Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 7 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i07.48599

PAPER

The Dynamics of Community Engagement in Distance Education: A Sociological Analysis Based on Online Learning Platforms

Aruna Tao(✉)

Academic Affairs Office, Inner Mongolia Open University, Hohhot, China

aruna_tao@126.com

ABSTRACT

The rapid advancement of information technology has redefined distance education as a fundamental component of modern education systems. The extensive deployment of online learning platforms has further propelled this transformation, catalyzing innovation in educational methodologies while simultaneously presenting novel challenges and demands in the realm of community engagement. In the sphere of online learning, considerable research has been conducted on the efficacy of these platforms. However, studies specifically dedicated to the effective cultivation and maintenance of community engagement through these platforms are notably scarce. Recognized as pivotal for educational outcomes, student satisfaction, and enduring academic success, community engagement within the context of distance education warrants comprehensive exploration. This study delves into this exploration by developing a dynamic model of interaction and a coupled network evolutionary game model that incorporates the nuances of social group dynamics. Initiating with a critical review of existing literature on community engagement in distance learning, the study identifies prevalent limitations. These limitations include an over-reliance on qualitative data, the absence of dynamic analyses, and an oversight of the intricacies of group interactions. To bridge these gaps, we propose a data-driven interaction dynamics model tailored for online learning platforms. Additionally, we suggest a network evolutionary game model that considers the interplay among social groups. These models collectively deepen our understanding of the evolution of community engagement over time and elucidate how both individual and collective behaviors influence the communal health of online learning environments.

KEYWORDS

distance education, community engagement, online learning platforms, communication interaction dynamics, network evolutionary game, social groups, mathematical modeling

Tao, A. (2024). The Dynamics of Community Engagement in Distance Education: A Sociological Analysis Based on Online Learning Platforms. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(7), pp. 4–18. https://doi.org/10.3991/ijim.v18i07.48599

Article submitted 2023-12-17. Revision uploaded 2024-01-23. Final acceptance 2024-02-02.

1 INTRODUCTION

In the digital epoch of the 21st century, distance education has been recognized as an integral element of the global educational framework. The advent of the COVID-19 pandemic marked a significant shift in online learning platforms, transitioning from emergency alternatives to pivotal components of daily educational experiences for numerous learners. Despite the increased adoption of these platforms, research dedicated to optimizing their educational efficacy and enhancing sustained community engagement remains inadequate. The correlation between community engagement and educational effectiveness is profound, playing a crucial role in fostering inclusive, supportive, and lasting learning environments [1–12].

Exploring and enhancing community engagement within the realm of distance education holds substantial significance for both academic research and practical application. With the increasing prevalence of online education, researchers and educators face the challenge of designing and implementing online learning platforms that promote deeper learner interaction and engagement [13, 14]. The impact of community engagement extends beyond academic achievement, influencing students' social skills, self-efficacy, and enduring dedication to education. An engaged online learning community is essential for promoting a comprehensive understanding of knowledge, enhancing critical thinking skills, and preparing learners to navigate the complexities of the 21st-century landscape [15–17].

Prevailing research methodologies in the study of community engagement within distance education reveal notable deficiencies. Predominantly, a substantial number of studies have focused on qualitative data, such as interviews and surveys, giving less emphasis to quantifiable interaction data [18–20]. Furthermore, the prevalent use of cross-sectional study designs has resulted in an oversight of the temporal dynamics inherent in community engagement [21, 22]. Additionally, there is a lack of attention given to the intricacies of interactions among social groups in online learning environments and their resulting impact on learner behavior and the overall well-being of the community.

This paper aims to address these research gaps by developing a model that focuses on the interaction dynamics within online learning platforms, with a specific emphasis on engagement. The initial segment presents an innovative mode of interaction dynamics, illustrating the development and progression of community engagement in online learning communities, supported by data-driven approaches. Subsequent investigations delve into the dynamics of groups within online learning networks. This exploration involves an analysis of how behaviors at both individual and group levels influence community engagement. It is facilitated through a coupled network evolutionary game model that encompasses social groups. The study not only provides models based on empirical data but also formulates equations outlining game dynamics. These equations are crucial for clarifying and predicting the dynamics of community engagement, thus offering significant implications for practices and policies in online education.

2 DEVELOPMENT OF A COMMUNICATION INTERACTION DYNAMICS MODEL CENTERED ON ENGAGEMENT

Recognized as vital for the efficacy of online learning, community engagement significantly contributes to enhancing student performance and fostering a sense of belonging and satisfaction. This study investigates the communication interaction behaviors and their dynamic mechanisms among group members on online learning platforms, uncovering the development and transformation of community engagement. A mathematical model has been formulated to simulate the discussion processes among platform users, scrutinizing the influence of varying group sizes on communication interaction dynamics. Additionally, this study conducts a comparative analysis of online learning platforms and other educational communication systems. The aim is to thoroughly comprehend and quantify the dynamic attributes of student communication interactions in online learning contexts. These analyses provide insights for designing and improving online learning environments to enhance community engagement.

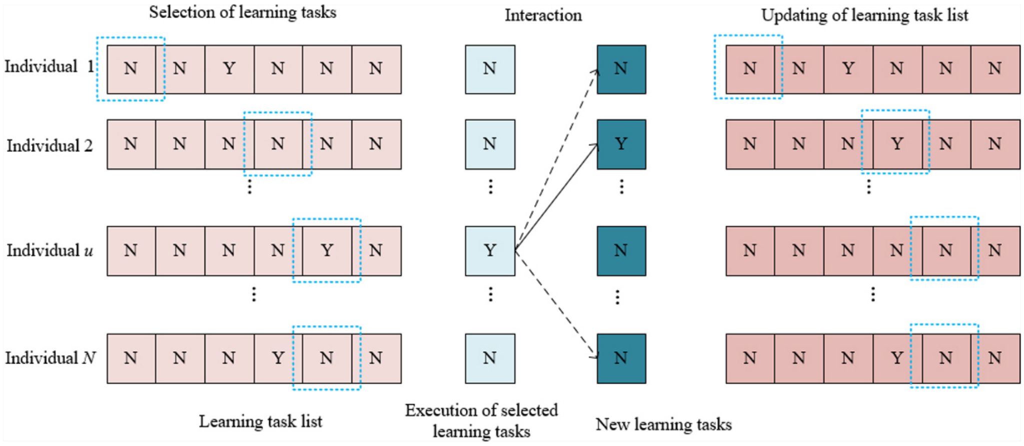

Fig. 1. Interaction process within the group (with Y indicating interactive tasks, and N non-interactive tasks)

In this context, community engagement is demonstrated when individuals initiate and respond to communication tasks on online learning platforms. A multi-agent interaction queue model, based on queuing theory, has been developed to analyze scenarios involving a fixed number of group members in an online learning environment. The model delineates how individuals probabilistically initiate new topics over time and engage in interactions with fellow members. Within this framework, each participant is not only obliged to respond to interaction tasks initiated by others, thereby contributing to community dialogues, but also to manage their personal task lists. These lists encompass non-interactive tasks for individual completion and interactive tasks that require collaborative efforts. Community engagement is characterized by individuals' ability to balance interactive and non-interactive tasks on their lists and their proactivity in initiating and participating in community discussions. This approach enables a quantitative assessment of community engagement, elucidating interaction patterns and participation dynamics within online learning communities. Subsequently, it guides the enhancement of pedagogical strategies and platform architecture. Figure 1 illustrates the individual communication interaction process within a group, encompassing both interactive and non-interactive tasks.

In the developed multi-agent queue model, grounded in task queue theory, the task initiation rate of an individual is defined as the frequency of initiating new tasks within a given time frame. According to the model's design, the task initiation rate is directly proportional to the temporal distribution of speech volume. The process for calculating the task initiation rate involves several steps. Initially, data concerning the temporal distribution of individual speech volumes is collected. This data is then analyzed to determine the temporal trend of speech volumes. Subsequently, a proportionality coefficient is determined, which translates the speech volume within a specific time unit into a task initiation rate. The final step involves multiplying the time distribution data by this coefficient to calculate the task initiation rate for each unit of time. It is posited that within a specific time interval, the frequency and distribution of an individual's speech behavior are proportionally related to their inclination to initiate new tasks. The task initiation rate, denoted as $\eta(s)$, along with group engagement (Λ), response rate (w), and the total number of individuals in the group (l), are incorporated into a formula to calculate each individual's initiation rate.

$$\eta(s) = \frac{\Lambda * v(s)}{l} \tag{1}$$

The evaluation of engagement in group interactions on online learning platforms in this study utilizes the statistical distribution of speech time intervals as a method to differentiate between initiating messages and responsive ones. This approach is based on the observed patterns of group speech behavior. The concept of characteristic time, which serves as the demarcation between power-law and Poisson distributions, is crucial in determining whether a time interval indicates active dialogue exchange or the initiation of new topics. In groups characterized by bimodal distribution, if the interval between two successive messages surpasses this characteristic time, the subsequent message is regarded as the initiation of a new topic. Conversely, if the interval is shorter than the characteristic time, it is considered a response to the preceding message. To estimate community engagement, the study incorporates not only bimodal distribution groups but also double power-law and single power-law groups. This is achieved by comparing their speech volumes to gauge engagement levels. The speech volume ratios of groups following double exponential-law and single exponential-law distributions, relative to those of bimodal distribution groups, provide a comparative measure of group activity. This facilitates the estimation of engagement levels across different types of groups.

In the process of estimating $v(s)$, which represents the temporal distribution of speech volume, considerations include individual lifestyle habits and time preferences, along with external influences such as community dynamics and platform features. Figure 2 demonstrates the simulated outcomes of individual speech timing sequences within a group. This distribution, indicative of a complex interplay between individual behaviors and group interactions, mirrors the active engagement and participation dynamics prevalent in online learning communities. The initial step involves tallying the count of speeches within each time segment to construct a preliminary distribution chart. Advanced statistical methods are then applied to explore the dynamic changes in speech volumes. A three-peak curve model is used to estimate speech volumes at different times throughout the day. Assuming $d_1(s)$, $d_2(s)$, and $d_3(s)$ symbolize three distinct normal distributions with varying parameters, the formula is presented as:

$$v_1(s) = \frac{0.315d_1(s) + 0.36d_2(s) + 0.35d_3(s)}{3600} \tag{2}$$

To elucidate the factors driving these variations, it may be necessary to employ qualitative research techniques such as surveys and interviews to collect feedback from community members. Should the distribution of daily speech volume $v_2(s)$ be consistent at various times across a week, it is required to meet the condition $\langle v_2(s) \rangle_s = 1/7$. Consequently, the final expression for the temporal distribution of speech volume is established as:

$$v(s) = 7v_1(s) * v_2(s) \tag{3}$$

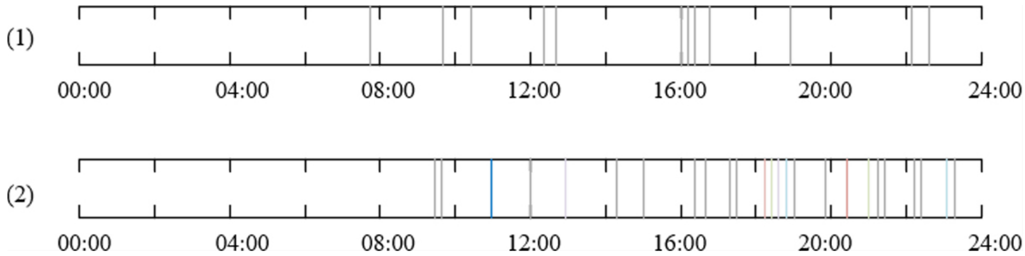

Fig. 2. Simulated individual speech timing sequences in a group

Furthermore, the task initiation rates of individuals within distinct groups on the online learning platform are assessed, considering potential influences from group traits, platform design, group size and diversity, intended objectives, and external factors. The process begins with defining and quantifying standards for measuring initiation rates. The individual response rate, denoted as w, and the group response rate, represented as W, are incorporated into the formula: $w = W/(l - 1)$. If V represents the average daily speech volume of the group, then W is defined as $W = (V - \Lambda)/V$. The initiation rate is defined as the ratio of the number of newly initiated topics to the total message count within a specified time frame. Subsequent steps involve performing statistical analyses for each group to determine their initiation rates, followed by the application of appropriate statistical methods for comparative analysis between the groups. Moreover, qualitative analysis might be required to decipher the sociopsychological factors influencing initiation rates. The final stage involves combining quantitative data and qualitative insights to form comprehensive analytical conclusions.

3 EVOLUTIONARY GAME ANALYSIS IN ONLINE LEARNING NETWORKS INVOLVING COUPLED SOCIAL GROUPS

To facilitate a comprehensive understanding of decision-making within complex social structures and to improve the effectiveness of collaborative efforts in educational settings, a strategy update rule that incorporates collective wisdom has been formulated and implemented in network evolutionary game analyses. Collective wisdom, in this context, signifies the decision-making capacity that emerges from group interactions, transcending individual intelligence. Optimal response strategies are defined as the most advantageous choices made by individuals, influenced by the current environment and the actions of others. Consequently, the study elucidates the process of strategy updates in evolutionary games through a series of algebraic equations, accomplished via mathematical modeling. This algebraic representation not only allows for a formal and precise description of the strategy update rules but also facilitates a thorough and methodical examination of the evolution of strategies over time and the adjustments in individual behavior guided by collective wisdom.

In real-world scenarios, individual decision-making is often influenced by others, with individuals drawing upon group insights to enhance the quality of judgment and decision-making. The advantage of collective wisdom is particularly evident in complex problem-solving situations, where relying on group insights can significantly enhance decision quality. Therefore, a strategy update rule incorporating collective wisdom has been introduced to achieve more accurate simulations of individual learning and adaptation within real decision-making environments. The proposed rule consists of two main components: the game interaction and the strategy update process. During the game interaction phase, participants engage with their peers within the online learning group, accruing payoffs from these interactions. This process allows them to assess the efficacy of their strategies through interpersonal exchanges. During the strategy update phase, individuals first analyze their counterparts' previous strategies to develop their optimal responses. Subsequently, they integrate opinions from other group members, employing a majority criterion to decide on the adoption of the most favored optimal strategy for future actions.

In the domain of game theory, the actions of each participant are aimed at maximizing utility, usually represented by payoff functions. These functions generally depend on the strategies chosen by the participant and those of other participants. In formulating expressions for payoff functions, consideration is given to the game's characteristics (such as zero-sum, non-zero-sum, cooperative, or non-cooperative nature) and potential strategy combinations. Payoff functions may adopt linear forms or more intricate non-linear structures, possibly incorporating probability distributions to account for elements of uncertainty. The following expressions illustrate the payoff function for participant n_u, where u ranges from 1 to v_1:

$$\begin{aligned}\psi_{n_u}\left(a_u(s-1), b_k(s-1) k \in VF_{n_k}\right) &= N_e^S(Z^S) \sum_{k \in VF_{n_k}} b_k(s-1) a_u(s-1) \\ &= N_e^S(Z^S)\, RO_u(Y) \prod{}^{v_2} b(s-1) a_u(s-1) : N'_{n_u} b(d-1) a_u(s-1)\end{aligned} \tag{4}$$

$$\psi_{q_u}\left(b_u(s-1), a_k(s-1) k \in VF_{q_u}\right) = N'_{q_u} a(s-1) b_u(s-1) \tag{5}$$

where, $N'_{qu} = N^S{}_e(Z^S)\, RO_u(Y^S) \sqcap^{v1}, u = 1, \ldots, v_2$.

$$w_{k,n_u} = MIN \operatorname{argmax}_{1 \le w \le j} Zpm_w\left(Ymj_k\left(N'_{n_u}\right)\right) \tag{6}$$

$$w_{k',q_u} = MIN \operatorname{argmax}_{1 \le w \le j} Zpm\left(Ymj_{k'}\left(V'_{q_u}\right)\right) \tag{7}$$

For each block within N'_{nu} and N'_{qu}, the smallest label identifying the maximum value is characterized by indices $k = 1$ to k^{v2} and $k' = m$ to j^{v1}. Following the establishment of payoff functions, the focus shifts to ascertaining each participant's optimal response strategy. The optimal response strategy, based on the strategies of others, is defined as the one that maximizes the participant's payoff function. This process typically involves maximizing the payoff function. Depending on the context, the optimal response could involve making an explicit strategic choice or may require solving differential equations or applying numerical methods to identify the most advantageous strategy. The following expressions represent the optimal response strategy for participants at a given time s:

$$YE_{n_u}(s) = \sigma_j\left[w_{1,n_u}, \cdots, w_{j_{v2},n_u}\right] b(s-1) \tag{8}$$

$$YE_{q_u}(s) = \sigma_j\left[w_{1,q_u}, \cdots, w_{j_{v1},q_u}\right] a(s-1) \tag{9}$$

In social and economic contexts, individual behaviors are inevitably influenced by the people around them. Therefore, it is imperative for individuals to observe and interpret the responses of others within the group. Participants adhere to the principle of conformity to the majority. The subsequent stage involves documenting the frequency of various optimal response strategies manifested within the group. This documentation can be achieved through direct observation, survey methods, or reliance on predefined models. This phase is essential for understanding the diversity of strategies within the group and the potential emergence of collective wisdom phenomena. The quantities $M'_{nu} = \sigma_j[w_1, n_u, \ldots, w_{jv2,nu}]$ and $M'_{qu} = \sigma_j[w_1, q_u, \ldots, w_{jv1,qu}]$ are utilized to represent these frequencies. To compile this data, the following matrices are computed:

$$H_{n_u} = RO_u(X_1 + U_{v_1})\begin{bmatrix} M'_{N_1} \\ \vdots \\ M'_{n_{v1}} \end{bmatrix} \tag{10}$$

$$H_{q_u} = RO_u(X_2 + U_{v_2})\begin{bmatrix} M'_{q_1} \\ \vdots \\ M'_{q_{v_2}} \end{bmatrix} \tag{11}$$

Upon analyzing the optimal response strategies of individuals and their frequencies, the focus shifts to developing equations that delineate how each participant revises their strategy. These equations typically involve temporal dynamics, depicting the evolution of strategic adjustments over time. For constructing such equations, methods such as differential equations, difference equations, or adaptive dynamic systems might be employed. The most frequently selected strategy, denoted by the smallest row label, is represented by $\beta_{t,VI} = MIN\ argmax_{1<=\beta<=j} RO_\beta(CO_t(H_{nu}))$, and $\alpha = MIN\ argmax_{1<=\beta<=j} RO_\alpha(CO_t(H_{qu}))$. The following expressions outline the strategy update equations for participants:

$$a_u(s) = \sigma_j\left[\beta_{1,n_u}, \cdots, \beta_{j_{v_2}, n_u}\right] b(s-1) = M_{n_u} b(s-1) \tag{12}$$

$$b_u(s) = \sigma_j\left[\alpha_{1,q_u}, \cdots, \alpha_{j_{v,1}, q_u}\right] a(s-1) = M_{q_u} a(s-1) \tag{13}$$

The algebraic expressions for the game dynamics of participants within the two-layer framework are further derived, with $CO_k(M_1) = {}^{jv1}{}_{u=1}\ CO_k(M_{nu})$ and $CO_k(M_2) = {}^{jv2}{}_{u=1}\ CO_k(M_{qu})$:

$$a(s) = M_1 b(s-1),\ b(s) = M_2 a(s-1) \tag{14}$$

The ultimate objective is to amalgamate the strategy update equations of all participants, forming an algebraic system that encompasses the network level. This system elucidates the game dynamics across the entire participant network. This endeavor may involve creating a sophisticated multi-agent model where the actions of each agent are influenced by their specific strategy update equations and their interactions with other agents. The algebraic expression representing the game dynamics for the entire network is as follows:

$$\begin{aligned} a(s)b(s) &= M_1 b(s-1) = M_1(U_{j^{v_2}} \otimes M_2) b(s-1)a(s-1) \\ &= M_1(U_{j^{v_2}} \otimes M_2) q_{[j^{v_1}, j^{v_2}]} a(s-1)b(s-1) \end{aligned} \tag{15}$$

where, $M = M_1(U_{j^{v_2}} \otimes M_2)Q_{[j^{v_1}, j^{v_2}]}$. The above equation can be expanded to:

$$a(s)\ b(s) = Mxa(s-1)b(s-1) \tag{16}$$

4 EXPERIMENTAL RESULTS AND DISCUSSION

In the analysis of the data presented in Table 1, a distinction in the power index was observed. The power index is a metric commonly used to quantify the distribution between a minority of active users and a majority of less active ones in a community. The data revealed notable differences in the levels of activity among the three groups. The bimodal distribution group showed more balanced participation, while the double and single power-law distribution groups were marked by a small subset of highly active users. In the double power-law distribution group, it was observed that lower early-stage power indices (e.g., 1.59) corresponded to lower average daily speech volumes (789.1), while higher early-stage power indices (e.g., 1.84) aligned with larger average daily speech volumes (2789.4). This trend indicates that groups with a larger early-stage power index are inclined towards higher daily average speech volumes. This suggests that a more heavy-tailed distribution in the early stage leads to increased overall engagement because of the presence of a greater number of moderately active users. The relationship between the size of a group and its activeness, although presumed to provide more opportunities for speech and thus greater activeness, was not found to be strictly linear. The interaction dynamics model for online learning platforms, which focuses on engagement and was developed in this study, effectively elucidates the relationship between diverse speech patterns and participation behaviors. It sheds light on why different community participation structures result in varied communication interaction dynamics.

Table 1. Comparison of speech situations on different online learning platforms

Speech Time Distribution Pattern	Power Index	Average Daily Speech Volume	Total Number of Speakers
Bimodal distribution	1.04	12.8	175
	1.36	54.2	215
	1.51	73.6	736
	1.52	215.5	336
	1.64	326.8	412
Double power-law distribution	1.59 (early stage): 2.26 (late stage)	789.1	2458
	1.69 (early stage): 2.23 (late stage)	945.7	1895
	1.71 (early stage): 2.37 (late stage)	1245.3	1123
	1.82 (early stage): 2.21 (late stage)	1896.3	1069
	1.84 (early stage): 2.45 (late stage)	2789.4	2457
Single power-law distribution	2.24	1895.3	3269
	2.26	4215.1	2578
	2.17	5689.4	4623
	2.36	7145.3	847
	2.38	9235.7	3268

Figure 3 illustrates the probability distribution of individual engagement, reply rate, and group engagement within bimodal groups. The graphical representation of the probability distribution for individual engagement and reply rates within these groups indicates significant heterogeneity. This diversity indicates significant differences in engagement levels among members of online learning communities. A minority of individuals often start discussions and engage in interactions, while the majority show minimal or no participation in communicative activities. A comparative analysis of the observed group with 14 other bimodal distribution groups revealed minor disparities in power indices but no significant divergence in their overall distribution patterns. The probability distribution of individual engagement follows a power-law distribution, a common occurrence in the social sciences. This pattern indicates that a small group of active individuals dominates the majority of communication interactions.

From these observations, it is inferred that the dynamics of group communication interactions in online learning communities are predominantly driven by a limited segment of highly active participants. The vast majority of the group shows decreased engagement in discussions and interactions, which can be attributed to factors such as time constraints, reduced motivation, or lack of confidence. Enhancing group engagement necessitates intervention by platform administrators or educators, who should consider implementing strategies such as incentive programs, more effective interaction designs, or tailored participation approaches. Given that the majority of individuals tend to be reserved in communication interactions, there is a strong need for platform designs to concentrate on engaging these individuals. This could be achieved through improved incentive mechanisms or by creating a learning environment that promotes inclusivity and support.

Figure 4 illustrates the correlation between individual engagement, reply rate, and group engagement in bimodal groups. The analysis revealed a positive correlation between individual engagement and overall group engagement. This suggests, that individuals who actively initiate discussions and interactions within the group tend to exhibit higher engagement levels across the group. Conversely, the correlation between an individual's response rate and group engagement was less noticeable. This suggests that high activity in initiating learning tasks does not necessarily correlate with maintaining a high reply rate in conversations, and vice versa; individuals with a high reply rate are not always those who frequently initiate learning tasks. The group interactions reveal two distinct participant roles: those who primarily contribute to advancing learning tasks (termed as active speakers) and those who engage more in responding and interacting, thus facilitating the completion of learning tasks (identified as active responders). It is inferred that individual participation within groups is multifaceted, encompassing various activities such as initiating topics and responding to peers. Activity in one dimension does not inherently translate to activity in others, indicating the need for a multidimensional approach to assessing engagement. Sole reliance on a single behavioral metric, such as the frequency of initiating discussions, does not comprehensively reflect an individual's engagement within the community. Various levels of activity are observed across different interaction aspects. The roles of promoters and completers within learning communities are complementary, collectively fostering the group's educational progression and development. Hence, understanding the interplay of these roles is pivotal for the effective design of online learning platforms. To enhance overall community engagement, customized motivational and guiding strategies should be developed to cater to the distinct roles. For example, individuals who often start discussions but receive fewer replies could be encouraged to improve their participantion in conversations by providing them with targeted feedback and support.

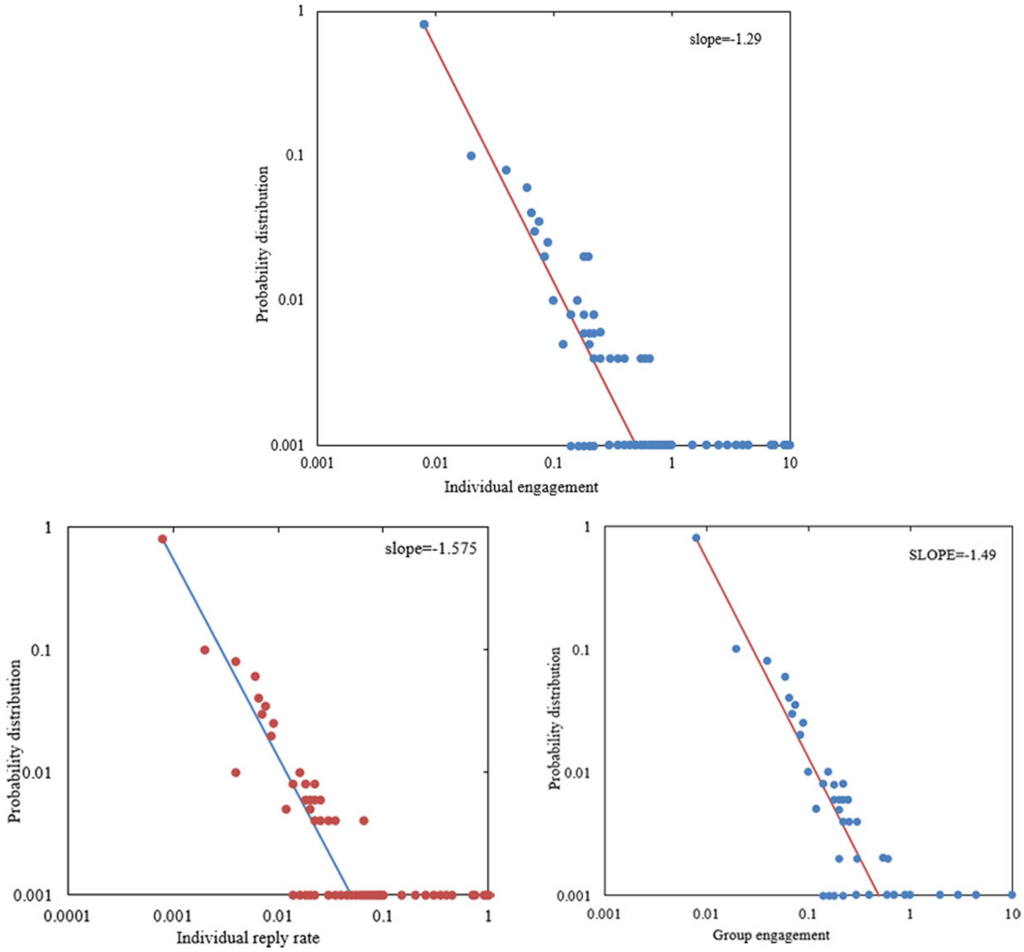

Fig. 3. Probability distribution of individual engagement, reply rate, and group engagement in bimodal groups

Figure 5 illustrates the distribution of individual engagement across various scenarios, highlighting differences in engagement levels among individuals. This heterogeneity is characterized by diverse rates of learning task initiation and reply rates among members, which impact the patterns of group communication interactions. When this heterogeneity is incorporated into the model, the simulation outcomes more accurately mirror empirical data, indicating that individual engagement diversity is integral to the participation patterns observed in online learning communities. Despite the influence of this heterogeneity on group communication dynamics, it was determined not to be the primary cause of the emergence of multiple non-Poisson characteristics at the group level. This finding implies that consistent engagement across individuals would not change the overall distribution pattern of the system. Thus, the research concludes that individual engagement heterogeneity is crucial for accurately simulating communication interactions within communities. The differentiation in participation among community members is essential for shaping group communication patterns. The inclusion of individual variability in the model significantly enhances its realism in simulating real-world scenarios, emphasizing the importance of considering individual differences in model development. The manifestation of non-Poisson distribution characteristics in the model's outcomes highlights the complexity of system dynamics in community communication interactions, which extend beyond the mere aggregation of individual behaviors.

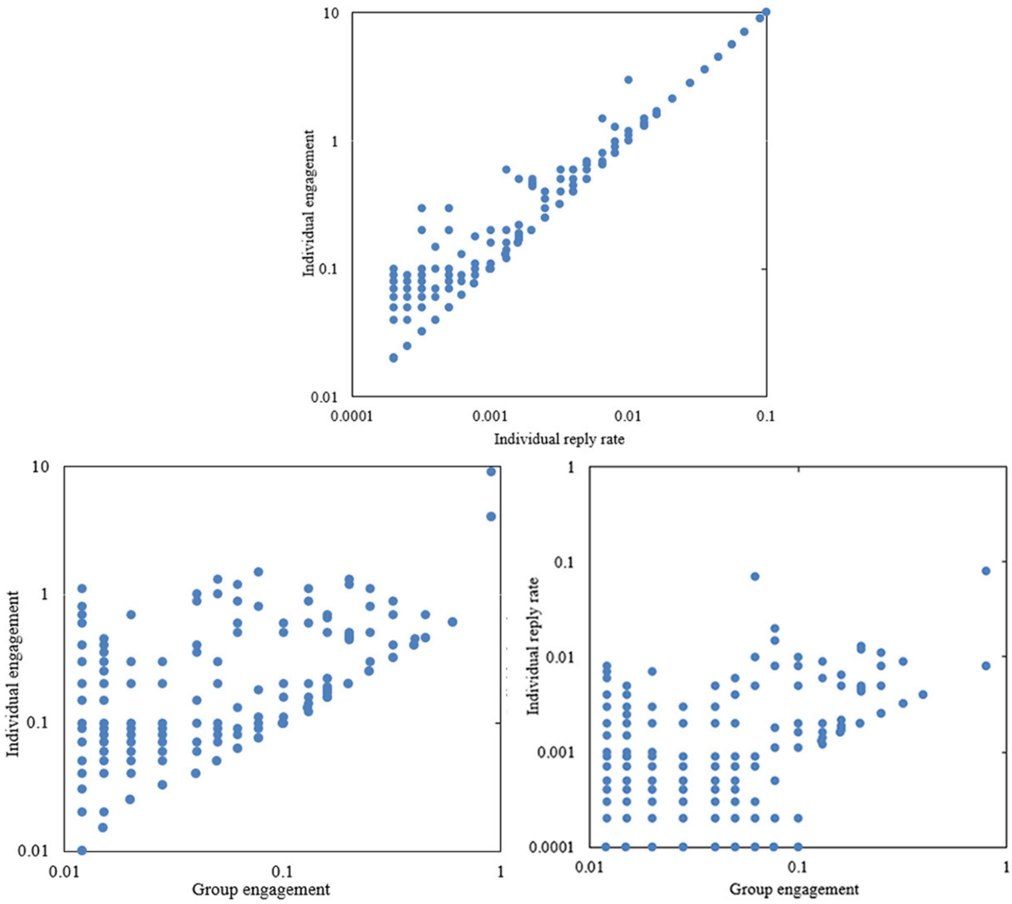

Fig. 4. Relationship between individual engagement, reply rate, and group engagement in bimodal groups

Table 2 elucidates the results of the online learning network model across various discussion topics, offering significant insights into the dynamics of network interactions. The significance levels of the parameters ($p < 0.001$) indicate a significant impact on network dynamics. The model's findings reveal that edge parameters are negative across all topics, implying non-random edge formation in the network. For instance, higher negative values in the community-building domain suggest more challenges in establishing connections. The reciprocity parameter, consistently positive, reflects an increased likelihood of reciprocal interactions following an initial communication attempt. Positive activities, influences, connectivity, contributions, and diverse participation effects suggest that these factors universally enhance network engagement. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) serve as model fit indicators, where lower values indicate a more precise fit. Although these values vary among topics, they collectively demonstrate the model's robustness in representing actual data patterns.

The model's significant coefficients underscore its effectiveness in capturing the statistical intricacies of group dynamics within online learning networks. Variations in coefficients and information criteria across different discussion topics allude to distinct interaction patterns influenced by the nature of the topic. This comprehensive analysis confirms the model's effectiveness in providing a nuanced understanding of group behavior dynamics in online learning environments, offering valuable implications for enhancing community engagement and optimizing remote education strategies.

Table 2. Online learning network model results for different topics

Parameters	Understanding and Discussion of Course Content	Sharing of Learning Resources	Learning Strategies and Methods	Coursework and Exam Tutoring	Community Building and Peer Support
Edge parameter	−7.2514***	−7.8452***	−6.6254***	−8.1247***	−8.4123***
Reciprocity parameter	2.2354***	2.6354***	2.2145***	2.3687***	2.4578***
Activity effect	0.4253***	0.3651***	0.1874***	0.4125***	0.3147***
Influence effect	0.6789***	0.9231***	0.5146***	0.5123***	0.4879***
Connectivity effect	−0.3652***	−0.1127***	−0.4215***	−0.3569***	−0.5123***
Contribution effect	0.5326***	0.4251***	0.8157***	0.5478***	0.9452***
Participation diversity effect	1.0244***	0.7126***	0.9147***	0.9235***	1.1236***
Positive interaction effect	0.2147***	0.1897***	0.3789***	0.6247***	0.2879***
AIC	42156	23547	51879	22345	23475
BIC	42157	23568	51932	22168	23165

Notes: ***indicates $p < 0.001$; **$p < 0.01$; *$p < 0.05$.

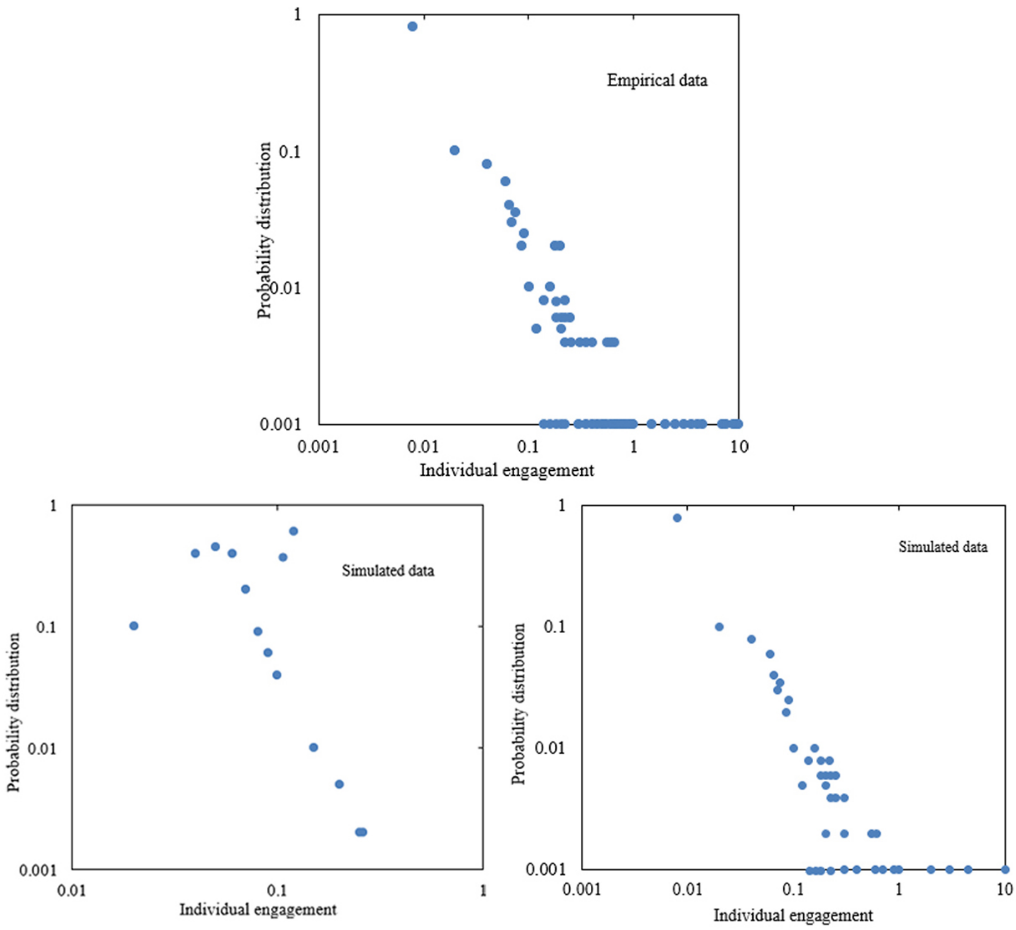

Fig. 5. Distribution of individual engagement under different scenarios

5 CONCLUSION

This study introduces an innovative model that encapsulates the formation and evolution of community engagement within online learning environments, utilizing a data-centric approach. The focal point of this model is to enhance engagement in distance education by strengthening community interactions. The paper methodically analyzes the dynamics of groups in online learning networks, employing a coupled social group network evolutionary game model. This approach examines the interaction between individual and group behaviors and their resulting impact on community engagement. Experimental assessments conducted across various online learning platforms delineate disparities in group reply rates, task initiation rates, and group sizes, underscoring the differential engagement levels across these platforms. The research further delves into the probability distribution and correlation between individual engagement, reply rates, and overall group engagement within bimodal groups. These analyses demonstrate the reciprocal influence of individual behaviors on the broader community engagement landscape. Investigations into the distribution of individual engagement under diverse conditions reveal how certain factors significantly influence the levels of individual activity within communities. Moreover, the study presents findings from the online learning network model across various discussion topics, revealing the influence of content on network interactions and engagement.

The models crafted in this paper, the communication interaction dynamics model and the coupled social group network evolutionary game model, emerge as novel theoretical and methodological instruments. These models help to understand and enhance community engagement in the context of remote education. By intricately simulating the interactions between individuals and groups, these models provide strategic insights into enhancing online learning engagement. The empirical results from these models provide essential support for optimizing online learning platforms. They guide the adjustment of social dynamic mechanisms to enhance the quality of user interactions and increase engagement.

6 REFERENCES

[1] M. Aziz, Y. A. Moshood, and A. M. Ahmad, "The effectiveness of using application as an online basic computer learning medium in higher education institution," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 13, pp. 107–117, 2022. https://doi.org/10.3991/ijim.v16i13.31583

[2] S. Kryshtanovych, O. Inozemtseva, O. Voloshyna, I. Ostapiovska, and O. Dubrova, "Modeling the effective digitalization of the education management system in the context of sustainable development," *International Journal of Sustainable Development and Planning*, vol. 18, no. 5, pp. 1507–1514, 2023. https://doi.org/10.18280/ijsdp.180521

[3] H. Huang and C. T. Hsin, "Environmental literacy education and sustainable development in schools based on teaching effectiveness," *International Journal of Sustainable Development & Planning*, vol. 18, no. 5, pp. 1639–1648, 2023. https://doi.org/10.18280/ijsdp.180535

[4] V. B. Marcus, N. A. Atan, S. M. Yusof, and U. Mastura, "Students' perception towards engaging factors of extreme e-service learning design for computer network course," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 5, pp. 100–115, 2021. https://doi.org/10.3991/ijim.v15i05.20901

[5] O. Shkvyr, H. Dudchak, N. Kazakova, O. Polianovska, and N. Sivak, "Mathematical modeling of information technology integration in digital education: A regional perspective," *Ingénierie des Systèmes d'Information*, vol. 28, no. 3, pp. 603–610, 2023. https://doi.org/10.18280/isi.280308

[6] Muthmainnah, S. Siripipatthanakul, E. Apriani, and A. Al Yakin, "Effectiveness of online informal language learning applications in english language teaching: A behavioral perspective," *Education Science and Management*, vol. 1, no. 2, pp. 73–85, 2023. https://doi.org/10.56578/esm010202

[7] H. B. U. Haq and M. Saqlain, "Iris detection for attendance monitoring in educational institutes amidst a pandemic: A machine learning approach," *Journal of Industrial Intelligence*, vol. 1, no. 3, pp. 136–147, 2023. https://doi.org/10.56578/jii010301

[8] S. Afifi, H. B. Santoso, and L. M. Hasani, "Investigating students' online self-regulated learning skills and their e-learning experience in a prophetic communication course," *Ingénierie des Systèmes d'Information*, vol. 27, no. 3, pp. 387–397, 2022. https://doi.org/10.18280/isi.270304

[9] M. Bhatia, P. Manani, A. Garg, S. Bhatia, and R. Adlakha, "Mapping mindset about gamification: Teaching learning perspective in UAE education system and Indian education system," *Revue d'Intelligence Artificielle*, vol. 37, no. 1, pp. 47–52, 2023. https://doi.org/10.18280/ria.370107

[10] S. Damjanovic and P. Katanic, "Employing microsoft excel for enhanced mathematical and statistical online pedagogy in economics amidst a pandemic," *Education Science and Management*, vol. 1, no. 2, pp. 58–72, 2023. https://doi.org/10.56578/esm010201

[11] B. N. S. Keller, M. T. Rezende, T. M. Machado, S. Delabrida, C. M. Carneiro, and A. G. C. Bianchi, "Perceptions on the use of an online tool in the teaching-learning process in microscopy," in *Proceedings of the 24th International Conference on Enterprise Information Systems*, 2022, pp. 325–331. https://doi.org/10.5220/0011062200003179

[12] L. Baturina and A. Simakov, "Students' attitude towards e-learning in Russia after pandemic," *Education Science and Management*, vol. 1, no. 1, pp. 1–6, 2023. https://doi.org/10.56578/esm010101

[13] H. Lin and M. Pryor, "Student intrinsic-motivational perceptions on a 3D immersive learning environment," in *2021 IEEE International Conference on Educational Technology (ICET)*, 2021, pp. 167–171. https://doi.org/10.1109/ICET52293.2021.9563100

[14] J. H. Zhao, P. X. Li, and W. J. Li, "Strategies of learning participation based on distance learning support: A case study of Hebei RTVU," in *2013 8th International Conference on Computer Science & Education*, 2013, Colombo, Sri Lanka, pp. 1135–1138. https://doi.org/10.1109/ICCSE.2013.6554087

[15] Y. Pang, "Action research on college English blended teaching mode based on dale's cone of experience," in *Proceedings of the 2023 8th International Conference on Distance Education and Learning*, 2023, pp. 151–155. https://doi.org/10.1145/3606094.3606128

[16] J. Li, C. Qin, and Y. Zhu, "Online teaching in universities during the Covid-19 epidemic: A study of the situation, effectiveness and countermeasures," *Procedia Computer Science*, vol. 187, pp. 566–573, 2021. https://doi.org/10.1016/j.procs.2021.04.100

[17] O. Esteban Bajo, I. Amarasinghe, N. F. Gutiérrez-Páez, and D. Hernández-Leo, "Using process mining techniques to discover the collective behaviour of educators in a learning community platform," in *International Conference on Collaboration Technologies and Social Computing*, 2022, pp. 175–189. https://doi.org/10.1007/978-3-031-20218-6_12

[18] H. Hu, X. Wang, Y. Zhai, and J. Hu, "Evaluation of factors affecting student participation in peer-assisted English learning based on online education platform," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 11, pp. 72–87, 2021. https://www.learntechlib.org/p/219983/

[19] W. Lin, “Factors that influence participation in online learning using an interpretive structural modeling,” in *2021 2nd Artificial Intelligence and Complex Systems Conference*, 2021, pp. 24–32. https://doi.org/10.1145/3516529.3516534

[20] V. V. Mukkawar, L. D. Netak, and V. B. Nikam, “Architectural view of non-face-to-face experiential learning through the immersive technologies,” in *International Conference on Intelligent Human Computer Interaction*, Springer, Cham, 2021, pp. 282–291. https://doi.org/10.1007/978-3-030-98404-5_27

[21] Y. Yang, “A ML-based efficient Chinese teaching platform design and implementation,” *Wireless Communications and Mobile Computing*, vol. 2022, Article ID: 2420396, 2022. https://doi.org/10.1155/2022/2420396

[22] Z. Zhao, F. Kang, J. Wang, B. Chen, M. Yang, and S. Qu, “Analysis and prediction of the factors influencing students’ grades based on their learning behaviours in MOOCs,” in *International Conference on Computer Science and Education*, Springer, Singapore, 2022, pp. 355–368. https://doi.org/10.1007/978-981-99-2446-2_33

7 AUTHOR

Aruna Tao is from Xing’an League, Inner Mongolia. She graduated from Inner Mongolia Normal University and is an Associate Lecturer. She is engaged in research in sociology and social work (E-mail: aruna_tao@126.com; ORCID: https://orcid.org/0009-0008-0172-9406).