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Exploring interactions in MOOC ecosystems: How learners, developers, experts influence engagement, performance, satisfaction, and trust

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ABSTRACT

Even though MOOCs have been growing rapidly, there are still some issues to tackle, such as a lack of student motivation, a high dropout rate, and low trust in MOOCs. However, most current research has been limited to one dimension of MOOCs, such as learner motivation, course design, and technology infrastructure, yielding a piecemeal view of MOOCs. To address this gap in the literature, this study proposes a cyclical interaction model that combines pedagogical and technological aspects under one umbrella and shows how they influence each other. In contrast to SRL models, connectivism, and gamification, this model presents the consistency and coordination of interactions between learners, designers, and subject matter experts as a critical factor for achieving high completion rates and trust in the platform, which has been overlooked in previous studies. In light of the data gathered from 223 participants, the results showed that intensive feedback and expert support had a strong impact on learner engagement and learning outcomes, whereas developer and expert collaboration had a positive impact on user satisfaction and trust. The analysis was conducted using a Structural Equation Modeling (SEM) approach with Smart Partial Least Squares (SmartPLS) and Analysis of Moment Structures (AMOS). This study has practical implications, as it provides a useful tool for universities and MOOC providers who want to develop online courses that have high retention rates, good learning quality, and high marketability.

Contribution/Originality: This study contributes to the existing literature on learner-developer/expert interactions in MOOCs. It proposes a circular model integrating pedagogical and technological concepts. This study is one of the very few that have investigated trust. The paper's primary contribution is finding that coordinated engagement reveals outcomes, including satisfaction and completion rates.

1. INTRODUCTION

The introduction of Massive Open Online Courses has had a significant impact on the educational landscape. Nevertheless, despite their growing popularity and high participation rates, MOOCs continue to face persistent issues: low completion rates, limited learner engagement, and concerns regarding content quality and trust in educational platforms. High dropout rates remain one of the most critical issues, largely associated with insufficient development of self-regulated learning (SRL) skills and the limited adaptation of courses to individual learner needs

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(Hmedna, Bakki, Mezouary, & Baz, 2023; Onah, Pang, & Sinclair, 2024). Another challenge is the need for timely responses to urgent forum comments, which is complicated by the rarity and difficulty of identifying such messages (Alrajhi, Alamri, Pereira, Cristea, & Oliveira, 2024).

Empirical studies examining the influence of well-being factors (e.g., PERMA) on learning outcomes in MOOCs remain limited (Yue & Saad, 2025). Analyses of existing platforms have revealed a lack of comprehensive methodological solutions, highlighting the need for integrated models that simultaneously consider both technological and pedagogical parameters (Mir & Khan, 2026). Most studies published between 2023 and 2026 examined MOOCs in isolation, focusing on motivation, instructional methods, or technological infrastructure. However, MOOCs operate as complex socio-technical ecosystems in which interactions among learners, developers, and experts collectively shape the educational process.

This study attempts to fill this void by suggesting a cyclical interaction model that considers both pedagogical and technological variables in one framework. The main difference from SRL models is that learning is not a matter of each person's strategies, but rather emerges from the interaction between the three parties. In contrast to connectivist perspectives, this study focuses on the recurrent and ongoing character of interactions, rather than merely forming network connections. Unlike gamification approaches that focus mostly on short-term motivation, the presented framework showed that trust in the expert community and the quality of pedagogical interaction are effective for promoting both academic performance and long-term engagement.

In summary, this study has three theoretical implications: First, it proposes an integrated cyclical model of pedagogy and technology within a single framework. Second, this can account for the observed decreases in dropout rates and increases in trust as a result of the joint action of the three actors. Third, it identifies trust in the expert community as a new key factor that acts as a systemic driver of learner engagement and achievement.

The goal of this study was to identify the connections between these communication properties and salient learning outcomes in MOOCs, including learner engagement, performance, satisfaction, trust, and course completion.

The following goals had been established: (1) to investigate the relationship between communication quality and learners' emotional response, engagement, satisfaction, and trust; and (2) to create a cyclical model for MOOCs by assessing the influence of expert support and feedback on course completion rates and student achievement.

Based on these objectives, the following hypothesis was formulated: A cyclical interaction model incorporating expert support and high-quality educational materials contributes to higher course completion rates and improved academic performance among students.

2. LITERATURE REVIEW

The methodology for developing massive open online courses (MOOCs) utilizes various models, approaches, and methods. Specifically, mediation models based on the PERMA concept (Yue & Saad, 2025) were used to assess positive emotions and English language test scores among Chinese students learning English as a foreign language (EFL) on a MOOC platform. A comparative analysis of factors influencing MOOC quality was conducted using the I-DEMATEL-ISM method (Zhou, Tang, & Liu, 2025). The development of MOOCs is based on methodologies involving gamification and mobile learning (Palmera & Rincón, 2025). As the demand for the integration of educational technologies into the curriculum increases, the need for teachers to develop the competencies and skills necessary to integrate technologies into their teaching methods increases (Smiling & Hollebrands, 2025).

A machine learning approach to review analysis and modified BERT models make it possible to determine perceived satisfaction with online courses. The methodology includes three approaches (Chen et al., 2025): machine learning for automatic classification of review helpfulness, BERT models for automatic classification of review topics, and multiple linear regression analysis to study factors influencing learner satisfaction. The experimental design for students' assessment of the quality of subtitles in a MOOC based on the accessibility of digital materials is a

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randomized, triple-blind, crossover study (Pérez-Arteaga, León, Pérez-Martín, Molanes-López, & Rodriguez-Ascaso, 2025). The literature presents an extensive list of studies on these methodological issues.

An analysis and identification of procrastination patterns in an online language learning course were conducted using a business process analysis method (Mendoza, Ramírez, & Aranda, 2024). The methodological approach chosen was to consider MOOCs as a tool for global development in the teacher-training system of Ethiopian universities. Educational platforms promise to democratize education worldwide and provide opportunities for professional development in resource-limited settings (Berde, Mengesha, Mola, & Remsei, 2024). The study (Pham & Abdullah, 2025) presents a structured method for testing and prioritizing key indicators necessary for the implementation of blended massive open online learning for English language learning using the fuzzy Delphi method.

Recommendations for various subject areas in MOOCs emphasize the graph capsule network approach using transfer learning as a model integrating graph capsule networks with knowledge-aware transfer learning (Lian & Zhuang, 2025). Using a systematic approach, a review of metrics for increasing learner engagement in massive open online courses was conducted (Ogunyemi, Quaicoe, & Bauters, 2022). Of interest is the study of the self-guided learning of MOOCs among a group of working people who take open, free, modular online courses and acquire knowledge that can be applied in their work on platforms managed by third parties and not controlled by the employer (Hamori, 2023). Another important aspect was to examine the influence of previous experience on blended and online learning. This study explored the use of machine learning in online education. This model allows for a detailed understanding of students' learning styles, aptitudes, and interests. The experimental results indicate that the system can accurately analyze learning behavior. For instance, the prediction of students' preference for a certain type of course can exceed 70% accuracy. Simultaneously, a personalized recommendation system is used to recommend courses and learning materials to students based on the analysis results, which greatly improves student engagement. The data shows that the course completion rate for students receiving personalized recommendations is approximately 30% higher than that for students not receiving such recommendations (Ma, 2025).

A review of platforms for massive open online courses showed that personalization, thanks to the peculiarities of the semantic network, offers wide opportunities (Kiselev & Yakutenko, 2020). The complexities of individual and collective learning are examined, and recommendations are provided regarding the capabilities and development of multi-level and multi-user online learning platforms (Du, Yu, & Li, 2024). A systematic literature review showed that a combination of knowledge tests and skill development tasks can be used to assess cognitive, behavioral, and affective learning outcomes in massive open online courses (Wei, Saab, & Admiraal, 2021).

Supporting learners' SRL within massive open educational platforms has been shown to have a positive impact on their course completion (Jansen, van Leeuwen, Janssen, Conijn, & Kester, 2020). A study examining the use of prompts to promote self-regulated learning in massive open online courses found that supporting self-regulated learning in MOOCs improved learners' time management (Wong, Baars, de Koning, & Paas, 2021). Researchers found that the limited addition of connectivist elements to online courses had no significant impact on learner engagement and motivation (Costa, Figueroa, & Steuer, 2024).

With the growth of the online education sector, universities are increasingly creating asynchronous online courses resembling MOOCs, characterized by reduced interpersonal interactions. Although these courses offer greater flexibility for students, many remain unaware of the impact of the design of these courses on student behavior and performance (Lipnickas, Harris, Qesja, & De Vos, 2025). Choosing the right MOOC is an important decision for learners, as it can significantly impact formal education and the curriculum. A hybrid approach provides a comprehensive understanding of the courses offered, covering both the broader context and the complex details (Mrhar & Abik, 2025).

To ensure effective student learning, the development of MOOC resources and their potential use were carefully planned, using the "flipped classroom" concept (Demazière & Fransson, 2024). Student interaction patterns and learning outcomes in the online course revealed the need for learner autonomy and mode choice in dual-mode

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chatbots. Based on a conceptual model linking learner autonomy, user factors, and learning outcomes, this study employed a mixed-method explanatory sequential design using chatbot interaction logs, learning management system logs, server data, and survey responses. The results showed that 41.3% of participants were unaware of or indifferent to using the mode choice feature, despite each interaction beginning with a system-generated message explaining the functionality of each mode (Han, 2026).

The results of a large-scale review analysis of MOOCs to support learner course selection showed that the numerical ratings of 2.4 million reviews (63% of which were five-star) were clearly biased (Gomez, Calderón, Sánchez, García Clemente, & Ruipérez-Valiente, 2022). Developing an online course is a complex and time-consuming process. One approach is the user experience design model for e-learning, which combines user experience design concepts such as agile methodology and design thinking (Hasani, Nuzulismah, Santoso, Junus, & Hardianto, 2024).

The motivational trajectories of learners taking an informal online course were determined using latent profile analysis. The results showed that course completion rates were low (Klose, Handschuh, Steger, & Artelt, 2024). Analyzing learning interactions during online learning is necessary for designing online courses and sequencing key interactions. The results showed that considering the correlation between a user's action and the time of its occurrence can significantly improve the performance of a neural network model, and the prediction results contribute to the study of dropout rates or online learning outcomes (Ren & Wu, 2023).

As most traditional higher education courses have moved to an online format, automated assessment and feedback tools and methods have become critical components of online learning systems, especially with regard to the assessment of short answers and essays (del Gobbo, Guarino, Cafarelli, Grilli, & Limone, 2023). The main objective of the study (Rodrigo, Iniesto, & Garcia-Serrano, 2024) was to apply andragogical models and use informal learning to improve teaching and adapt assignments and assessments to the needs of undergraduate students in inclusive design within the computer engineering curriculum. Regarding the methodology, informal input of relevant content from an external MOOC was included in the program. This allowed students to gain educational experience and promote knowledge sharing and collaboration with other students.

The development of an AI-based predictive model for classifying and predicting student behavior in online learning in Thailand showed that the AI model successfully classified learners based on their online learning behavior (Chonraksuk & Boonlue, 2024). The study by Dečman, Klun, and Stare (2025) focused on two online social science courses delivered in a flipped learning format and included a quantitative analysis of the data collected before and after the courses. The surveys examined perceived and experienced factors that facilitated and hindered the implementation of flipped learning, including the use of video lectures, self-study, self-discipline, social isolation, motivation, and time management. Additionally, the study examined the impact of group activities on exam grades, such as discussions, presentations, and interpretive tasks related to non-technical subjects.

Based on the neural network-based deep learning algorithm and taking into account its characteristics, such as high processing performance and strong data adaptability, a study was conducted on online course student preferences, learner characteristics, and other areas, and a course resource recommendation algorithm based on deep learning was constructed. Through algorithm experiments, it was found that the NCF model's performance improved by 57.7% compared with that of the CF model when RMSE was used as the evaluation metric. When MAE was used, performance improved by 58.5%, indicating that integrating the neural network-based deep learning algorithm can achieve better results (Wu, 2023).

The study by Rahimi and Ghorbani (2025) presented the first empirical examination of the persistence and boredom avoidance of language learners in online courses. A new conceptual framework for computer-assisted language learning was also developed. Overall, environmental factors accounted for 38%, 47%, and 37% of language learners' ratings of control, intrinsic value, and extrinsic value, respectively. Furthermore, cognitive appraisal and environmental factors significantly influenced language learners' persistence and boredom avoidance, accounting for 47% and 54% of the variance, respectively.

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It should be emphasized that the positive effect on job retention is homogeneous across different geographic and economic regions and is generally higher for individuals who have previously participated in more online courses (Castaño-Muñoz & Rodrigues, 2021). A study on self-regulated learning and student anxiety in online courses at universities showed that students actively use self-regulated learning strategies and contribute significantly to online learning outcomes (Apridayani, Han, & Waluyo, 2023).

In summary, most of the reviewed studies highlight a growing interest in incorporating various aspects, including pedagogical models, self-regulated learning, personalization, artificial intelligence, learning analytics, and learner support, into MOOC development. These approaches have demonstrated some success in increasing engagement, satisfaction, persistence, and course completion, but they have significant shortcomings: self-regulation and motivation do not always prevent students from dropping out, technological affordances do not always lead to deep learning engagement by learners, and models based on AI focus more on prediction than on explaining their pedagogical effects. Additionally, prior research has usually focused on only one aspect of technology, pedagogy, or behavior, but the correlations among these aspects are not well understood. This implies that there is a need to investigate the joint effects of educational design, learner support, interaction, and engagement on learning outcomes in MOOCs.

3. MATERIALS AND METHODS

A total of 223 students from Toraighyrov University in Pavlodar, Kazakhstan, participated during the 2025–2026 academic year. This study examined interaction and support in the MOOC ecosystem. This was, I guessed, a pedagogical study. This may indicate the current state of things. Energy and civil engineering students participated in the study. Engineering and computer science students also participated. Construction was also involved in several ways. Humanities and social sciences students joined. Economics and law students might have been part of this. The agricultural sciences were likely represented. It seems that most aspects have been covered, although there is still some uncertainty. This part gets a bit messy. Most of the sample consisted of students aged 17 and 20 years. This was 82 percent. The remaining 18 percent were between 21 and 25 years old. Overall, this seems to be a young group. It is not completely clear how this relates to the findings. It may be argued that the ages are sufficiently close to be irrelevant. Of the sample, 80 (36%) were first-year students, 71 (32%) were second-year students, and 72 (32%) were third- and fourth-year students. The distribution of participants by sex was 148 males (66%) and 75 females (34%) (Table 1).

Table 1. Demographic characteristics of participants.

Parameters	Category	Frequency	Percentage
Age	17-20	183	82%
	21-25	40	18%
Year of Study	1st year	80	36%
	2nd year	71	32%
	3rd year	36	16%
	4th year	36	16%
Gender	Male	148	66%
	Female	75	34%

The survey was conducted after the subjects had finished the course on the AshykBilim MOOC platform. This study was conducted voluntarily. The survey included questions about feedback, learning achievement, expert assistance, quality of education, course completion, methodological communication, satisfaction and trust.

In addition, quantitative analysis, frequency analysis, comparative analysis, and interpretation of data were used as data processing methods. The analysis included descriptive statistics, with absolute frequencies, percentages, and

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cumulative percentages computed for each indicator. This allowed researchers to determine the modal responses, as well as any general trends in responses, such as a positive skew in participant assessments.

A comparison of the distributions of different variables (e.g., feedback intensity and trust) enabled the identification of relationships between them. Qualitative analysis found a positive relationship between feedback and student engagement and satisfaction, suggesting that communication plays an important role in online learning.

3.1. To Investigate the Relationship Between Communication Quality and Learners' Emotional Response, Engagement, Satisfaction, and Trust

An evaluation of the present level of engagement and assistance in the MOOC environment was conducted using a custom-built survey with a five-level Likert scale. Statistical models were built for SmartPLS and AMOS analyses. The variables included feedback, involvement, learning success, expert support, course quality, course completion, instructional interactivity, satisfaction, and trust (Table 2).

Table 2. Measurement items.

Construct	Code	Approval of the questionnaire
Feedback Intensity	FI1	Feedback from participants is also considered when the course is developed.
	FI2	This course is revised in accordance with student outcomes.
	FI3	The changes to the course were made in response to participant feedback and requests.
Engagement	ENG1	I complete my assignments for the course.
	ENG2	I keep up with my readings for the course.
	ENG3	I participate in course discussions and course activities.
Learning Performance	LP1	I am doing well in the class.
	LP2	I'm currently completing the assigned tasks and tests.
	LP3	My knowledge and abilities have increased because of the course.
Expert Support	ES1	I have been able to receive answers to my questions from the instructors in a prompt manner.
	ES2	The answers provided by the instructors were clear and helpful.
	ES3	The presentation of the course material is up to a good standard.
Learning Quality	LQ1	The course material is presented to a high standard.
	LQ2	The activities and resources align well with the objectives of the course.
	LQ3	Tasks and materials correspond to the course objectives.
Completion	COM1	I will definitely complete the course.
	COM2	I plan to complete all major tasks of the course.
	COM3	Even in case of some problems, I will try to complete the course.
Developer–Expert Interaction	DEI1	The course seems to be developed together with experts.
	DEI2	The course materials seem to be based on experts' advice.
	DEI3	The methodological and technical parts of the course fit well.
Satisfaction	SAT1	In general, I am happy with the course.
	SAT2	The course fits my expectations.
	SAT3	I would recommend this course to other students.
Trust	TR1	I believe in the AshykBilim educational platform.
	TR2	I believe that what I learned on the platform was true.
	TR3	I will continue to study on the AshykBilim platform in other fields of study.

These models (SmartPLS and AMOS) can be used to graphically illustrate the complex causal relationships between observed and latent variables. The interactions among learners, developers, and experts formed a circular system in which feedback and expert support promoted trust, whereas learning quality and methodological collaboration promoted participation and course completion.

Therefore, the MOOC system can be considered a cyclic and interactive process where learners, developers, and experts affect one another, thereby providing fertile ground for academic success and the long-term viability of education.

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The hypotheses were tested by performing structural equation modeling (SEM) using SmartPLS and AMOS. Finally, SEM was used to examine the relationships among the main constructs: feedback, expert assistance, developer–expert interaction, involvement, contentment, and trust, and to validate the proposed cyclical model. SEM allowed for the determination of both direct and indirect relationships between the variables, which helped increase the reliability and validity of the results. Model fit indices and the reliability and validity of both the measurement and structural models were assessed.

The study also used a five-point Likert scale in a quantitative survey of 223 participants, complemented by qualitative methods to better understand the interaction processes in the MOOC environment.

Semi-structured interviews were conducted with fifteen students to identify the subjective factors of trust and engagement; semi-structured interviews were carried out with 15 students. In addition, content analysis of discussion forums on the MOOC platform "AshykBilim" was conducted to study patterns of feedback sharing and experts' engagement. Invitations were sent through personal student accounts to students who were interested in participating in an interview. Consequently, 15 students at different levels (1–4) indicated that they wanted to express their opinions about MOOCs. The interviews were conducted face-to-face, audio-recorded after electronic informed consent had been obtained from participants through their personal student accounts, and then transcribed. The length of each interview was approximately five to seven minutes. The interview protocol included questions on the participants' experience of using massive open online courses (MOOCs), interaction with instructors and experts, use of artificial intelligence (AI) tools, the influence of AI on their comprehension of the course content, the elements that influenced their engagement in and completion of a MOOC course, their satisfaction with the quality of teaching, and the challenges and limitations of using MOOCs and AI (Ospanova et al., 2026).

To measure the quality of communication, as well as learners' affective responses (emotions), attention, satisfaction, and trust, experts created a questionnaire by synthesizing existing validated scales and previous studies focusing on communication and learners' experiences within digital and online contexts. Relevant measurement items were also adapted during questionnaire development to reflect the unique characteristics of the educational setting under investigation. To establish content validity, experts in digital education and educational research evaluated the questionnaire.

The research followed ethical principles concerning voluntary participation and confidentiality, along with obtaining informed consent from everyone. The consent process was handled through the AshykBilim platform using student accounts before anything began. Participants received an information sheet explaining what the study was about, how the data would be used, and their option to stop at any time. It appears that consent was given when they clicked to continue with the survey.

The same approach worked for those fifteen students in the interviews. They got the sheet in their accounts, too, and gave the go-ahead electronically first. I think this kept everything consistent, but maybe it feels a bit repetitive if you look at how both groups were treated. Some details on anonymity stand out here, though I'm not sure how much it changes things overall.

3.2. To Create a Cyclical Model for MOOCs by Assessing the Influence of Expert Support and Feedback on Course Completion Rates and Student Achievement

Hypothesis testing was conducted through structural equation modeling (SEM) using AMOS and SmartPLS software. AMOS was used for confirmatory factor analysis (CFA), model fit testing, reliability (Cronbach's Alpha, Composite Reliability), and validity (AVE, Fornell-Larcker test).

SmartPLS was employed to analyze the latent variable model and examine the direct and indirect effects between the indicators (feedback → engagement → trust).

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The analysis involved multiple steps:

1) Data Preparation. Data collection was conducted using a student survey. The sample consisted of 223 students (ages 17-25, years 1-4, ~66% men, ~34% women). They contained measures of 9 constructs: Feedback Intensity, Engagement, Learning Performance, Expert Support, Learning Quality, Completion, Developer-Expert Interaction, Satisfaction, and Trust.

2) The application of the CFA (AMOS) method allowed for testing the factor structure of each variable, excluding weak indicators (factor loading < 0.5), and confirming construct validity.

Confirmatory factor analysis (CFA). Stage 1: Confirmatory Factor Analysis (CFA) in AMOS. Aim: To test the reliability and validity of scales measuring latent variables (Learner Engagement, Academic Performance, Satisfaction, Trust, Course Completion). Factor loadings (FL), composite reliability (CR), and average variance extracted (AVE) were tested. The criteria were CR > 0.7 and AVE > 0.5. The Fornell-Larcker criterion was used to establish discriminant validity.

3) The use of the SEM (SmartPLS) technique led to the development of a relationship model.

- Feedback Intensity → Engagement → Satisfaction/Trust.
- Expert Support → Learning Quality → Completion.
- Developer–Expert Interaction → Satisfaction → Trust.

Path significance test (bootstrapping, $p < 0.05$).

Model quality assessment (R^2, Q^2, and SRMR).

Purpose: To test hypotheses concerning relationships among latent variables.

Structural equations:

$$Engagement = \beta_1 \cdot Feedback + \beta_2 \cdot ExpertSupport + \epsilon_1$$

→ The level of engagement is determined by the intensity of experts' feedback and support.

$$Performance = \beta_3 \cdot Engagement + \beta_4 \cdot LearningQuality + \epsilon_2$$

→ Performance depends on student engagement and teaching quality.

$$Satisfaction = \beta_5 \cdot Engagement + \beta_6 \cdot Performance + \epsilon_3$$

→ It increases satisfaction through involvement and the attainment of good grades.

$$Trust = \beta_7 \cdot Satisfaction + \beta_8 \cdot DeveloperExpertInteraction + \epsilon_4$$

→ As for how trust developed, it comes from user satisfaction and interactions between users and experts/developers.

$$Completion = \beta_9 \cdot Performance + \beta_{10} \cdot Trust + \epsilon_5$$

→ A student's ability to complete the course depends on their academic performance and confidence in the system.

Engagement acted as a mediating factor by increasing Performance and Satisfaction. Performance directly affected Satisfaction and Completion. Satisfaction strongly influenced trust.

Finally, Trust and Performance jointly affect the likelihood that users will complete the course.

Therefore, the model shows how feedback and expert support directly affect Engagement, Performance, Satisfaction, Trust, and Course Completion.

Although the questionnaire included nine constructs, the CFA and SEM analyses focused on the five principal latent variables: Engagement, Learning Performance, Satisfaction, Trust, and Completion. Feedback Intensity, Expert Support, Learning Quality, and Developer–Expert Interaction were treated as exogenous variables in the structural model.

This study uses the "AshykBilim" platform for three key reasons. It is among the largest national MOOC platforms in Kazakhstan with thousands of users, and thus represents a significant environment for investigating online education practices in the country. It is also a blended system that combines both technology and pedagogy, which makes it appropriate for investigating the relationships between course designers, subject-matter experts and students. Finally, there was an abundance of platform data, such as course completion rates and forum discussions,

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that could be used as valid and reliable measures. This paper is a pioneering systematic study of an MOOC ecosystem in the Central Asian region that increases both the originality and international importance of the work. Little research has been conducted on MOOCs from the perspective of Central Asia. Thus, a study in the Kazakhstani context fills this void and adds to the geographical coverage of digital education research.

A potential extension of this study would be to include other MOOC platforms, such as Coursera or edX, as well as other universities in the sample. Comparative studies of "Kazakhstan and other countries" could be useful for identifying cultural and/or institutional differences that may influence learner engagement, trust and academic performance. This increases the external validity and generalizability of the proposed model.

This mixed-methods approach helped to provide more context for the quantitative results and enabled a deeper exploration of the forces that determine interactions among the different actors in the ecosystem.

4. RESULTS

4.1. Communication Quality and Its Relationship with Learner Engagement, Satisfaction, and Trust

These tables present descriptive statistics on students' and developers' feedback, engagement, success, expertise, training quality, course completion, methodological interaction, satisfaction, and trust.

Table 3. Frequency of feedback intensity.

Feedback intensity	Frequencies	% of total	Total %
1	26.0	11.7%	11.7%
2	18.0	8.1%	19.7%
3	36.0	16.1%	35.9%
4	93.0	41.7%	77.6%
5	50.0	22.4%	100.0%

These are the frequency counts for the strength of feedback provided in each category on a 5-point Likert scale. The highest proportion (41.7%) of respondents scored intensity at Level 4, which reflects a relatively high level of perceived support and communication. The proportion of responses at levels 4–5 was more than 64%, indicating that the overall emotion was positive. Values of 1 or 2 were rare, occurring in less than 20% of the sample. Most participants rated the feedback as appropriately intense, resulting in high engagement and satisfaction ratings (Table 3).

Table 4. Frequency of engagement.

Degree	Frequencies	% of total	Total %
1	15.0	6.7%	6.7%
2	32.0	14.3%	21.1%
3	31.0	13.9%	35.0%
4	81.0	36.3%	71.3%
5	64.0	28.7%	100.0%

There was a preponderance of high values on the Likert scale for learner engagement measures. Similarly, 36.3% of respondents gave themselves a score of 4 for engagement, while 28.7% gave themselves a score of 5 for engagement. All of these categories make up almost two-thirds of the sample (65%), which demonstrates an obviously positive tendency toward active involvement in educational activities. Finally, only 21% of respondents scored at low levels (1-2), while average ratings (level 3) were recorded by 13.9% of the participants. The data confirmed that the learners had a high degree of affective involvement and satisfaction within the MOOC space (Table 4).

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Table 5. Satisfaction rates.

Degree	Frequencies	% of total	Total %
1	13.0	5.8%	5.8%
2	29.0	13.0%	18.8%
3	34.0	15.2%	34.1%
4	78.0	35.0%	69.1%
5	69.0	30.9%	100.0%

The distribution of learner satisfaction indicators on the Likert scale revealed a preponderance of higher scores. Most respondents had a satisfaction level of 4 (35.0%), followed by a satisfaction level of 5 (30.9%). These categories represented over two-thirds of the sample (65.9%), suggesting that respondents tended to have a favorable view of the learning process in the MOOC environment. Average ratings (level 3) accounted for 15.2% of responses, while low ratings (levels 1–2) accounted for approximately 18.8%. According to the data, it can be concluded that most learners were very satisfied with the course, as shown by their comments on communication, support, and teaching quality (Table 5).

Table 6. Trust frequencies.

Trust	Frequencies	% of total	Total %
1	20	9.0%	9.0%
2	40	17.9%	26.9%
3	36	16.1%	43.0%
4	67	30.0%	73.0%
5	60	26.9%	100.0%

Out of two hundred twenty three people the scale ran from one as the lowest up to five as the highest. It seems like most leaned toward higher trust overall. Sixty seven picked four which works out to thirty percent and sixty went with five at nearly twenty seven percent. That makes seventy three percent at the top two scores which points to a pretty positive view in the group. Moderate trust at three showed up with thirty six people while the lower end had forty at two and twenty at one. Some of the numbers feel close when you line them up but I am not totally sure how much that changes the picture. The high scores are what stand out though. (Table 6).

Table 7. Learning performance frequencies.

Learning performance	Frequencies	% of total	Total %
1	15.0	6.7%	6.7%
2	22.0	9.9%	16.6%
3	31.0	13.9%	30.5%
4	86.0	38.6%	69.1%
5	69.0	30.9%	100.0%

4.2. Empirical Findings and Structural Model Validation

The distribution of the learning performance indicators on the Likert scale was predominantly at higher values. The majority (38.6%) assessed their performance as Level 4, followed by 30.9% who gave themselves the maximum score of Level 5.

Together, these categories accounted for almost 70% of the sample, demonstrating a significant improvement in learning outcomes and effectiveness in the MOOC ecosystem. Average ratings (Level 3) were reported by 13.9% of the respondents, while low ratings (1–2) accounted for only approximately 16.6%. The results confirmed the high level of learning productivity and success of the majority of learners (Table 7).

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Table 8. Frequency of learning quality.

Degree	Frequencies	% of total	Total %
1	10.0	4.5%	4.5%
2	15.0	6.7%	11.2%
3	30.0	13.5%	24.7%
4	85.0	38.1%	62.8%
5	83.0	37.2%	100.0%

The majority of values in the distribution for each measure of the quality of learning on the Likert scale were in the higher range. On the other hand, the majority of students chose the fourth level (38.1%), whereas 37.2% rated it as level 5. Overall, these three categories comprised 75.3% of the total, suggesting that students perceived the quality of the educational process in the MOOC ecosystem to be at a high level. On the other hand, an average rating (level 3) was recorded by 13.5% of the participants, and low ratings (levels 1–2) were recorded in approximately 11.2% of the responses. These findings demonstrate that the majority of students considered the quality of learning to be good, showing that the applied educational methods were effective (Table 8).

Table 9. Completion frequencies.

Degree	Frequencies	% of total	Total %
1	4.00	1.8%	1.8%
2	12.00	5.4%	7.2%
3	33.00	14.8%	22.0%
4	68.00	30.5%	52.5%
5	106.00	47.5%	100.0%

The completion rates on the Likert scale were mostly concentrated at the higher end. Most of the responses, namely, 47.5%, were at the maximum completion level (5), followed by 30.5% for Level 4. Altogether, these categories accounted for over 78% of the sample, reflecting a relatively high degree of completion within MOOCs. However, 14.8% of the respondents reported average grades (Level 3), while low levels (1-2) accounted for only approximately 7.2%. The findings indicated that most learners completed their learning modules, thus proving the effectiveness and sustainability of the process (see Table 9).

Table 10. Expert support frequencies.

Degree	Frequencies	% of total	Total %
1	5.00	2.2%	2.2%
2	24.0	10.8%	13.0%
3	28.0	12.6%	25.6%
4	68.0	30.5%	56.1%
5	98.0	43.9%	100.0%

There was a high concentration of expert support scores in the upper region of the Likert scale. The most common response (43.9%) was Level 5 (maximum level of support), followed by Level 4 (30.5%). These four categories made up almost 3/4 of the total (74.4%), suggesting that the quality of expert assistance is generally satisfactory within the MOOC community.

The proportion of average responses (Level 3) was 12.6%, with low levels (1–2) making up approximately 13% of the total. Based on the findings in Table 10, it can be concluded that most participants found expert support helpful, effective, engaging, and successful in their learning.

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Table 11. Frequency of developer-expert interactions.

Degree	Frequencies	% of total	Total %
1	16.0	7.2%	7.2%
2	26.0	11.7%	18.8%
3	36.0	16.1%	35.0%
4	80.0	35.9%	70.9%
5	65.0	29.1%	100.0%

As can be seen in the above tables, the Likert score for interaction between developers and experts was consistently higher. Most respondents (35.9%) selected level 4 as the response, and 29.1% selected level 5. These categories together made up nearly two-thirds of the sample (65%), indicating that the quality of professional interactions in the MOOC ecosystem was perceived positively. Of the respondents, 16.1% received average (level 3) ratings, while low (levels 1–2) ratings accounted for approximately 18.8% of the total responses. As can be seen from Table 11, the majority of respondents noted that the interaction between developers and experts was a productive and important aspect of improving the quality of the educational process.

The research has shown statistical regularities that prove the connection between the level of interaction (feedback) and the affective component of students' attitudes, as measured by indicators of engagement, satisfaction, and trust.

An analysis of descriptive statistics revealed a consistent prevalence of high scores across all key educational ecosystem parameters, including engagement, satisfaction, trust, quality of instruction, expert support, and course completion. In particular, 60-75% of respondents gave consistently high scores (Likert scale scores of 4-5), implying a positive opinion of the educational process and the efficacy of participant interactions.

This finding supports the hypothesized cyclic interplay of learning elements, in which intensive feedback as a mediating factor leads to higher levels of engagement, satisfaction, and trust, which subsequently enhance the quality of learning, learning achievement, and course completion. The findings from this study show that expert support and methodological interaction between developers and instructors significantly influence objective learning outcomes such as course achievement and completion rates and contribute to a sustainable learning environment. The relationships among feedback intensity, learner engagement, satisfaction, trust, expert support, developer–expert interaction, learning quality, academic performance, and course completion are illustrated in Figure 1.

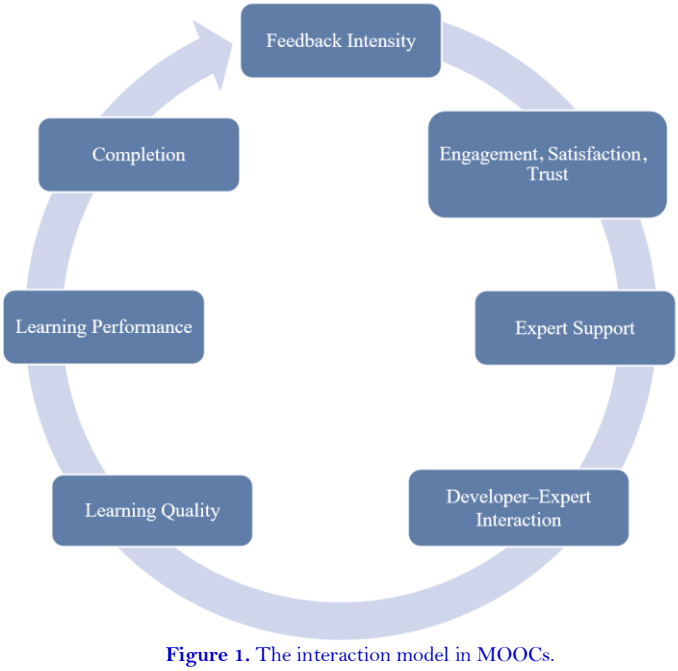


Figure 1. The interaction model in MOOCs.

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Regarding the measurement model, the CFA findings showed acceptable reliability and factorial validity. The factor loadings of all the indicators ranged from 0.62 to 0.88, which are above the recommended value of 0.50. This confirms that the questions measured the relevant latent variables.

Table 11a. Reliability and convergent validity.

Construct	CR	AVE
Engagement	0.84	0.57
Learning performance	0.81	0.54
Satisfaction	0.86	0.59
Trust	0.88	0.61
Completion	0.79	0.52

Table 11a shows the outcome of the reliability and convergent validity tests on five major latent variables that were considered in the CFA and SEM analyses. The composite reliability (CR) scores range between 0.79 and 0.88 which are above the minimum level of 0.70 showing acceptable internal reliability. Meanwhile, the average variance extracted (AVE) scores range between 0.52 and 0.61 which are above the minimum threshold of 0.50 showing sufficient convergent validity for the measurement model.

Table 12. Fornell - Larcker Matrix.

Construct	ENG	LP	SAT	TR	COM
ENG	0.755	0.534	0.512	0.515	0.482
LP	0.534	0.735	0.489	0.495	0.491
SAT	0.512	0.489	0.768	0.567	0.495
TR	0.515	0.495	0.567	0.781	0.485
COM	0.482	0.491	0.495	0.485	0.721

The Fornell-Larcker matrix in Table 12 was generated to assess discriminant validity between the constructs. The square roots of AVE are on the diagonal and correlation values between the constructs are located off the diagonal. This criterion was used to determine if each construct is unique or distinct from the other constructs in the model.

As indicated in Table 12, discriminant validity was evaluated by comparing the square root of the AVE for each construct with its correlations with other constructs. Thus, these results demonstrate discriminant validity and show that each construct represents a distinct facet of the concept under examination and is empirically distinguishable from the other constructs in the model. Therefore, CFA showed that each of the five latent variables (Engagement, Performance, Satisfaction, Trust, and Completion) had high reliability and validity. Subsequently, SEM analysis was performed to examine the structural relationships among the constructs.

In structural equation modeling (SEM), the relationship between the measured variables in the model was found to be significant. In particular, feedback intensity had a positive and significant impact on students' engagement ($\beta = 0.42$, $p < 0.01$), as did expert support ($\beta = 0.36$, $p < 0.01$). This indicates that students were more engaged in learning when they received regular feedback and professional guidance.

Likewise, student engagement positively affected academic performance ($\beta = 0.48$, $p < 0.001$). Instructional quality had a significant positive effect on academic achievement ($\beta = 0.39$, $p < 0.01$). Therefore, student engagement and perceptions of high teaching quality were positively related to achievement. Factor analysis revealed a significant relationship between student satisfaction and engagement ($\beta = 0.33$, $p < 0.01$) and performance ($\beta = 0.41$, $p < 0.001$). This suggests that student satisfaction depends not only on the degree of students' involvement in the educational process but also on their academic achievement.

In the trust construct, learner satisfaction had the most significant effect ($\beta = 0.57$, $p < 0.001$). In addition, the interaction between developers and experts was found to have a positive and statistically significant effect on trust (β

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= 0.29, $p < 0.05$). Hence, trust in the education system is largely based on positive learning experiences and satisfaction, as well as effective interaction between developers and experts. Finally, course completion was significantly associated with academic performance ($\beta = 0.44$, $p < 0.001$), and students' trust in the system ($\beta = 0.38$, $p < 0.01$). The analysis suggests that students' success in completing a course is influenced by both their grades and trust in the education system. The model's explanatory power was determined to be 0.51 for Engagement, 0.56 for Performance, 0.62 for Satisfaction, 0.67 for Trust, and 0.59 for Completion. Hence, the model can explain 51%–67% of the variation in the dependent variables, indicating that the model has good explanatory power. A value of 0.07 for SRMR suggests that the model fits the observed data adequately. All the structural paths are significant at $p < 0.05$; however, most of them show higher statistical significance at the $p < 0.01$ level.

In summary, the results of the SEM analysis indicate that student engagement plays an important role in the proposed model, as it has a direct effect on students' academic achievement and satisfaction. Satisfaction was a major predictor of trust. Both trust and academic performance contribute to course completion. These findings largely confirm the hypothesized structural model of the relationships between communication, engagement, academic achievement, satisfaction, trust, and completion.

Therefore, the CFA confirmed that the measurement model was reliable, and the SEM revealed that engagement and academic performance affected satisfaction, satisfaction affected trust, and trust and academic performance affected course completion.

5. DISCUSSION

The results show that coordination helps significantly with how involved students become and with their grades. Trust builds up on platforms when this occurs among learners, developers, and experts. This appears to be a key aspect, although the measurement procedures are not entirely clear.

The cyclical model attempts to address something missing from earlier works. Studies have usually taken the teaching and technological sides on their own. What comes out here is how those parts depend on each other in a back-and-forth manner. It seems that this link has not been the main focus before. The main objective is to bring them into one view. Some people may still view them as distinct, but the model opposes this view.

A comparison with other widely known models shows how it is unique in its own way. Learning is seen as a result of three actors interacting collectively rather than focusing on individual student strategies, as self-regulated learning models usually do. Thus, the influence of feedback and expert support on engagement and trust comes across more as a system-level issue. Some people might see the individual focus as sufficient on its own. That appears to ignore the part of the problem that is collective, which is hard to describe briefly without being verbose.

In contrast to the connectivist view, which focuses on connections within the network, our approach highlights the repetitive and ongoing character of engagement, showing that effective collaboration between developers and experts contributes to lowering dropout rates.

Unlike gamification models, which are mostly designed to achieve short-term goals, our model points out that trusting a community of experts can be a lasting factor for academic performance and long-term student engagement.

The practical implications of this study stem from the fact that this model may be used to improve MOOC platforms and university programmes.

Implementing consistent feedback loops, improving access to experts, and increasing collaboration between teachers and technologists may help reduce dropout rates, improve student engagement, and build confidence in online learning tools.

Thus, the results of this study have practical applications for instructional designers and universities and can help create a more sustainable learning space and enhance the competitiveness of digital education. Although the sample is restricted to an analysis of only the AshykBilim platform, the novelty of the case study (as the first systematic study of MOOCs in Central Asia) provides a unique contribution to research and can serve as a basis for

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new international comparisons. This model is a useful theoretical and practical guide for developing MOOC courses that can provide higher levels of retention, engagement, and trust. Thus, this model can be a useful tool for both local universities and international online learning platforms.

In addition, the empirical results also imply that MOOCs are not just technologies but rather interactive learning environments in which feedback plays a key role in connecting learners' participation, satisfaction, and trustworthiness. The high ratings across all categories examined suggest that good stakeholder communication is a factor that not only enhances the learning experience, but also enhances learners' intention to finish courses and engage in future online learning. This finding is also supported by prior work that shows that learner support and course co-design are essential for MOOC quality improvement.

However, the present study moves beyond the current literature by incorporating pedagogical, technological, and social elements in one cycle. The proposed model should be examined in future studies with larger, more representative samples, over time (using a longitudinal design), and through different analytical methods such as structural equation modeling.

These studies help us better understand the links between feedback, engagement, trust, and learning outcomes within digital learning contexts. The results of this study confirmed the effectiveness of the proposed cyclical model of interaction in the MOOC ecosystem (see Table 1-9). A high number of Likert scores of 4-5 on the main parameters (feedback, involvement, satisfaction, confidence, learning quality, expert assistance, interaction between developers and experts, course effectiveness, and completion of courses) indicates a positive attitude toward the educational process. These results are consistent with the research conducted by the Kazakh-British Technical University (Zhumabayeva, Mezin, & Knysheva, 2024), in which the Level UP course showed a higher-than-average completion rate (10% versus 5-8%), as well as with Abayeva, Zhurov, and Mustafina (2024), who confirmed the growth of research skills in students, and the study by Issakov et al. (2023), which revealed the positive impact of MOOCs on the formation of the competence of future geography teachers.

The advantages of the model include the integration of subjective and objective measures, validation using empirical data, and its high practical applicability to MOOC design and optimization.

This finding is consistent with findings from other research, thus enhancing its generalizability and validity.

Therefore, the presented analysis indicates that the proposed cyclic model has considerable applied value, is based on actual facts, and conforms to the results of other researchers, but needs further refinement and adaptation for broader use.

6. CONCLUSION

Empirically, the present study confirms that communication and interaction are essential aspects of the MOOC ecosystem. The most important factor that influences learners' emotional responses is the intensity of feedback, which in turn affects learner engagement, satisfaction, and trust. High ratings predominated in each of the analyzed indicators, with scores ranging between 60% and 75% on the Likert scale. These results indicate that stakeholder perceptions of the educational process were positive, and their interactions were effective. Learners experienced the effect of methodological collaboration between course developers and instructors, and expert support provided by developers. These empirical findings support the cyclical interaction model. Feedback is a key element in ensuring that education can remain sustainable. The relationships between engagement, satisfaction, trust, educational quality and expert support can be viewed as interdependent. When combined, these factors create a comprehensive learning environment that ultimately increases effectiveness. Theoretically, this study developed a new cyclical interaction model that combines the elements of pedagogy and technology into a comprehensive framework. According to the model, better coordination of interactions in this framework would enhance learners' trust in MOOCs and decrease dropout rates. This model offers an extension of the existing theory and proposes an alternative explanation of how

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the collaboration of learners, developers, and experts can affect the quality of learning experiences. Therefore, this study makes a meaningful contribution to the theoretical advancement of digital education.

Thus, this study intends to improve educational quality, increase student engagement, and reduce the probability of students dropping out. The proposed model can be used for the design and development of online courses.

Future research should use regression and correlation methods to test the causal relationships among the components of the proposed model. The study proposes extending the sample to include data from various educational platforms, which will make the results more generalizable. Collecting data from various platforms can reveal more insights into the cultural and institutional differences that influence trust and engagement in online learning environments.

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Informed Consent Statement: Electronic informed consent was obtained from all participants through their personal student accounts before data collection commenced. All survey and interview data were anonymized to protect participants' confidentiality.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
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