Qualitative Simulation of Causal Dynamics in Higher Education using Fuzzy Cognitive Maps

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***Abstract*—Universities are complex organizations that are comprised of semi-autonomous interacting units that adapt to evolving demands and regulations. Administrative decision-making requires viewing a university as an adaptive system with a complex causal network of interactions. This paper presents a qualitative causal simulation model based on the Fuzzy Cognitive Map (FCM) formalism to demonstrate exploratory cause-effect analysis of resource tensions and quality in public higher education institutes. The model is focused on a selected subset of factors with the primary aim of demonstrating the use of FCM to support model-centric thinking. The FCM formalism is simulated under a factorial experiment design that examines the interaction among state funding, teaching capacity, and research capacity.**

***Index Terms*—qualitative simulation; fuzzy cognitive map; higher education; complexity**

I. Introduction

According to the Education Data Initiative [1], as of July 2022, 73.0% of college students at all levels attend public institutions. Policies aimed at these institutions have a significant influence on higher education. In recent years, increasing fiscal challenges in the public higher education environment resulted in the development of new administrative models that emphasize the ability to generate income to provide additional revenue. Among such capabilities are sponsored research activities based on contracts and patents. Such activities promoted an environment that can sustain fundable research with implications on hiring policies and incentives for promotion and balance teaching load with increasing research commitments.

Increasing fiscal tensions in state funding of public higher education impact the quality of education, graduation rates, and overall organizational performance of universities [2]. Factors that influence organizational performance can be classified into separate activity and policy categories, such as state funding, affordability, target population characteristics, faculty teaching and research load, compensation, and admission. These separate activity zones interact through complex mechanisms, making it challenging to predict the outcomes of decisions and emergent behavior due to positive and negative feedback loops among factors.

Improving graduation rates, research funding, and overall system quality can involve exploring various options, including staff compensation, faculty incentives for productive participation, teaching and research loads, hybrid instruction, and improving access and affordability to the target population. In this paper, the systems approach with an exploratory modeling and analysis strategy is advocated to provide a foundation to demonstrate policy analysis in the context of higher education. The proposed model is focused on a selected subset of factors with the primary objective of demonstrating the use of the computational Fuzzy Cognitive Map (FCM) [3] formalism to support model-centric thinking.

The rest of the paper is structured as follows. In section 2, background on simulation methodologies used in the simulation of university dynamics is reviewed. FCM formalism is introduced in section 3 to specify the fundamental principles of FCMs and the dynamics of the FCM model. Section 4 presents the implementation and preliminary experiments with the model, as well as a sensitivity analysis of the dynamics to discern cause-effect relations under hypothetical scenarios. Section 5 concludes with a summary of the findings and limitations of the model.

II. Background

Computational models are effective tools in evaluating organizational dynamics to assess the effectiveness of policies in the presence of a multitude of interacting factors. Simulation modeling can help explore the effectiveness of university operations in achieving organizational outcomes while providing a predictive and prescriptive tool for policy evaluation. The use of computational models in education has a rich history. Although the use of qualitative simulations of higher education with FCM models remains to be explored, both Agent-based Modeling (ABM) [4] and system dynamics models [5] [6] are widely used. Next, we provide a brief review of selected ABM and System Dynamics (SD) approaches, followed by a discussion on how the FCM formalism, which is the focus of this paper, can complement the ABM and the SD perspectives.

A. Agent-Based Modeling

Agent-based modeling is a methodology for developing computational models of systems in terms of autonomous agents to simulate the decisions, actions, and interactions of discrete entities. Such entities can represent a broad range of

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system elements, from individual humans to collectives, such as organizations and communities. Agent-based simulation models examine a broad range of aspects of the higher education system and its interactions with the broader context.

In [7], an agent-based model of a public university is developed to study the impact of various organizational decisions on institutional performance with a specific focus on the financial perspective. During the Covid pandemic, universities faced significant challenges in avoiding the spread of outbreaks on campus [8]. Computational studies of randomized testing, contact tracing, and quarantining reveal the effectiveness of alternative strategies in protecting students, faculty, and staff [9]. Simulation models of innovation dynamics explore industry-university links to examine the impact of collaboration structures on innovation effectiveness [10].

Simulation models grounded in theory facilitate understanding system behavior if the real-world behavior unfolds consistently with the premises of the respective theory. For example, in [11], social impact theory tests social communication and resource allocation on STEM yield. Besides education systems, agent-based models are used to study scientific activity and clustering of research activity into scientific domains and disciplines [12]. Similarly, [13] uses a simulation model to represent scientific activity as a sociopolitical system.

B. System Dynamics

System Dynamics (SD) modeling [5] is a mathematical modeling approach to represent systems and their continuous non-linear behavior over time. SD models are used to explain and predict the dynamics of complex issues and problems ranging from artificial to social and natural systems.

System dynamics modeling in higher education has a long history with a broad range of applications overviewed by an early taxonomy of SD models in higher education [14]. Relatively recent research in this area involves capacity planning and policy evaluation. In [15], the implementation of sustainable development education programs is examined with a focus on the sustainability competencies of students. As a decision support tool, system dynamics models contribute to exploring efficient resource management and capacity planning for academic programs [16] [17].

Alternative simulation formalisms, including semi-quantitative and highly interpretable causal simulation formalisms, such as FCM, can also offer avenues to perform thought experiments before developing detailed high-resolution models.

C. Fuzzy Cognitive Maps

FCMs model feedback causal relations in webs of causality and system design/policy/strategy variables [3]. FCM formalism combines neural network theory and fuzzy logic [18] synergistically. FCMs are fuzzy signed directed graphs that allow degrees of causal influence and event occurrence. Such causal models can simulate a wide range of system designs, scenarios, and decision processes. Their nonlinear dynamics permit forward-chaining inference from input causes and design options to output effects. Users can directly add detailed dynamics and feedback links to the causal model or infer them with statistical learning laws [19]. Users can fuse or combine FCMs from multiple experts by weighting and adding the underlying fuzzy edge matrices recursively if needed.

III. Foundations of the Fuzzy Cognitive Map Formalism

An FCM concept node is fuzzy because it can take values in the unit interval [0,1]. Therefore, its values over time define a fuzzy set. This implies that a concept node that describes a property or system state both occurs and does not occur to some degree at the same time. A simple FCM consists of n concept nodes C_j and n^2 directed fuzzy causal edges e_{ij}. The concept nodes $C_1, C_2, \ldots, C_n$ are nonlinear and represent variable concepts or factors in a causal system. The activation value of a concept node $C_i(t_k)$ measures the degree to which the concept C_i occurs in the causal dynamics at time t_k. The FCM state vector $\mathrm{C}(t_k)$ provides a snapshot of the FCM system at time t_k. In addition to the non-linear dynamics of the concept nodes, an FCM model must also specify the n^2 directed and signed causal edge values e_{ij}.

The activation value of the concept j is determined at time t_k on the scalar input $x_j(t_k)$ that reaches and aggregates all the causal activation inflowing to C_j. A non-linear function Φ_j converts $x_j(t_k)$ into the concept's new state $C_j(t_{k+1})$.

$$C_j(t_{k+1}) = \Phi_j(\sum_{i=1}^{n} C_i(t_k)\, e_{ij}(t_k) + I_j(t_k))$$

where $I_j(t_k)$ is an external input at time t_k. The simplest threshold function is a hard threshold that produces bivalent, on-off concept node values:

$$C_j(t_{k+1}) = \begin{cases} 0 & if \sum_{i=1}^{n} C_i(t_k)\, e_{ij}(t_k) + I_j(t_k) \leq 0 \\ 1 & if \sum_{i=1}^{n} C_i(t_k)\, e_{ij}(t_k) + I_j(t_k) > 0 \end{cases}$$

The external input can be set to high (or low) values to ensure that a concept is always on (or off). By fixing the activation value of a node, specific strategy configurations can be tested. A monotonic increasing Φ_j nonlinear function can be used for a continuous dynamic system. Logistic causal activation functions have a sigmoidal structure that approximates the hard threshold function if the shape parameter $c > 0$ is large enough:

$$C_j(t_{k+1}) = \frac{1}{1 + exp(-c \sum_{i=1}^{n} C_i(t_k)\, e_{ij}(t_k) - cI_j(t_k))}$$

Alternative approaches to modeling causal worlds are System Dynamics (SD) models [20] and Bayesian Belief networks (BBNs) [21]. System-dynamics models facilitate representing and simulating causal interactions. Domain experts or random experiments often choose static parameters of the subsystems and their interconnections. On the other hand, FCMs allow data-driven adaptation of the model structure and parameters.

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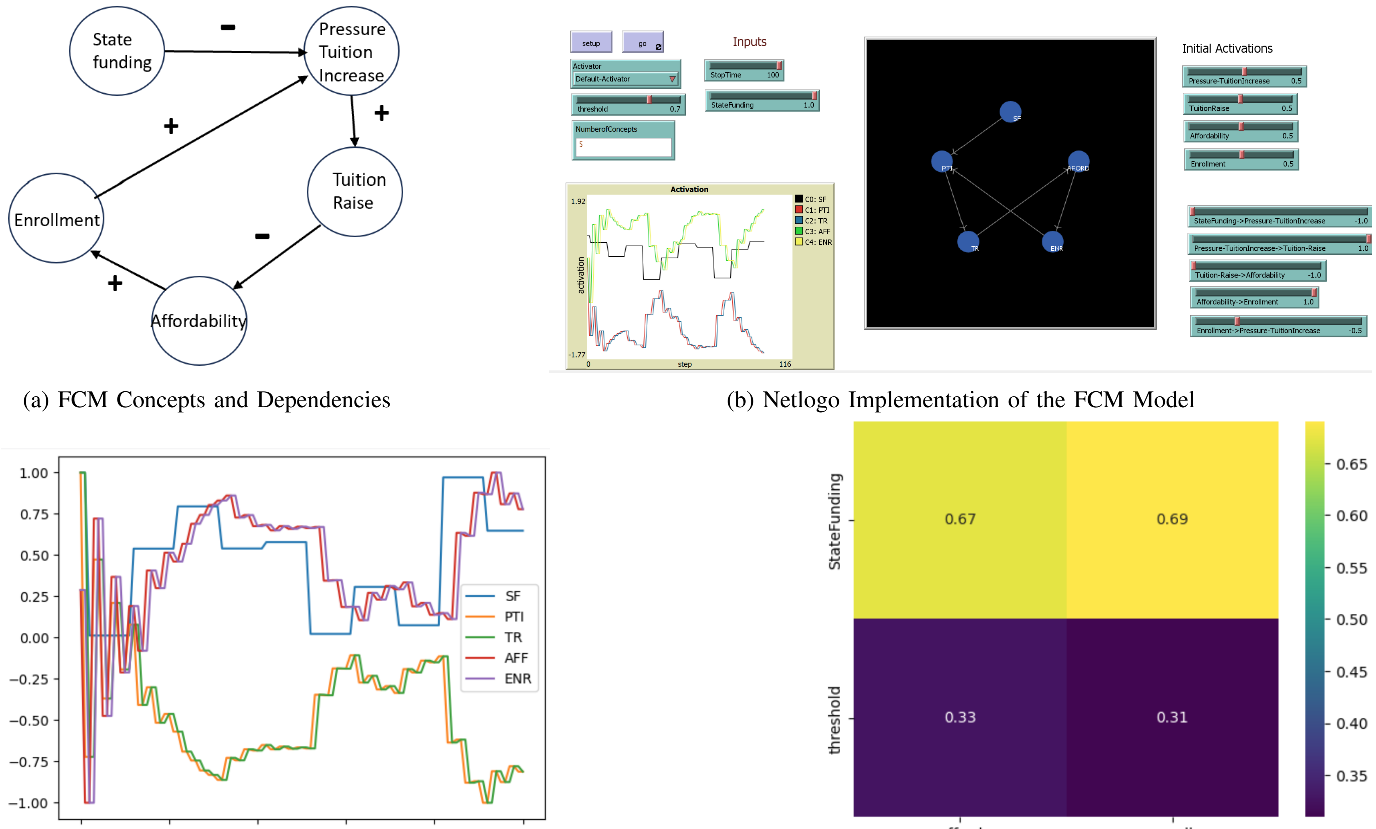

(a) FCM Concepts and Dependencies

(b) Netlogo Implementation of the FCM Model

(c) Normalized Activation Levels

(d) Feature Scoring

Fig. 1: Face Validity of the FCM Implementation

Statistical learning algorithms estimate causal edges from training data. Experts can also state edge values directly. While SD models include stochastic behavior through sensitivity analyses at the end of modeling, FCMs build uncertainty into the causal structure.

BBNs model uncertain causal worlds with conditional probabilities that require using a known joint probability distribution over all the nodes of the directed graph. This may not be practical for a large number of nodes. Forward inference on a BBN also tends to be computationally intensive. Furthermore, the directed graph is usually acyclic and thus has no closed loops. The acyclic structure simplifies the probability structure but ignores the feedback of the causal units.

IV. A Qualitative Simulation Model of University Activity Dynamics

To illustrate the utility of qualitative simulation of university activities via a Fuzzy Cognitive Map, we start our analysis with a baseline model with minimal features. The baseline model is intended to assess the accuracy and face validity of implementing FCM in the NetLogo environment [22]. Figure 1a presents five concepts and their relations.

The *State Funding* is the input concept that is varied to assess the impact of fiscal tensions on the affordability and enrollment levels. According to [23], the decrease in state funding levels increases *pressure for a tuition increase*, which then results in an increased likelihood of *tuition increase*. These relations are specified as qualitative positive and negative dependencies. The extent of the impact of tuition increases on the affordability of higher education is well documented. Using the empirical findings reported in [24], the FCM model shown in Figure 1a introduces a negative relation between tuition raise and affordability. Furthermore, according to [25], decreasing affordability reduces enrollment levels. In relation to the dependency between enrollment levels and pressure for tuition increase, we consider the empirical results that suggest diseconomies of scale for large universities [26]. Finally, the causal link between enrollment and tuition closes the feedback loop.

The conceptual model is implemented within the NetLogo environment shown in Figure 1b. The Netlogo model is available at *github.com/yilmale/University*. In the implementation, the values of the weights of causal dependencies between variables are set to 1.0 for positive causal relations and -1.0 for negative relations. The *StateFunding* variable is updated episodically every 10 time steps and kept constant during each interval to validate the expected trends in the activation levels of enrollment and affordability. As shown in Figure 1c, the increase (decrease) in affordability and enrollment follows with a slight lag the increase (decrease) in the state funding level. Similarly, the change in the activation of pressure for tuition raise and the tuition rate follows the change in the state funding activation in the expected direction. Feature scoring analysis of simulation data, shown in Figure 1d, reveals the significance of the *state funding* variable on affordability and enrollment levels. The minimal baseline model facilitates instilling confidence in implementing the interactive activation dynamics process underlying the FCM formalism.

The model is extended with additional concepts representing the student-faculty ratio, student retention, graduation rate, and quality of experience. In the absence of new faculty hiring and everything else being equal, an increase in enrollment levels results in an increase in student-faculty ratio, negatively influencing student retention. Lower levels of student retention are expected to reduce graduation rates. Furthermore, higher levels of student-faculty ratio adversely affect experience quality, which is an important criterion for increasing graduation rates. The minimal FCM, shown in Figure 1a, is extended in Figure 2 to explore the impact of *State Funding* on *Graduation Rate* under the hypothetical frame characterized by the selected concepts and conjectured dependencies.

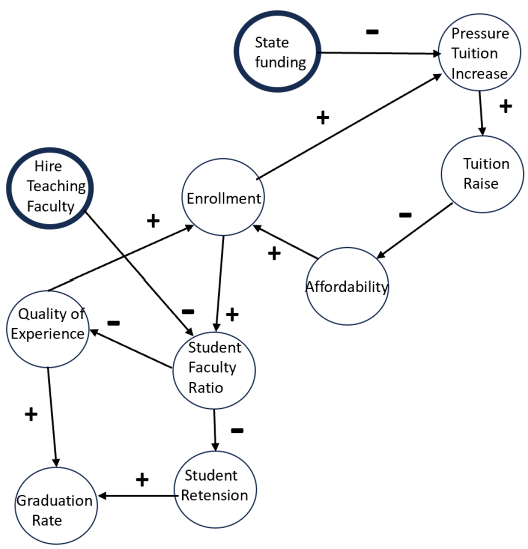

Fig. 2: Extended FCM Model.

Simulation of the FCM with the extended model reveals in Figure 3 that graduation rates decline regardless of state funding activity in the absence of teaching faculty hiring activity.

The factorial experiment examining the interaction between state funding and hiring teaching faculty shows that hiring teaching faculty is critical to increasing graduation rate activity. State funding does not produce sufficient graduation activity at lower teaching support levels, assuming that state funding does not contribute to reducing the student-faculty ratio through other mechanisms. The heatmap shown in Figure 4, in the absence of other factors, illustrates the significance

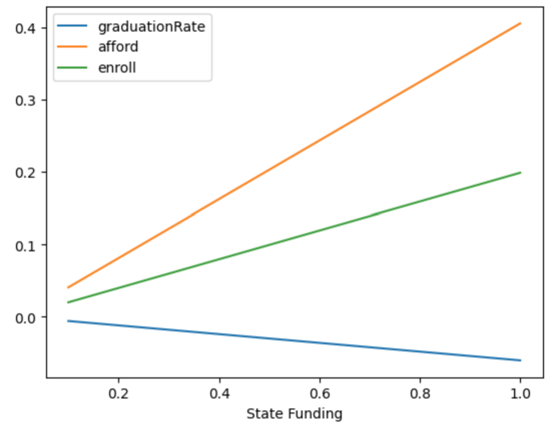

Fig. 3: Impact of State Funding on Graduation Rate in the Absence of Teaching Faculty

of teaching faculty on the graduation rate.

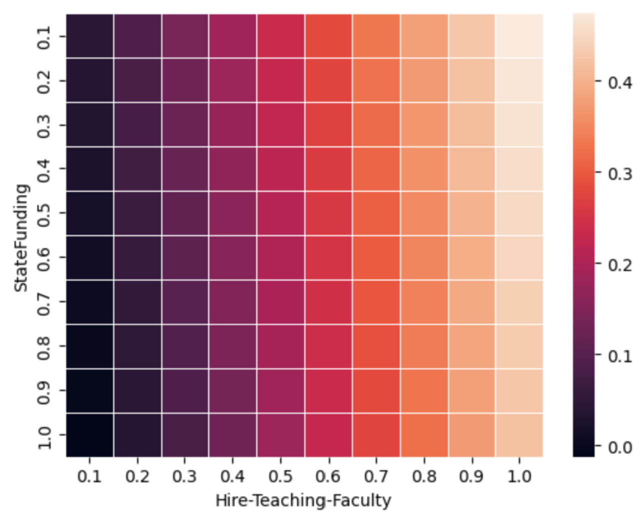

Fig. 4: Impact of State Funding and Teaching Faculty on Graduation Rate

To examine the role of the research component of a university, we extend the model to include additional concepts and dependencies involving sponsored research. However, exploring research activities and their impact on the quality of experience and graduation rates are limited to the current framework shown in Figure 5. In the extended model, for illustration purposes, *Hiring-Research-Faculty* is considered as an input concept that can be controlled by the university administration. By hiring research faculty, the university can be expected to increase the level of *Sponsored Research*, which generates new *Revenue*. Additional resources generated by sponsored research offices through indirect cost recovery mechanisms, as well as patents and innovations, stemming from the increased research activity, lower the pressure for tuition increase.

Sponsored research is expected to increase the research activity by faculty specified by the Faculty-Research node in the

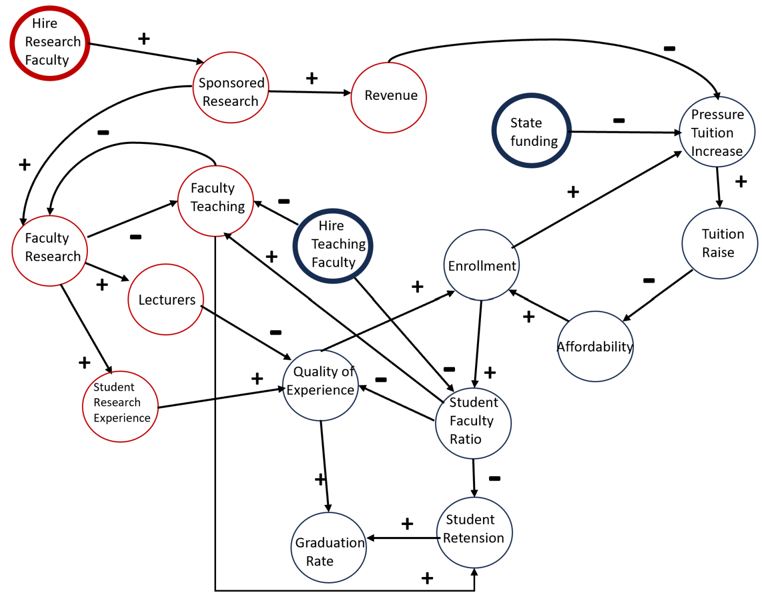

Fig. 5: Extending the FCM Model with Activities in the Research Zone

FCM. However, more faculty research results in lower levels of teaching activity due to administrative policies such as course buyouts or assigning teaching responsibilities to graduate students or lecturers. Delegation of teaching to lecturers reduces the quality of experience for students, resulting in an adverse impact on graduation and student retention. On the other hand, with increased faculty research activity, students have more opportunities to be involved in research, and such research experience contributes to an increased quality of experience. These conjectured causal dependencies are conceptualized in the FCM model shown in Figure 5.

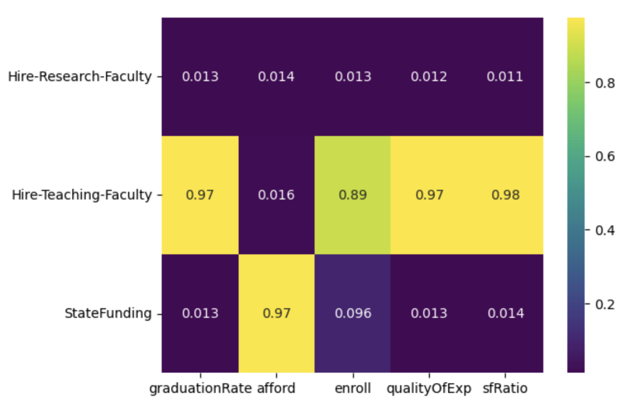

Fig. 6: Feature Analysis of the Extended Analysis

The simulation of the extended FCM explores the tension among state funding, research faculty hiring, and teaching faculty hiring. The model does not make resource allocation decisions among research and teaching activities. Instead, at a given level of state funding, and given the causal relations shown in Figure 5, the teaching faculty factor significantly impacts all outputs except *affordability*. On the other hand, as shown in Figure 6, state funding affects affordability, and the research component does not have significance on output metrics under the causal constraints of the model. Regarding the availability of teaching resources, the graduation rate declines with small levels of teaching faculty capacity. As shown in Figure 7a, increasing the teaching resource capacity beyond the inflection point consistently improves the graduation rate performance.

On the other hand, an increase in the research capacity improves the graduation rate through moderate levels of increase in student research experience that positively affects overall student experience. However, increasing the research load over the inflection point decreases the overall student experience and graduation rate due to its impact on suppressing teaching capacity. Figure 7b shows the observed behavioral trend.

The detailed ANOVA analysis, shown in Figure 8, of the quality of experience outcome supports the Feature Scoring analysis by highlighting the significance of state funding and teaching capacity. Two-way interactions between the factors reveal that the impact of individual factors is not dependent on other factors.

V. CONCLUSIONS

Analyzing policies in the higher education system requires understanding nonlinear dependencies between factors, including positive and negative feedback loops that can lead to nontrivial outcomes. For such complex systems, the tools and models of complexity can offer reliable frameworks to gain insight into the causal dynamics of constituent elements. In this paper, we demonstrated a semi-qualitative model based on the Fuzzy Cognitive Map formalism and conducted experiments to examine the tension among state funding, research capacity, and teaching capacity in relation to the quality of student experience and graduation rates. The causal dependencies

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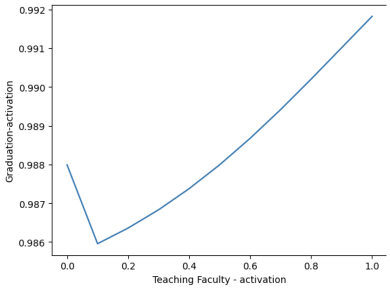
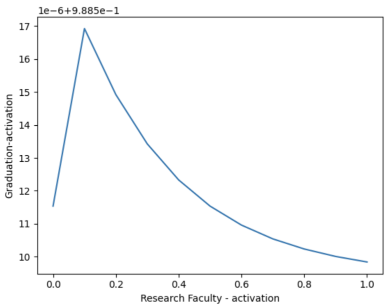


(a) The Impact of Teaching Capacity on Graduation Rate



(b) The Impact of Research Capacity on Graduation Rate

Fig. 7: Impact of Teaching and Research Capacity on Graduation Rate

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q: Quality of Experience, S: State Funding, T: Teaching Faculty, R: Research Faculty
==============================================================================
Dep. Variable:                      q   R-squared:                       0.815
Model:                            OLS   Adj. R-squared:                  0.814
Method:                 Least Squares   F-statistic:                     970.7
                                        Prob (F-statistic):               0.00
                                        Log-Likelihood:                 2956.4
No. Observations:                1331   AIC:                            -5899.
Df Residuals:                    1324   BIC:                            -5862.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.2839      0.004     75.393      0.000       0.277       0.291
S              0.0055      0.006      0.987      0.324      -0.005       0.016
T              0.1728      0.006     30.922      0.000       0.162       0.184
R             -0.0001      0.006     -0.027      0.979      -0.011       0.011
T:R        -6.101e-05      0.007     -0.008      0.993      -0.014       0.014
S:R         1.571e-05      0.007      0.002      0.998      -0.014       0.014
S:T            0.0024      0.007      0.335      0.737      -0.012       0.017
==============================================================================
Omnibus:                      304.477   Durbin-Watson:                   0.093
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              543.789
Skew:                           1.463   Prob(JB):                    8.27e-119
Kurtosis:                       4.116   Cond. No.                         21.5
==============================================================================
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Fig. 8: ANOVA Analysis

presented in the model are based on theoretical and empirical findings reported in the extant literature. The results indicate the significance of teaching capacity on graduation rates, while state funding affects the affordability of higher education.

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