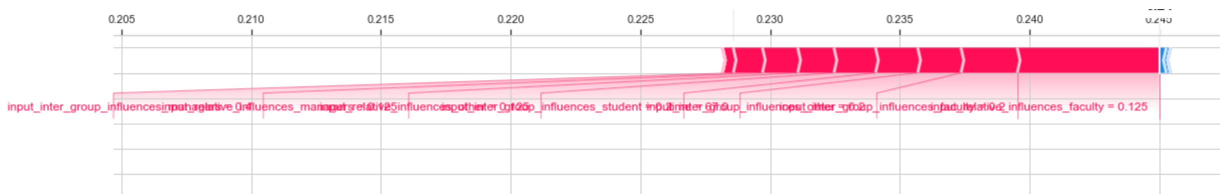

Figure 14: SHAP Variable Importance for Organizational Routine, Other Proportion

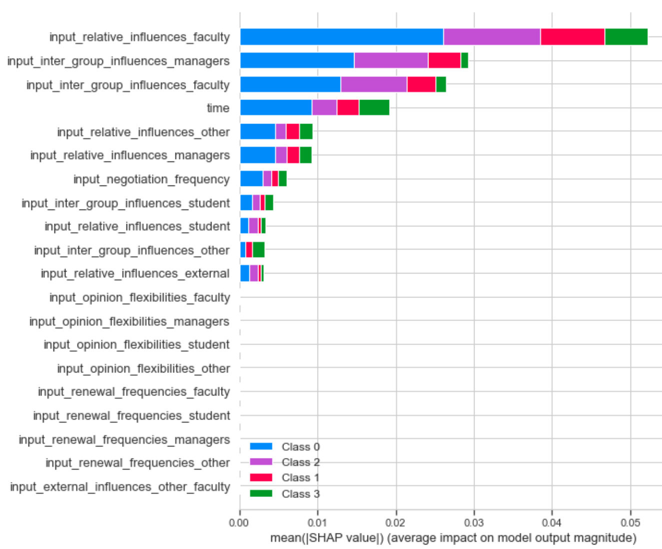

Figure 15: SHAP Variable Importance Summary Plot

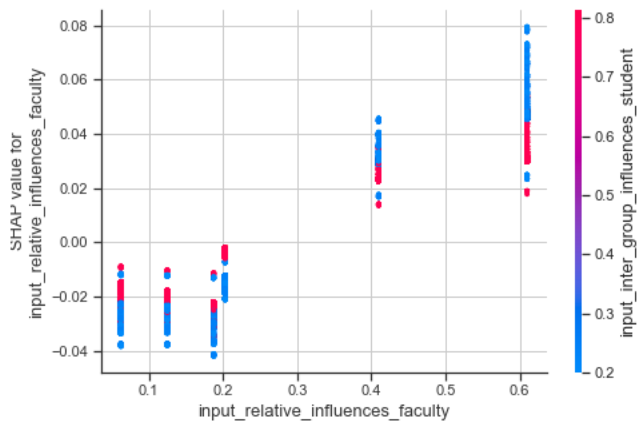

Figure 16: SHAP Variable Dependence Plot between Faculty Relative Influence and Organizational Routine, Student

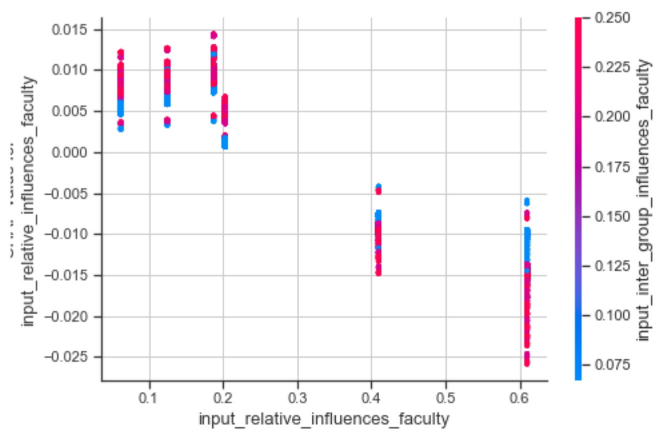

Figure 17: SHAP Variable Dependence Plot between Faculty Relative Influence and Organizational Routine, Faculty

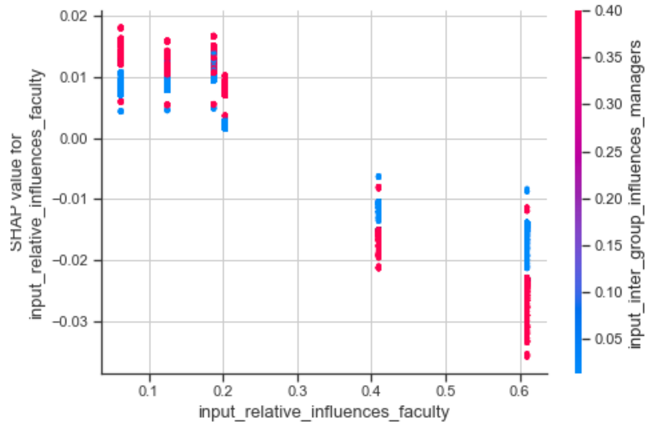

Figure 18: SHAP Variable Dependence Plot between Faculty Relative Influence and Organizational Routine, Manager

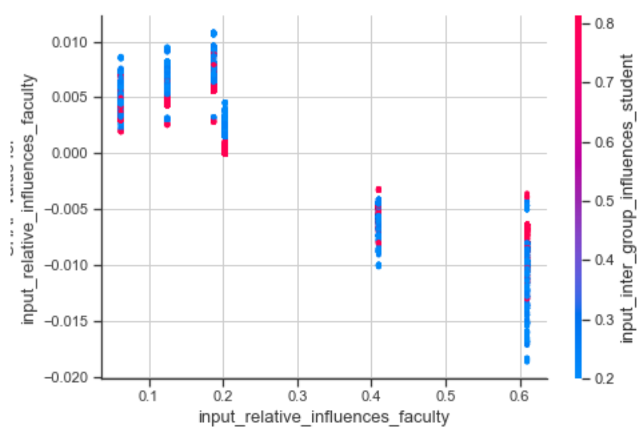

Figure 19: SHAP Variable Dependence Plot between Faculty Relative Influence and Organizational Routine, Other

Glossary

NOTE: Definitions found below are original and created through the synthesis of different sources found within the associated literature. The intent behind offering these definitions is to offer the reader context regarding the overall project. They are not intended to be robust, and in many cases are certainly reductionist.

organizational ambidexterity the balance found between an organization's capability to leverage previously derived insights (exploitation) and the capability of seeking out new insights (exploration). 2

organizational co-evolution application of Darwinian theory to organizational behavior. In this model, organizational routines can be viewed as the *replicator* and the organization as whole can be viewed as the *interactor*. Routines develop through a variation-selection-retention paradigm. 2

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