The Impact of Teacher Support and Learning Interaction on Online Learning Continuation Willingness: A Flow Experience Perspective

https://doi.org/10.3991/ijet.v17i17.34029

Ying Gu[1], Chenchen Song[2](✉), Yifan Zhong[3], Ubaldo Comite[4]
[1]Yangzhou Polytechnic Institute, Yangzhou, China
[2]Guangling College of Yangzhou University, Yang Zhou, China
[3]Faculty of Business and Law, Curtin University, Bentley, Australia
[4]Department of Business Sciences, University Giustino Fortunato, Benevento, Italy
luckyscc@126.com

Abstract—With the deep integration of Internet technology into online education in recent years, the online education model has gained increasing recognition, while there has also been a problem with students' lack of interest in continuing their online education. Using the structural equation model as an analytical tool, this paper starts from three aspects, learning interaction, teacher support, and flow experience, and studies the influencing factors of online learning continuation willingness, and constructs a theoretical model of these factors to understand students' continuation willingness to learn online and the mechanism of related influencing factors. The findings of the study demonstrate that the continuation willingness of online learning is affected by learning interaction and teacher support via the mediation effect of flow experience.

Keywords—learning interaction, flow experience, online learning, continuation willingness

1 Introduction

The online education sector has benefited greatly from the quick development and broad use of cutting-edge information technologies like cloud computing, big data, and blockchain. Online learning is the use of contemporary digital resources, supported by a variety of Internet learning techniques, where learners are motivated by learning to modify their cognitive behavior as well as complete the creative processing of knowledge [1]. The new era of online learning space is a different learning environment that incorporates interaction, sharing and convenience, and reflects the openness, personalization, precision and interconnectedness of education. Relevant institutions can efficiently integrate distance online education resources through various mobile terminals like smartphones and tablet computers, enabling students to receive ubiquitous learning support across multiple platforms and interactions in a variety of environments anytime, anywhere [2].

It is a key means to realize learning anytime, anywhere, regardless of stage, venue, or time. It is also an important interface for personalized and scenario-based teaching from the perspective of information empowerment and data empowerment. However, the current online learning platform is also faced with certain development obstacles, such as the students' failure to complete their studies, the lack of continuous enthusiasm for the course, the poor interaction during the course, and the lack of teaching support. Unexpected abandonment during use has become a common phenomenon. The participation experience in the online learning space has a key influence on the students' willingness to continue online learning. To improve the sustainability of their participation, it is necessary to deeply study the mechanism of teacher support and learning interaction, and it is expected to reveal the main driving process and driving force by mining factors. mechanism to further enrich and develop online education. This paper theoretically constructs a model of influencing factors of online learning continuation willingness and conducts empirical analysis through a structural equation model to provide targeted and feasible teaching suggestions.

2 Research hypothesis

At present, a large number of academic literature have explored the influencing factors of online learning continuation willingness from different perspectives. Hoffman et al. (1996) considered that the flow experience is an internal factor that can motivate people to continue to participate in an activity, and it is a self-purpose experience [3]. Hoffman et al. (2009) researched that users' participation in Internet activities and the use of mobile APPs will produce a flow experience, and confirmed that the flow experience can have an impact on users' cognition, behavioral intentions, attitudes, and satisfaction [4]. Many educators and researchers have found that online learning is influenced by many factors, including personal motivations and attitudes [5] and socio-environmental factors, such as levels of interaction [6]. However, there is little research on how flow experience and other influencing factors affect online learning continuation willingness. This paper aims to address this research gap by studying the factors that affect the continuation willingness of online learning into three factors: teacher support, learning interaction, and flow experience.

2.1 Teacher support

Teachers support students by encouraging them, taking the time to help and support them, treating them fairly, and giving them opportunities to make choices, and students who perceive teacher support are more motivated and perform better in school [7]. Teachers play a critical part in students' academic lives and teachers' expectations of students have a significant impact on their academic achievement [8]. The teacher expectation model believes that teachers have different expectations according to the characteristics of students, which will affect teachers' behavior toward students, and students will have internal psychological changes through perceiving teachers' behavior, which will ultimately affect academic performance. Therefore, this paper uses autonomic support, emotional support, and cognitive support to measure the impact of teacher support on learning interaction, flow experience, and online learning continuation willingness. Based on this, this paper proposes hypotheses H1, H2, H3.

H1: Teacher support has a significant positive effect on learning interaction.
H2: Teacher support has a significant positive effect on flow experience.
H3: Teacher support has a significant positive effect on online learning continuation willingness.

2.2 Learning interaction

Information tools connect teachers and learners, learners and learners, learners use forums to interact, and use public platforms to work together to create learning resources [9]. The characteristics of autonomy, diversity, openness and interactivity lead to a result that more learners are interacting on the platform. Learner interaction is mainly manifested in learners' exchange and discussion in forums, mutual assessment of assignments, and real-time communication through built-in forums or social tools [10]. Therefore, this paper uses the learning system to remind in advance, effectively interact with teachers, and communicate with other students in a timely manner to measure the impact of learning interaction on flow experience and continuation willingness to learn online [10]. Based on this, this paper proposes hypotheses H4 and H5.

H4: Learning interaction has a significant positive effect on flow experience.
H5: Learning interaction has a significant positive impact on online learning continuation willingness.

2.3 Flow experience

The theory of flow experience was put forward by psychologists in the 1960s. It believes that when a person concentrates on a certain thing, the flow will occur, which is manifested as a high concentration of attention, a feeling of being in a good mood, and not much [11]. Learning pressure and other experience can significantly reduce the psychological problems of learners in the online learning environment, so that they have the motivation to further participate in an activity [12]. Research by other scholars has also shown that the premise of allowing participants to continue participating in activities is that they feel interested and fulfilled [13]. This flow experience can stimulate learners' motivation and achieve better results. Therefore, this paper proposes the following hypothesis.

H6: Flow experience has a significant positive impact on online learning continuation willingness.

2.4 Continuation willingness to learn online

Continuation willingness refers to a user's intention to reuse an online learning platform after using it for the first time, which means that the user has a certain degree of stickiness or loyalty to the online learning platform [14]. In the research of this paper, the continuation willingness of online learning is the main dependent variable, and other variables will directly or indirectly affect this factor. The user's continuation willingness to study online will be determined by whether the user intends to continue to study in this online course instead of dropping out, insist on studying in this online course instead of using other alternative means, and recommend this online course to surrounding classmates or friends. measure in one aspect.

3 Data sources and study design

3.1 Questionnaire design and data collection

This study adopts the Likert five-point measurement method to design the scale, and the questionnaire design items such as basic information and teacher support, interactive learning, flow experience and online learning continuation willingness of the respondents [15]. In order to ensure the validity and reliability of the scale, the scale design refers to the mature scales of relevant research at home and abroad, and considers the characteristics of Chinese students. Before the design, a small-scale survey was firstly organized, and some items and sentence expressions were modified according to the feedback [16]. On this basis, questionnaires were distributed among students who participated in online learning in colleges and universities. It lasted for 5 days. After 17 questionnaires with incomplete information were deleted, a total of 284 valid questionnaires were collected. The questionnaire response rate of this study was 94.35%.

3.2 Research design

The structural equation model is suitable for the exploration and analysis of complex multivariate data. It can analyze the causal relationship between multiple variables at the same time [5]. It is a powerful data statistical analysis method. There are hypothetical constructs in the fields of education, psychology, marketing research, organizational behavior, and economics that cannot be directly observed or directly measured. Hypothetical constructs are just abstract concepts that cannot be directly known and are often multi-scale, so they cannot be effectively analyzed through traditional factor analysis or multiple regression analysis [17]. The statistical technique of the structural equation model fusion factor analysis and the simultaneous regression analysis of multiple variables can estimate and verify the significance of various complex factors affecting the continuation willingness of online learning in online learning and the degree of influence of each factor. Since this article is an exploratory study and the sample size is relatively small, SmartPLS3.0 is used to build the model and verify the hypothesis.

4 Data analysis and results

4.1 Measurement model

The measurement of the pros and cons of the measurement model involves two angles of reliability and validity. Reliability can be tested by the composite reliability and Cronbach's Alpha of the variables. As shown in Table 1, the combined reliability values of the variables in this paper are all above 0.813, and the Cronbach coefficient is above 0.856. According to relevant literature [18], the combined reliability and the Cronbach coefficient above 0.8 are sufficient to indicate that the measurement model has high reliability.

Table 1. Confirmatory factor analysis

	Composite Reliability	Cronbach's Alpha	AVE
Teacher support	0.815	0.889	0.729
Learning interaction	0.813	0.889	0.729
Flow experience	0.845	0.906	0.763
Continuation willingness	0.849	0.856	0.768

The AVE (Average Variance Extracted) in Table 1 is the average extracted variance value. According to the relevant literature, if the AVE is greater than 0.5, it can be considered that the scale has good convergent validity. As can be seen from Table 1, the values of AVE are all in the Therefore, it can be considered that the convergent validity of the measurement model meets the conditions and is ideal. Discriminant validity was tested by comparing the correlation between the square root of the AVE value and the latent variables of the model [19]. It can be seen from Table 2 that the correlation coefficients of all latent variables on the off-diagonal line are much smaller than the square root of the AVE value on the diagonal line, which indicates that the latent variables have relatively high discriminant validity with other latent variables.

Table 2. Discriminant validity analysis

	Learning Interaction	Flow Experience	Continuation Willingness	Teacher Support
Learning interaction	0.854			
Flow experience	0.437	0.874		
Continuation willingness	0.332	0.608	0.877	
Teacher support	0.220	0.371	0.294	0.854

4.2 Structural equation model fitting

The calculation results of path analysis are shown in Figure 1, where the path coefficient reflects the relationship and influence degree between latent variables in the model, and the value of R^2 indicates the degree to which endogenous latent variables are explained by exogenous latent variables. In order to better measure the validity of the model, the GoF index is used to test the goodness of fit of the model [20]. The value of GoF is 0.417, which is much larger than the effective critical value of 0.36, indicating that the model has a good global goodness of fit.

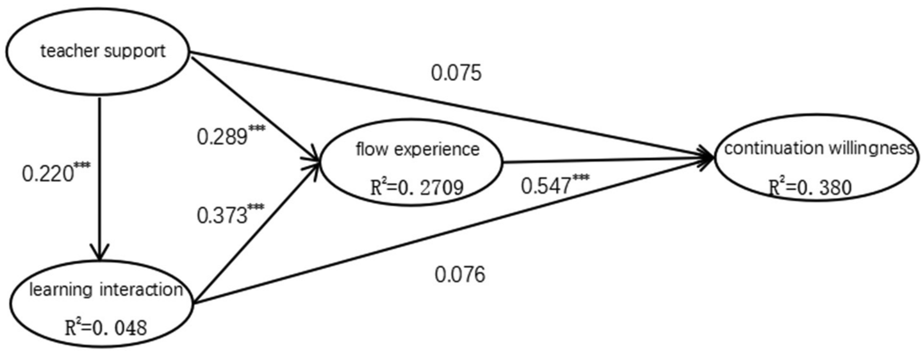

Fig. 1. Key variable path analysis

Note: ***indicates that P is less than 0.001, **indicates that P is less than 0.01, and *indicates that P is less than 0.05.

In the PLS path analysis, it is calculated that teacher support has a significant impact on learning interaction (0.220, P<0.001), and H1 is confirmed. Teacher support and learning interaction have a significant impact on flow experience (0.289, P<0.001; 0.373, P<0.001), and H2, H4 are confirmed. The effect of teacher support on continuation willingness to learn online Insignificant (0.075, P>0.05), H3 is not supported; learning interaction has no significant effect on online learning continuation willingness (0.076, P>0.05), H5 is not supported. Flow experience has a significant impact on online learning continuation willingness (0.606, P<0.001), H6 is supported.

As shown in Table 3, the T-value test shows that all path coefficients pass the significance test at the 0.001 level, and 95% of the intervals are positive numbers, excluding 0, which verifies that interactive learning plays an important role in teacher support and flow experience, and flow experience in teacher support and learning interaction play a mediating role in online learning continuation willingness [21].

Table 3. Mediating effect test

Indirect Effect Path	Indirect Effect Point Estimate	Bootstrap 1000 Times			95% Confidence Interval	
		SE	T	P	Low	Upper
Teacher Support –> Learning Interaction –> Flow Experience	0.083	0.024	3.362	<0.001	0.040	0.132
Teacher Support –> Flow Experience –> Continuation willingness	0.157	0.038	4.176	<0.001	0.084	0.238
Learning Interaction –> Flow Experience –> Continuation willingness	0.204	0.037	5.505	<0.001	0.132	0.288

This shows that the influence of each latent variable on the continuation willingness of online learning is the result of the combined effect of direct influence and indirect influence [22]. The total influence coefficient can be determined by calculating the sum of the direct influence coefficient and the indirect influence coefficient, as shown in Table 4.

Table 4. Total effect

	Teacher Support	Learning Interaction	Flow Experience	Continuation Willingness
Teacher Support		0.220	0.289	0.075
Learning Interaction			0.373	0.076
Flow Experience				0.547

From Figure 1, Table 4 and the results of the significance test of the mediation effect, it can be seen that teacher support, learning interaction and flow experience all have a significant impact on the continuation willingness to learn online [23]. Among them, the factor of flow experience has the greatest influence on the continuation willingness of online learning (0.547). The two factors, teacher support and learning interaction, have indirect effects on the continuation willingness of online learning, that is, they indirectly affect the continuation willingness of online learning through the influence on the flow experience [24]. This shows that for every 1 standard deviation increase in the effects of teacher support, learning interaction and flow experience, online learning persistence intention will increase by 0.075, 0.076 and 0.547 standard deviations, respectively.

5 Implications for improving the teaching effectiveness of service learning

5.1 Improve teacher support

The value of teachers is to help students reduce the difficulty of participating in interaction, guide students to learn independently and efficiently, and enable students to gradually construct their own knowledge system in the process of interaction [25]. Teachers should play a leading and supporting role in online learning and build a flow experience-oriented teacher support system [26]. In terms of components, online learners are given comprehensive support from three aspects: autonomous support, cognitive support and emotional support, providing them with sufficient autonomy and flexibility, resource support and method guidance, positive attention and emotional feedback [27]. In terms of process design, according to the three stages of self-regulated learning, namely planning and preparation, execution and control, evaluation and reflection, the self-regulated learning process of online learners is supported through a series of structured learning activities [28]. For example, in the planning and preparation stage, teachers can achieve their guiding role through tasks such as task negotiation, learning goal confirmation, and expectation transmission. In the execution and control stage, teachers can implement learning strategy guidance, learning process monitoring and feedback, and answering questions and other interactive activities. In the assessment and reflection stage, teachers promote learners' self-evaluation and attribution of success or failure by providing learning feedback, guiding self-evaluation and reflection and other activities [29].

5.2 Improve the enthusiasm for interactive learning

Students interact with the environment through the use of tools/modules to quickly understand the use of the platform, and through some search tools and tracking tools, students can more easily and quickly find the resources they need [30]. Interaction is an indispensable link in classroom learning, and an important means of emotional and knowledge flow between teachers and students, as well as between students. Strong-effect interaction is helpful for learners to acquire knowledge, express emotions and establish a sense of belonging to the community [31]. Therefore, guiding learners to actively participate in interaction and improve the effectiveness of interaction in online learning is of great significance for improving the efficiency of online learning. Teachers should actively participate in the interaction, give timely feedback to learners' evaluations, answers, and questions, and guide learners in marginal positions to participate in discussions. An instant interaction area can be provided in the course, allowing learners to know the thoughts and opinions of others at a certain time during the learning process, bringing more timely feedback to learners and providing a more authentic classroom experience [32]. In addition, the online learning platform should reward active users who actively speak and interact, especially users who share their learning experience and learning resources to improve users' enthusiasm for interaction.

5.3 Promote the formation of flow experience

It is of certain significance to apply the flow experience perspective to the study of continuation willingness for online learning. The flow experience runs through the entire process of online learning activities, its generation requires certain preconditions, and it will affect the learners' willingness to continue learning [33]. The flow experience of online learners refers to the overall feeling that users have when they are fully engaged in online learning, which is characterized by a sense of pleasure, a high degree of concentration, a sense of time distortion, and the fusion of action and consciousness. It is also affected by factors such as teacher support and interactive learning [34]. Therefore, the quality of teaching resources and platforms should be further optimized to promote online learners to have a flow experience. On the other hand, it can also improve the interaction of learning, including improving the interaction between teachers and students, the interaction between students and human-computer interaction to create an environment conducive to online learning. Promote students' flow experience and improve students' willingness to learn.

6 Limitations and research prospects

Based on the flow experience perspective, this study explores the conditional factors that generate flow experience during online learning and the resulting factors that result from flow experience. Taking the online education platform as an example, according to the collected valid data, the reliability and validity were analyzed with Smart PLS3.0 software, and the structural equation model and hypothesis test results of the influence of flow experience on the continuation willingness of online learning were obtained and put forward corresponding suggestions from three aspects: teacher support, interactive learning and flow experience. The biggest feature of this study is that it not only explores how the flow experience affects the willingness to continue online learning, but also explores the conditional factors that affect the flow experience. The conclusion has certain theoretical and practical significance. It should be pointed out that many factors exert different influences on each link of the continuous willingness of online learning. The existing literature shows that the main influencing factors include platform quality, content performance, teacher support, and students' use of online learning, total time, course content, and etc. This paper mainly considers teacher support, learning interaction and flow experience in the study. It can act as preliminary research in attracting new ideas. In the future, it is necessary to fully consider the internal and external conditions and complexity, and reasonably consider the mechanism of different factors on the continuation willingness of online learning, so that the online learning teaching can achieve the preset teaching goals.

7 Acknowledgment

The research of this project is funded by the 2022 Party Building and Ideological and Political Research Project of Yangzhou Polytechnic Institute (No. 2022DJSZ033), and the General Project of Philosophy and Social Sciences Research in Jiangsu Universities (No. 2020SJA2372).

8 References

[1] Bdair, I. (2021). Nursing students' and faculty members' perspectives about online learning during COVID-19 pandemic: A qualitative study [J]. Teaching and Learning in Nursing, 16(3), 220–226. https://doi.org/10.1016/j.teln.2021.02.008

[2] Pokhrel, S., & Chhetri, R. (2021). A literature review on impact of COVID-19 pandemic on teaching and learning [J]. Higher Education for the Future, 8(1), 133–141. https://doi.org/10.1177/2347631120983481

[3] Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations [J]. Journal of Marketing, 60(3), 50–68. https://doi.org/10.1177/002224299606000304

[4] Hoffman, D. L., & Novak, T. P. (2009). Flow online: Lessons learned and future prospects [J]. Journal of Interactive Marketing, 3(1), 23–34. https://doi.org/10.1016/j.intmar.2008.10.003

[5] Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges [J]. Educational Research Review, (12), 45–58. https://doi.org/10.1016/j.edurev.2014.05.001
[6] Dennen, V. P., Aubteen Darabi, A., & Smith, L. J. (2007). Instructor-learner interaction in online courses: The relative perceived importance of particular instructor actions on performance and satisfaction [J]. Distance Education, 28(1), 65–79. https://doi.org/10.1080/01587910701305319
[7] Mercer, S. H., Nellis, L. M., Rebecca, S., et al. (2011). Supporting the students most in need: Academic self-efficacy and perceived teacher support in relation to within-year academic growth [J]. Journal of School Psychology, 49(3), 323–338. https://doi.org/10.1016/j.jsp.2011.03.006
[8] Roorda, D. L., Jak, S., Zee, M., et al. Affective teacher-student relationships and students' engagement and achievement: A meta-analytic update and test of the mediating role of engagement [J]. School Psychology Review, 2017, 46(3), 1–23. https://doi.org/10.17105/SPR-2017-0035.V46-3
[9] Bernard, R. M., Abrami, P. C., et al. A meta-analysis of three types of interaction treatments in distance education [J]. Review of Educational Research, 2009, 79(3), 1243–1289. https://doi.org/10.3102/0034654309333844
[10] Moore, M. G. (1989). Three types of interaction [J]. American Journal of Distance Education, 3(2), 1–7. https://doi.org/10.1080/08923648909526659
[11] Kim, D., & Ko, Y. J. (2019). The impact of virtual reality (VR) technology on sport spectators' flow experience and satisfaction. Computers in Human Behavior, 93, 346–356. https://doi.org/10.1016/j.chb.2018.12.040
[12] Özhan, S. C., & Kocadere, S. A. (2020). The effects of flow, emotional engagement, and motivation on success in a gamified online learning environment [J]. Journal of Educational Computing Research, 57(8), 2006–2031. https://doi.org/10.1177/0735633118823159
[13] Yang, D., Lavonen, M. J., Niemi, H. Online learning engagement: Factors and results-evidence from literature [J]. Themes in eLearning, 2018, 11(1), 1–22.
[14] Guo, Z., Xiao, L., Toorn, C. V., Lai, Y., & Seo, C. (2015). Promoting on-line learners' continuance intention: An integrated flow framework [J]. Information & Management, 53(2), 279–295. https://doi.org/10.1016/j.im.2015.10.010
[15] Joseph, F., Hair, J. R., Tomas, M. Hult. Structural Equation Modeling-Partial Least Squares Method PLS-SEM [M]. Higher Education Cultural Enterprise Co., Ltd. Chinese Taipei, 2016.
[16] Nitzl, C., Roldan, J. L., Cepeda, G. (2016). Mediation analysis in partial least squares path modeling [J]. Industrial Management & Data Systems. 116(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302
[17] Black, A. E., Deci, E. L. The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self-determination theory perspective [J]. Science Education, 2000, 84(6), 740–756. https://doi.org/10.1002/1098-237X(200011)84:6<740::AID-SCE4>3.0.CO;2-3
[18] Korkmaz, O., & Kaya, S. Adapting online self-regulated learning scale into Turkish [J]. Turkish Online Journal of Distance Education, 2012, 13(1), 52–67.
[19] Pike, G. R., Kuh, G. D., & McCormick, A. C. (2011). An investigation of the contingent relationships between learning community participation and student engagement [J]. Research in Higher Education, 52(3), 300–322. https://doi.org/10.1007/s11162-010-9192-1
[20] Özhan, Ş. Ç., & Kocadere, S. A. (2020). The effects of flow, emotional engagement, and motivation on success in a gamified online learning environment. Journal of Educational Computing Research, 57(8), 2006–2031. https://doi.org/10.1177/0735633118823159

[21] Zhao, Z., Cui, Z., Zeng, J., Yue, X. (2011). A new stochastic algorithm used to produce initial values for constrained optimization problems. Proceedings of the 2011 International Conference of Soft Computing and Pattern Recognition, SoCPaR 2011, art. no. 6089150, pp. 523–527. https://doi.org/10.1109/SoCPaR.2011.6089150

[22] Zhao, Z., Cui, Z., Zeng, J., Yue, X. (2011). Artificial plant optimization algorithm for constrained optimization problems. Proceedings—2011 2nd International Conference on Innovations in Bio-Inspired Computing and Applications, IBICA 2011, art. no. 6118680, pp. 120–123. https://doi.org/10.1109/IBICA.2011.34

[23] Mai, F., Yue, X., Zhao, Z. (2010). Intelligent search engine model based on similarity computation (2010). Proceedings of the 2010 2nd International Conference on Future Computer and Communication, ICFCC 2010, 1, art. no. 5497851, V14–V16. https://doi.org/10.1109/ICFCC.2010.5497851

[24] Mai, F., Yue, X., Zhao, Z. (2010). Research on Chinese subjective questions scroing algorithm based on natural language processing. Proceedings—2nd IEEE International Conference on Advanced Computer Control, ICACC 2010, 2, art. no. 5487190, 106–108. https://doi.org/10.1109/ICACC.2010.5487190

[25] Yue, X., Di, G., Zhao, T., Yang, Y., Zhao, Z., Dong, Y. (2012). The application of Chinese word segmentation in malicious code detection. Lecture Notes in Electrical Engineering, 138 LNEE, pp. 655–660. https://doi.org/10.1007/978-1-4471-2467-2_77

[26] Yue, X., Di, G., Yu, Y., Wang, W., Shi, H. (2012). Analysis of the combination of natural language processing and search engine technology. Procedia Engineering, 29, 1636–1639. https://doi.org/10.1016/j.proeng.2012.01.186

[27] Biqing, L., Weili, G., Shiyong, Z., Xiaoguang, Y. Optimisation design of corn precision seeder based on multi-route and multi-channel control (2015). Journal of the Balkan Tribological Association, 21 (4), pp. 1215–1223.

[28] Sun, C., Yue, X. G. Method based on rough set and improved petri net for transformer fault diagnosis (2015). International Journal of Online Engineering, 11(8), 25–28. https://doi.org/10.3991/ijoe.v11i8.4879

[29] Wang, G.-Z., Yue, X.-G. Prediction of transport tanks safety based on general regression neural network (2015). Journal of Computational and Theoretical Nanoscience, 12(8), pp. 1560–1562. https://doi.org/10.1166/jctn.2015.3928

[30] Ren, Q. G., Zhang, G., Yue, X. G., Liao, W. C. Deep foundation pit monitoring based on CX-3C inclinometer (2014). Applied Mechanics and Materials, 484–485, 404–407. https://doi.org/10.4028/www.scientific.net/AMM.484-485.404

[31] Yuan, D. C., Yue, X. G., Wang, C., Zhang, J. F. Gas emission prediction based on coal mine operating data (2014). Applied Mechanics and Materials, 484–485, 604–607. https://doi.org/10.4028/www.scientific.net/AMM.484-485.604

[32] Yue, X.-G., Zhang, G., Wu, Q., Li, F., Chen, X.-F., Ren, G.-F., Li, M. Wearing prediction of stellite alloys based on opposite degree algorithm (2015). Rare Metals, 34 (2), 125–132. https://doi.org/10.1007/s12598-014-0430-0

[33] Sun, Y., Cao, Y., Xiong, F., Yue, X., Qiu, J., He, X., Zhao, F. The wood slice cell image identification algorithm based on singular value decomposition (2015). Journal of Computational and Theoretical Nanoscience, 12(12), 5372–5378. https://doi.org/10.1166/jctn.2015.4529

[34] Cao, Y., Xiong, F., Yue, X., Zhao, Y. (2015). Computer simulations find the optimum combination of solexa sequencing libraries. Journal of Computational and Theoretical Nanoscience, 12(12), 5059–5065. https://doi.org/10.1166/jctn.2015.4474

9 Authors

Ying Gu is an assistant researcher at Yangzhou Polytechnic Institute, her research interests including education, logistics management research. (email: yzguying@126.com).

Chenchen Song is a lecturer at Guangling College of Yangzhou University, her research interests including online education management, international trade management. (email: luckyscc@126.com).

Yifan Zhong is a lecturer at Faculty of Business and Law, Curtin University. (email: yifan.zhong@curtin.edu.au).

Ubaldo Comite is a Professor at University Giustino Fortunato. (email: u.comite@unifortunato.eu).

Article submitted 2022-06-15. Resubmitted 2022-08-01. Final acceptance 2022-08-01. Final version published as submitted by the authors.