ASYMMETRIC EFFECTS OF PSYCHOLOGICAL AND INSTITUTIONAL SUPPORT ON EDUCATIONAL INNOVATION DIFFUSION: A BILAYER ISING MODEL EXTENSION

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Abstract - The diffusion of educational innovations can be viewed as a complex social process shaped by peer influence, external support, and personal psychological attitudes. Conven-tional diffusion analyses often struggle to quantitatively capture the probabilistic nature of decision-making, the psychology–be-havior gap, and peer interactions; moreover, they typically re-quire long-term longitudinal data. To address these limitations, a bilayer Ising model that separates the psychological and behav-ioral layers has been proposed to analyze diffusion phenomena using only a single cross-sectional survey. However, because this model treats psychological support (hin) and institutional support (hout) as a single combined policy intervention (hin=hout), the indi-vidual effects of each support type and the impact of asymmetric interventions cannot be independently evaluated. This paper pro-poses an extended bilayer Ising model in which psychological and institutional support are treated as independent variables. Heat map visualizations of the combined effects of both support types on the mean implementation rate reveal that intervention effec-tiveness varies depending on the group environment and individ-ual attitude bias ( ). Furthermore, the results suggest that, in the environments examined, prioritizing institutional support over psychological support may more effectively promote innovation diffusion. These findings provide quantitative guidelines for de-signing educational policies tailored to the characteristics of spe-cific school environments.

Keywords - Bilayer Ising Model, Diffusion of Innovations, Education Statistical Mechanics, Inquiry-based learning, Mean-field Approximation

I. INTRODUCTION

As educational policies evolve rapidly worldwide, teachers are constantly required to adopt new teaching methods, such as Inquiry-Based Learning (IBL) and the use of ICT. As Rogers demonstrated, variation among adopters is inherent in any innovation diffusion process; even when organizational or institutional support is provided, implementation rates in actual educational settings often fall short of policy expectations [1]. Therefore, elucidating how collective dy-namics at the school level contribute to the acceptance of or resistance to innovations is a crucial challenge in educational research and policy design.

Existing theoretical frameworks, such as Rogers' diffusion of innovations theory [1], have provided important insights into adopter categories and the role of social networks. Re-cently, computational approaches using agent-based mod els and social network analysis have attempted to extend these insights into quantitative settings [2], [3]. However, these conventional diffusion models often treat teachers' decision-making as simple binary events, failing to formalize the probabilistic nature of human choice or the collective ef-fects resulting from peer interactions. Furthermore, there is a lack of frameworks that dynamically capture the gap between internal psychological states—such as teaching confi-dence or perceived importance—and external behavioral practices in actual classrooms. In addition, dynamic analyses using conventional models often require longitudinal data tracking individual state changes over a long period, present-ing significant methodological limitations in terms of data collection costs and feasibility. To resolve these issues, based on sociophysics approaches that apply statistical mechanics to analyze social phenomena [4], [5], a "bilayer Ising model (Educational Statistical Mechanics)" framework that separates the psychological and behavioral layers has been proposed [6]. This model has a strong advantage: not only can local interactions among teachers describe macro-level group diffusion phenomena, but it can also analyze these phenomena using a single cross-sectional survey data set to estimate parameters through the inverse Ising problem, eliminating the need for long-term longitudinal data.

However, in handling external fields (external support) that represent policy interventions, the conventional bilayer model defined psychological support (hin), such as teacher training, and institutional support (hout), such as financial assistance or environmental setup, as a uniformly linked, com-bined policy intervention (hin = hout). Consequently, it had the limitation of being unable to independently evaluate the in-dividual impact of each support type on diffusion or the com-bined effects when asymmetric intervention strengths occurred.

To address this methodological shortcoming, this paper constructs an extended bilayer Ising model in which psycho-logical support and institutional support are treated as inde-pendent variables. We apply this model to the diffusion of IBL in Japan, where implementation status varies signifi-cantly

across schools, and quantitatively visualize the impact of combinations of these two independent supports on the mean behavioral implementation rate using a 2D heat map. Through simulations using interaction coefficients estimated from empirical survey data, we analyze the optimal combi-nation of support based on the group environment and indi-vidual attitude bias ( ).

The remainder of this paper is structured as follows: Sec-tion II models the decision-making process using the bilayer Ising model. Section III presents the simulation methods and environmental conditions. Section IV conducts the simula-tion, and Section V provides an educational interpretation of the results. Finally, Section VI states the conclusion and out-lines future research directions.

II. MODELING THE DECISION-MAKING PROCESS

A. Formulating Educational Innovation Diffusion via the Bi-layer Ising Model

To handle the diffusion of innovations in educational set-tings quantitatively and probabilistically, this paper uses the framework of "Educational Statistical Mechanics (ESM)," which applies the Ising model used in statistical mechanics to describe ferromagnetic phase transitions. In systems where many teachers influence each other, such as school organizations, individual micro-level decision-making gener-ates local peer pressure, which in turn forms the macro-level diffusion state of the entire group-establishing a formal anal-ogy with the physical phenomena of spin systems. In the following sections, we explain this using the diffusion of IBL among Japanese school teachers as a case study.

In the diffusion process of educational innovations, it is known that teachers' internal psychology influences their ex-ternal behavioral changes [7]. Therefore, we introduce a bi-layer Ising model that separates each teacher's state into a "psychological layer" and a "behavioral layer". Specifically, we model decision-making by dividing it into two steps: "the formation of psychological attitudes through dialogue and training" and "the choice of practical behavior based on these attitudes". This represents a one-way flow in which in-ternal acceptance states (e.g., confidence, perceived im-portance) encourage external behavior (actual teaching) via the intra-personal coupling coefficient K.

We define the state variable in the psychological layer of teacher i (i=1,2,...,N) as $x_i^{in} = \pm 1$, where $x_i^{in} = +1$ denotes an "acceptance state (confident, perceived importance, positive image)" toward IBL, and $x_i^{in} = -1$ denotes a "resistance state (hesitation, lack of perceived importance, negative image)". Simultaneously, we define the state variable in the behavioral layer as $x_i^{out} = \pm 1$, where $x_i^{out} = +1$ denotes "has IBL teaching experience" and $x_i^{out} = -1$ denotes "no IBL teaching experience". While the conventional bilayer model assumed external support h acted equally on both layers ($h^{in} = h^{out} = h$), in actual educational policies, "psychological support" (e.g., mentoring, training) and "institutional support" (e.g., environmental setup, budget allocation) are often implemented independently. Thus, this study removes the restriction of unified interventions and constructs an extended model that completely separates psychological support h^{in} and institutional support h^{out} as independent variables. In this case, the energy function $E(\boldsymbol{x}^{in},\boldsymbol{x}^{out})$ is formulated as shown in Eq. (1).

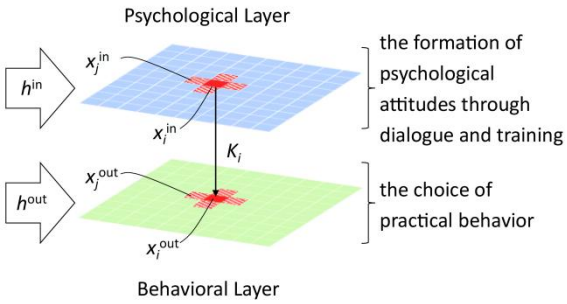


Fig.1 Overview of the bilayer ising model

$$E(\mathbf{x}^{\text{in}},\mathbf{x}^{\text{out}}) = -\sum_{\substack{(i,j)\\N}} J_{ij}^{\text{in}} x_i^{\text{in}} x_j^{\text{in}} - \sum_{\substack{(i,j)\\N}} J_{ij}^{\text{out}} x_i^{\text{out}} x_j^{\text{out}} - \sum_{i=1}^{N} K_i x_i^{\text{in}} x_i^{\text{out}} - \sum_{i=1}^{N} \left(h^{\text{in}} + \theta_i^{\text{in}}\right) x_i^{\text{in}} - \sum_{i=1}^{N} \left(h^{\text{out}} + \theta_i^{\text{out}}\right) x_i^{\text{out}} \quad (1)$$

Here, $\sum_{(i,j)}$ represents the sum over adjacent teachers. J_{ij}^{in} is the peer interaction between adjacent teachers in the psychological layer, J_{ij}^{out} is the peer interaction in the behavioral layer, and K_i is the internal coupling strength (psychology-behavior coupling coefficient) between the two layers within individual teacher i. θ_i^{in} and θ_i^{out} represent the pre-existing psychological attitude bias and practical attitude bias held by each teacher, respectively.

B. Derivation of Self-Consistent Equations via Mean-Field Approximation and One-Way Coupling

Assuming the entire system follows a canonical distribution, we apply the mean-field approximation, which assumes each teacher receives an average influence from their sur-roundings. This approximation allows for a concise represen-tation of the macro-level diffusion process of the group without complicating the model. Through this approximation, the self-consistent equations determining the mean psycho-logical implementation rate min and the mean behavioral im-plementation rate mout are derived as Eq. (2) and Eq. (3), respectively.

$$m_{\text{in}} = \tanh\{\beta(J^{\text{in}} z m_{\text{in}} + K_{\text{out-in}} m_{\text{out}} + h^{\text{in}} + \overline{\theta^{\text{in}}})\} \quad (2)$$

$$m_{\text{out}} = \tanh\{\beta(J^{\text{out}} z m_{\text{out}} + K_{\text{in-out}} m_{\text{in}} + h^{\text{out}} + \overline{\theta^{\text{out}}})\} \quad (3)$$

Here, $\beta = 1/k_B T$ (with k_B=1 in this paper) is the receptivity (sensitivity) to external influence, z is the number of adjacent teachers (z = 4 for a 2D square lattice), J^{in} is the mean peer interaction from psychology, J^{out} is the mean peer interaction from teaching experience, and $\overline{\theta^{\text{in}}}$ and $\overline{\theta^{\text{out}}}$ are the mean psychological and practical attitude biases, respectively. To strictly evaluate the psychology-driven decision-making process where teacher psychology encourages behavioral practice, we follow previous research [7] and employ a one-way coupling model by setting the feedback from behavioral change to psychological state ($K_{\text{out-in}}$) to zero. This assumes an environment in which the psychological layer is driven solely by psychological influences from colleagues and by psychological support. Furthermore, since this paper assumes a model where internal psychology influences external behavior, we set $\overline{\theta^{\text{out}}} = 0$. The educational significance of each parameter is shown in Table I.

Parameter	Educational Interpretation	In Case of Positive Value	In Case of Negative Value
m_{in}	Mean state of psychological acceptance	Psychologically positive toward practice	Psychologically resistant or hesitant
m_{out}	Mean behavioral implementation rate	Majority is implementing (adopted state)	Majority is not implementing (unadopted/resistance state)
J^{in}	Strength of psychological attitude propagation among colleagues	Open environment prone to empathy and alignment	Divided environment with backlash against surrounding mindsets
J^{out}	Strength of behavioral peer interaction	Strong peer pressure environment ("doing because others do")	Non-interference environment ("not doing if others do")
h^{in}	Psychological training and mentoring	High-quality training that improves motivation	Top-down enforcement that drains motivation
h^{out}	Institutional setup and financial support	Environmental setup reducing physical hurdles (e.g., reduced workload)	Institutional constraints hindering practice (e.g., excessive workload)
$\overline{\theta^{\text{in}}}$	Mean pre-existing attitude bias	Generation with IBL experience / positive school culture	Success experiences with rote-learning / negative school culture
$\overline{\theta^{\text{out}}}$	Mean past practical experience bias	Teachers with successful IBL experiences	Teachers with past IBL failures and instructional trauma

Table I The educational significance of each parameter

III. SIMULATION METHOD AND CONDITIONS

To verify the effectiveness of the proposed model, this study addresses the diffusion process of IBL among Japanese high school teachers. First, from empirical survey data of 210 high school teachers, we calculated the proportions (basic statistics) of the psychological attitude toward IBL (x^{in}, integrated and binarized from confidence, image, and perceived importance) and the presence of actual teaching experience (x^{out}). Then, to ensure statistical stability in the simulation, we generated a 25x25 (total 625 data points) virtual state matrix using random numbers based on these actual proportions. By performing parameter estimation using connected correlation on this generated matrix, we estimated the mean peer interactions J^{in} and J^{out} in the high school group environment. As a result, the peer interaction in the psychological layer was estimated as J^{in} = 0.0451, and in the behavioral layer as J^{out} = -0.0028. This indicates an environment with almost no peer pressure regarding teaching experience, yet where psychological interactions positively influence colleagues. In this simulation, receptivity to external influence is set to β = 1.0, and the internal coupling strength is set to $K_{\text{in-out}}$ = 1.0. Setting β = 1.0 corresponds to a baseline assumption in which uncertainty and randomness in teacher decision-making are at moderate levels, while Kin-out = 1.0 signifies a unit coupling state in which psychological acceptance is equally transmitted to the behavioral layer. Setting these parameters to 1.0 allows independent evaluation of the impact of external support (h^{in}, h^{out}) and peer interactions (J^{in}, J^{out}) on diffusion. Verifying the sensitivity of changes in β and $K_{\text{in-out}}$ on the results is left for future studies. In this simulation, we derive the mean implementation rate using these estimated values.

IV. SIMULATION RESULTS

Based on the established high school network characteristics (J^{in} = 0.0451, J^{out} = -0.0028, $K_{\text{in-out}}$ = 1.0, β = 1.0), we calculated the distribution of the mean behavioral implementation rate (m_{out}) while varying psychological support (h^{in}) and institutional support (h^{out}) respectively from -2.0 to 2.0. Fig. 2(a) through (c) display 2D heat maps illustrating environments where the mean pre-existing attitude bias is negative ($\overline{\theta^{\text{in}}}$ = -1.0), neutral ($\overline{\theta^{\text{in}}}$ = 0.0), and positive ($\overline{\theta^{\text{in}}}$ = 1.0), respectively. In each figure, the horizontal axis represents psychological support h^{in}, the vertical axis represents institutional support h^{out}, and the mapped brightness represents the mean behavioral implementation rate m_{out} (red denotes the adopted state $m_{\text{out}} > 0$; blue denotes the unadopted state $m_{\text{out}} < 0$). The dashed line indicates the position where the sum of both supports equals zero ($h^{\text{in}} + h^{\text{out}} = 0$).

From these heat maps, we can confirm that in all $\overline{\theta^{\text{in}}}$ environments, a phase transition from the unadopted state to the adopted state occurs depending on the combination of h^{in} and h^{out}. Additionally, the contour lines representing the same m_{out} value have a gentler slope than the dashed line. This indicates that changes along the vertical axis (h^{out}) impact the system more significantly than changes along the horizontal axis (h^{in}). This characteristic is distinctly observed by tracing the trajectory along the dashed line ($h^{\text{in}} + h^{\text{out}} = 0$). Moving from the bottom-right (high psychological support, low institutional support) to the top-left (low psychological support, high institutional support) along the dashed line, the system clearly undergoes a phase transition from an unadopted to an adopted state despite the total amount of external support remaining constant .

Furthermore, focusing on the differences in $\overline{\theta^{\text{in}}}$, as it changes from negative to positive, the adoption region (red area) significantly expands toward the bottom-left of the heat map, while maintaining the basic shape of the contour lines. This visually demonstrates that environments where the group possesses a positive pre-existing attitude bias can reach the adopted state with far less external support.

V. EDUCATIONAL INTERPRETATION

First, we discuss the asymmetrical support policies. The gentle slope of the contour lines confirmed in Section IV indicates an asymmetry in support: institutional support (h^{out}) acts more directly in increasing the implementation rate than psychological support (h^{in}). This reflects the difference in the psychological and physical structures underlying teachers' decision-making processes. Psychological support (h^{in}), such as training and mentoring, is an approach that first elevates a teacher's internal acceptance state (m_{in}) and indirectly ripples into behavioral practice. However, even if a

teacher holds "confidence" or "recognition of importance" regarding IBL, there are physical barriers, such as "time burdens" or "lack of equipment," in the process of translating that into actual practice. Due to the model's structure, psychological support h^{in} only acts on the behavioral layer through the indirect pathway via the psychological layer ($h^{in} \rightarrow m_{in} \rightarrow m_{out}$), so its effect is attenuated by passing through the tanh function. This serves as the mathematical rationale for why h^{out} exerts a more direct influence on m_{out} than h^{in}. On the other hand, institutional support (h^{out}), such as workload reduction to create time for lesson preparation and environmental setups, directly lowers the physical hurdles to practice. Therefore, the support functions directly as a driving force for practice. This superiority of institutional support provides a particularly important implication under conditions where the total amount of external support is zero ($h^{in} + h^{out} = 0$). As indicated by the dashed line on the heat maps, even in situations where no new additional budgets or resources exist, merely shifting support by reducing excessive, ineffective training and meetings (h^{in}) and allocating those resources reducing teacher workloads and creating time for lesson preparation creating time allowance (h^{out}) can push the entire group into an adopted state. In this established environment, to efficiently increase the implementation rate with limited budgets and resources, the findings suggest that an asymmetric external support strategy prioritizing institutional support (such as workload reduction and environmental setups) is more effective than the "unified psychological and institutional support ($h^{in} = h^{out}$)" assumed by conventional bilayer models.

Next, we discuss the impact of the mean pre-existing psychological attitude bias $\overline{\theta^{in}}$ on diffusion phenomena. The heat maps show that in environments where the teacher group holds a negative bias toward IBL ($\overline{\theta^{in}} < 0$), an approach that simply increases external support volume is inefficient compared to environments with positive bias ($\overline{\theta^{in}} > 0$). As shown in Fig. 2(c), in environments strongly characterized by success experiences with rote-learning or a preference for the status quo, immense amounts of psychological and institutional support are required to reach the adopted state. In contrast, as shown in Fig. 2(a) and 2(b), if $\overline{\theta^{in}}$ can be raised, the external support necessary for diffusion drops. These results suggest that to promote diffusion, it may be effective to improve the group's pre-existing attitude psychological bias $\overline{\theta^{in}}$ rather than relying solely on qualitative and quantitative improvements to external support.

These results indicate the direction of policy approaches to promote the diffusion of IBL in the environment established in this study. To drive the group toward an adopted state within limited resources, it is effective to reassess psychological support approaches and allocate resources toward institutional support. Furthermore, to maximize the effectiveness of external support, it is not only necessary to address the quality and quantity of support but also to implement experiential learning in teacher training programs and in-school training to positively transform the teacher group's pre-existing attitude bias toward IBL. Thus, this study demonstrates that individually optimized policies—which carefully assess the pre-existing attitude bias of school organizations and selectively determine the volume, quality, and allocation of support—are the key to the diffusion of IBL in educational settings.

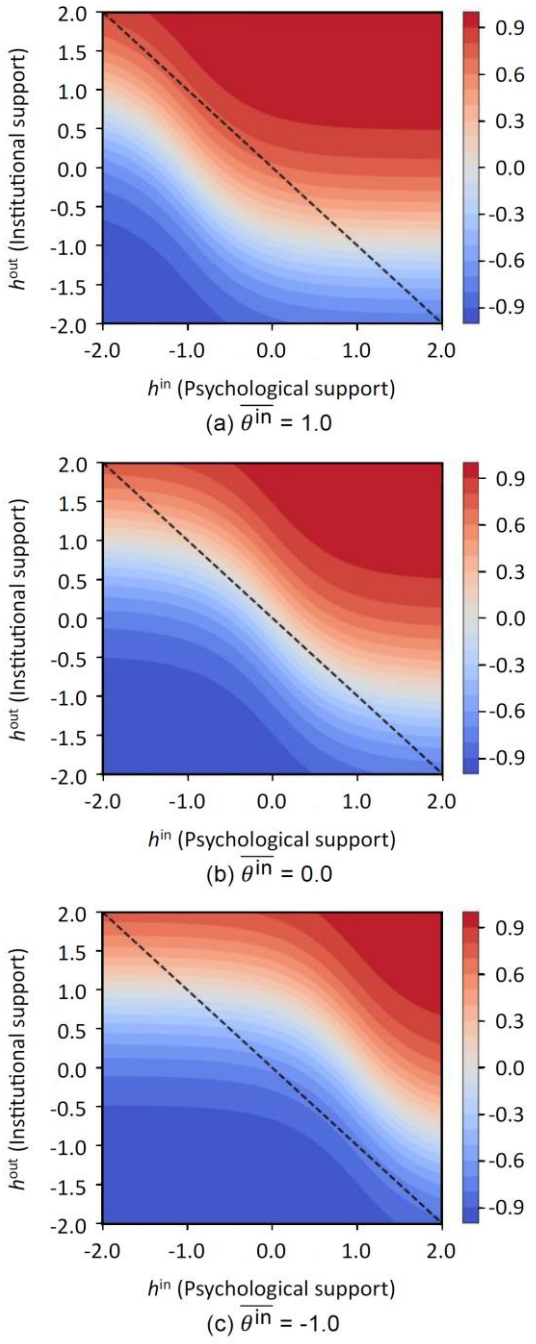


Fig. 2 Heat maps of the mean implementation rate

VI. CONCLUSION AND FUTURE CHALLENGES

In this paper, to capture the diffusion process of educational innovations in educational settings, we expanded the conventional educational statistical mechanics framework and constructed a bilayer Ising model that separates psychological support (h^{in}) and institutional support (h^{out}) as independent variables. Using the interaction coefficients J^{in} and

J^{out} estimated from empirical high school survey data, we quantitatively visualized the effects of these two external supports on the mean behavioral implementation rate (m_{out}) via 2D heat maps. As a result of the analysis, under the environment established in this study, the contour lines had a gentle slope, suggesting that prioritizing institutional support over psychological support may be effective in improving the implementation rate. Additionally, it was clarified that the group's pre-existing attitude bias is a parameter that dictates the amount of external support required to trigger a phase transition in diffusion. In environments where the group possesses a negative bias, we demonstrated that it is crucial not only to strengthen external support but also to positively transform the group's pre-existing psychological bias to promote diffusion.

However, this study has several limitations and directions for future work. First is the verification of hysteresis associated with chronological reductions in support. While this paper addressed phase transitions of equilibrium states in a static external field space, actual policy interventions sometimes see support reduced midway due to budget cuts. In such cases, it is necessary to verify whether the reduction margin in the behavioral implementation rate (m_{out}) can be kept small if institutional support (h^{out}) is decreased only after sufficiently investing psychological support (h^{in}) in the initial stages to establish teachers' internal acceptance states (m_{in}). Second is the introduction of a more micro-level, detailed network analysis using Monte Carlo simulations. The mean-field approximation used in this study assumes a homogeneous environment where all teachers within a school organization influence each other uniformly, ignoring heterogeneity in local human relationships and hierarchical structures (such as grade levels or subject departments) seen in actual staff rooms. By introducing Monte Carlo methods that track probabilistic spin flips at the micro level and driving the proposed model across diverse network topologies, such as small-world and scale-free networks, we expect to be able to simulate the diffusion process with greater accuracy. This framework is applicable to diffusion analyses of other educational innovations beyond IBL, and moving forward, we aim to develop it as a quantitative evaluation tool for educational policies.

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