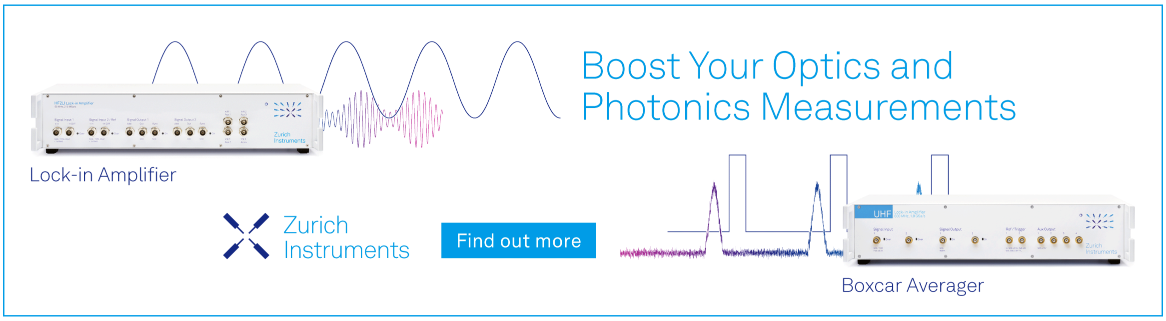
RESEARCH ARTICLE | MARCH 07 2024

The framework for enhancing mathematical higher order thinking skills using technology enhanced learning environment and learning analytics

Mohd Shafie Rosli ✉; Nor Shela Saleh; Azlah Md. Ali; Suaibah Abu Bakar; Khairunesa Isa

AIP Conf. Proc. 2895, 060007 (2024)
https://doi.org/10.1063/5.0195068



The Framework for Enhancing Mathematical Higher Order Thinking Skills Using Technology Enhanced Learning Environment and Learning Analytics

Mohd Shafie Rosli[1, a)], Nor Shela Saleh[2], Azlah Md. Ali[3], Suaibah Abu Bakar[3] and Khairunesa Isa[2]

[1]*School of Education, Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia, Johor Bahru, Malaysia.*
[2]*Department of Social Science, Centre for General Studies and Co-Curricular, Universiti Tun Hussein Onn Malaysia, Johor Bahru, Malaysia.*
[3]*School of Human Resource Development & Psychology, Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia, Johor Bahru, Malaysia.*

[a)]*Corresponding author: shafierosli@utm.my; drshafierosli@gmail.com*

Abstract. Improving the mathematical HOTS of students is a recurring global issue. Substantial evidence indicates that constructivism is a promising learning strategy that is capable of resolving the issue. As digitalisation increases, technology-enhanced learning environments are gaining importance in contemporary education. However, scant literature exists on the process of improving mathematical HOTS while students use technology-enhanced learning environments. The purpose of this paper is to posit a learning process that could improve students' mathematical HOTS based on technology-enhanced learning environments, which were developed through constructivism and tested by the authors using data from learning analytics technology. Sixty samples participated in this study to learn about and interact with technology-enhanced learning environments. Comparing the mathematical HOTS of the samples before and after their interaction with the technology-enhanced learning environments revealed significant differences in the directions of higher HOTS. The sequential analysis technique was applied to 10 759 logs extracted from the learning analytics. Four types of learning engagement activities emerged as a result of empirical testing: Content Engagement, Exercises Engagement, Activities Engagement, and Evaluation Engagement. Analysis utilising Pearson's correlation and linear regression demonstrated that the students' mathematical HOTS were positively affected by their engagement with the content, exercises and activities provided in the technology-enhanced learning environments. The framework was found to be capable of explaining 69% of the mathematical HOTS enhancement process among the samples. This implies that for students' mathematical HOTS to improve or for a technology-enhanced learning environment to have a cognitive implication on students, emphasis must be placed on exercises and online activities. Evaluation was given less weight but remains a necessary component of formal education. This research also demonstrated that, when designed appropriately, technology-enhanced learning environments can enhance students' mathematical HOTS. Therefore, educational technology is a promising solution to the educational problems of the information age.

3rd International Conference on Applied & Industrial Mathematics and Statistics 2022 (ICoAIMS2022)
AIP Conf. Proc. 2895, 060007-1–060007-9; https://doi.org/10.1063/5.0195068
Published by AIP Publishing. 978-0-7354-4820-9/$30.00

INTRODUCTION

Currently, the majority of students in Malaysia are striving to achieve and master higher-order thinking skills (HOTS), particularly in STEM-related subjects such as science and mathematics. This was established as a national agenda in the educational system of Malaysia and has been ingrained in the country's educational framework for decades. Today, the calls for HOTS improvement efforts can be heard throughout the nation (1,2). As Malaysia moves toward a creative and knowledge-based economic foundation to ensure the economic sustainability of Industrial Revolution 4.0, HOTS proficiency is a national imperative.

The country's educational approaches have been enhanced to provide students with effective and impactful learning experience. As a result, constructivism was viewed as the central tenet of contemporary education in Malaysia, with classrooms having evolving around this philosophy. Despite the benefits of constructivism, it is less efficient in terms of time and unfamiliar to the majority of Malaysian students (3). This void has allowed technology-enhanced learning environments to emerge as an effective tool for cultivating students' critical thinking abilities. Prior research has demonstrated that technology-enhanced learning environments could improve students' HOTS, including in a mathematical context. However, there is a research gap regarding the learning process through which students attain HOTS when utilizing technology-enhanced learning environments.

This study addresses the knowledge gap regarding the learning process through which students develop their thinking skills at lower levels in order to achieve mathematical HOTS using technology-enhanced learning environments. The learning process was thoroughly analysed using the emerging technology of learning analytics, which is gaining popularity in the education sector. This paper's final deliverable is a framework of learning processes and activities designed to improve students' mathematical HOTS, which could be employed in teaching and learning strategies that encompass technology-enhanced learning environments. The framework was developed using learning analytics technology. The objectives of the current study are as follows:

a. Study the effects of technology-enhanced learning environments on the performance of students' mathematical HOTS.
b. Study the learning process of students while engaging with technology-enhanced learning environments using learning analytics.
c. Propose a framework for a learning process that enhances students' mathematical HOTS.

LITERATURE REVIEW

In the 1990s, the first technology-enhanced learning environment was implemented (3). In 1995, the term first appeared in academic writing, when it was introduced by Shapiro et al. (4). The subsequent decades involved the expansion of technology-enhanced learning environments in higher education and other academic institutions. Multimedia-capable computers play a crucial role in facilitating the development of technology-enhanced learning environments (5), not to mention the technology that enables classroom contact with the outside world – the invention of networking technologies (6). Presently, researcher are pursuing the ideal teaching and learning methods to use in technology-enhanced learning environments (7), and the implementation of technology-enhanced learning environments continues to this day (8,9) beside other technologies such as the acceptance of mobile learning (10) and other teaching and learning technologies (11).

To date, the constructivist learning theory has become the focal point of computational education tools (12–15). Logically, this evolution had produced the various strategies and frameworks associated with the technology-enhanced learning environment. Multiple approaches have been developed as a result of the constructivist's legacy. Constructivism is a learning theory that emphasises the hierarchical nature of knowledge and encourages active learning. Knowledge is presented operationally as a means to establish contexts that encourage discovery, investigation, manipulation, and collaboration. Inquiry-based pedagogies, such as problem-based learning, project-based learning, and discovery learning, represent the vanguard of innovative and new pedagogies. These pedagogies have emerged due to the viability of technology-enhanced learning environments, which significantly altered many educational beliefs and practices (16,17) including the one in mathematics (18).

In the new millennium, the constructivist theory of learning reached a new milestone. The technology-enhanced learning environment was a synthesis of novel breakthroughs in the learning approach. In the new millennium, researchers have determined that to maximise students' comprehension of science subjects such as mathematics, a method that simulates scientists' laboratory conditions would produce the best results. This modern approach established a bridge between the construction of knowledge and the situation in which it originated or would ultimately be applied. This trending method is the renowned inquiry-based learning - a constructivist learning approach or learning strategy that envisages the postmodern science classroom as featuring investigation, active experimentation, planning, discussion, and questioning. Although numerous constructivist pedagogical strategies exist, inquiry is particularly suited for students to attain higher levels of deduction. This action has laid solid foundations for addressing scientific difficulties and misconceptions in school and university science education (19–21).

The development of the Internet has enhanced our capacity to disseminate knowledge. The web is a versatile, effectively utilized platform that transcends geographical and social barriers. The Internet has accelerated the development of web-based computer simulation, a variant of the technology-enhanced learning environment. Al-Zoubi and Wainer (22) defined web-based computer simulation as an attempt to exploit web technology to support the future of computer simulation. The advent of the Internet in the 1990s prompted the exploration and development of both new and old instructional strategies and teaching methods. This resulted in a rapid shift toward a more individualised approach to learning. With simulation as their partner, the new technologies were recognised as highly effective and efficient. The methodologies of student-centred learning and educational simulation serve as effective illustrative tools (23). During the knowledge construction process, educational activities can be separated into three distinct domains: cognitive, affective, and psychomotor (24,25). With the context of a traditional classroom, all three domains have been examined in depth. However, in technology-enhanced learning environments, research focuses almost exclusively on the cognitive and psychomotor domains (26,27). Nonetheless, online interactions that go beyond these domains, such as interactions that cover the affective domain, are also crucial, particularly among adolescents (28). Affective domains, such as emotional intelligence, are crucial not only in student’s future workplace (29). The affective ties is also influential toward student’s and institution relationship (30).

According to classroom research, the affective domain involving students' navigation is significantly associated with academic achievements and study strategies (31). The potential for predicting the navigation behaviour of current users, which may contribute to the personalization of the web, is afforded by the establishment of navigation profiles that are based on the parallel behaviour of website users. This also allows designers to improve the organisational or design quality of websites, based on the profiles obtained. Numerous studies have been initiated to clarify the identified issue by attempting to comprehend navigation in cognitively diverse positions. Many researchers - such as Bannert et al. (32) and Kornmann et al. (33) have inspected the issues in various angle with different methodologies to comprehend how characteristics (domain knowledge, for example) could justify the differences in navigational patterns within technology-enhanced learning environments. Aesaert et al. (34) constructed a learning analytics model using log files to probe samples’ ICT competency. The triangulation of log files to construct a learning analytics framework using audio conversation (35) and video recording (36) created new thrust in learning analytics techniques. Beside physical engagement (28), online engagement is also imperative in modern classroom. The researcher identified several techniques for analysing the navigation patterns of multimedia courseware, based on a review of the relevant literature. These techniques are as follows:

The Cluster Analytic Technique: the differences between groups of individuals signifying various profiles of navigation in multimedia courseware could be evaluated using the cluster analytic technique (37). The current technique necessitates the use of a scoring rubric; the creation of a new scoring rubric may affect the validity and reliability of the analysis. The cluster analytic technique evaluates and calculates the frequency of choices, the frequency of access to screens and deviations, the selections of the Help button, the movies viewed, and the total navigation time, as well as shifts from one subdivision to another. The cluster analysis technique was also practiced by Endert et al. (38) and Kandogan (39). This technique reached a new benchmark in 2015 as an analytical method for comprehending the development of the human brain and its complex neuron system (40).

Lag sequential is the complementary analysis technique used with procedures interrelated to the contingency table analysis (41). It was also defined as a technique for determining the sequences of multiple series of behaviours and tracing overall sequential behavioural patterns. The lag sequential technique involves four imperative measures: 1 - calculation of the transition matrix's frequency, 2 - computing the conditional frequency matrix, 3 - calculating the expected value matrix, and 4 - calculating the table of adjusted residuals. The consecutiveness of these measures enables the researcher to infer the behavioural sequence transition diagram, which depicts statistically significant structures, as well as to visualise sequential behavioural patterns for detecting behavioural patterns during an explicit time frame (44).

The change pattern technique can be piloted by drawing a graphical representation of the navigation of samples throughout the system. This representation is a pyramid with four distinct sectors on each of its four edges. The connections between each sector are interdependent and account for 100 percent of the total change pattern. Briefly, the navigation pattern technique can be implemented through a series of bar charts representing the navigation of samples from one page to another. The graphical representation reveals what the sample did at a particular time while using the system and how they approached the learning task. This information is readily discernible at a glance using the change pattern technique.

METHODOLOGY

This study employed a pre-experimental research design involving 60 samples from schools in Malaysia. The intervention began with a pre-test administered with the samples to determine their current level of mathematical HOTS prowess. Moodle was used to create the technology enhanced learning environments created for testing purposes. The technology-enhanced learning environments were designed through learning strategies based on constructivism, and they were organised in phases for learning mathematics. In the first stage, the students had to interact with the given problem and develop a solution strategy. The students then implemented the plan, reported their findings, and concluded by reflecting on their experiences.

The data collected is the students' pre- and post-test performance on the HOTS test. The second type of data collected is engagement data, which is recorded and stored in Moodle's learning analytics feature. Then, these data were statistically analysed in order to comprehend the students' mathematical HOTS achievement and the learning process involved in attaining the HOTS.

The Shapiro-Wilk normality test was performed on the pre- and post-test data to determine the nature of the data distribution. Once the data distribution had been understood, the choice was made between parametric and nonparametric tests. Later, the analytic data gathered using the learning analytics technology implanted in Moodle to understand the nature of student to technology-enhanced learning environments engagement. In total, 10 759 activity logs were extracted from the data logs, and 5 054 views data were extracted from the activity completion report. The Sequential Analysis technique was applied to all of these data sets. From the pre- and post-test data, samples that had attained mathematical HOTS were identified, and their data logs were analysed to develop an engagement framework. To develop a mathematical HOTS cultivation model, the previously constructed framework was evaluated with the Pearson's Correlation and regression tests.

FINDINGS

The Shapiro-Wilk test conducted after the intervention revealed that the datasets were normally distributed with $p > .05$. Therefore, paired sample t-tests were utilised to continue the testing. The results of the paired sample t-tests indicated that the samples' pre-test and post-test scores were significantly different, $p < 0.0001$. From this, it was concluded that interaction with the technology-enhanced learning environments had enhanced the students' mathematical HOTS.

Decoding the analytics data revealed the online activity sequences of the samples. The activity completion report's decoded data and activities were organised into engagement patterns. Then, the validity of the online activities was evaluated by measuring the amount of time spent on each sequence. For the analysis, only valid engagement data was selected. Four main engagement categories were derived from the data after the screening processes. The categories were Content Engagement, Exercises Engagement, Activities Engagement and Evaluation Engagement. The number of hits in terms of views and engagement time was then determined. The samples were divided into two groups, designated Alpha and Beta. The framework output for Alpha Group is shown in Fig. 1.

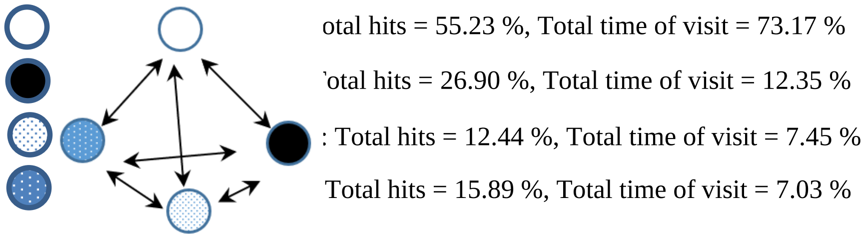


FIGURE 1. The HOTS enhancement framework using learning analytics for Alpha Group.

The outcomes indicate that 55.23 per cent of the samples engaged with the content, the engagement category with the greatest number of hits. This was also the most frequent activity performed by the samples. The sample engagement with exercises was the lowest at 26.90 per cent, but the frequency was moderate at 12.35 percent. The engagements with the lowest frequency account for slightly more than seven per cent of the total percentage of engagements. The interaction between each engagement was calculated using the Sequential Analysis Technique and based on the overall percentage of navigation from one engagement to another, as shown in Table 1.

TABLE 1. Percentage of interactions between each engagement for Alpha Group.

Interaction between Engagement	Percentage, %
Content ↔ Exercise	29.32
Exercise ↔ Evaluation	2.26
Evaluation ↔ Activities	0.75
Activities ↔ Content	25.56
Activities ↔ Exercise	36.9
Content ↔ Evaluation	6.02

Figure 1 and **Table 1** show that content and exercises were significant in terms of engagement for cultivating HOTS, accounting for 91.32 per cent of all hits. Samples spent the majority of their time engaging with the content (54.67%), while their engagement with exercises and activities was balanced (16.99%); both were longer than their engagement with evaluation (13.18%). In terms of the interaction between each type of engagement, content, activities, and exercises account for 91.78 per cent of the total. For the Beta Group, the framework constructed is shown in Fig. 2.

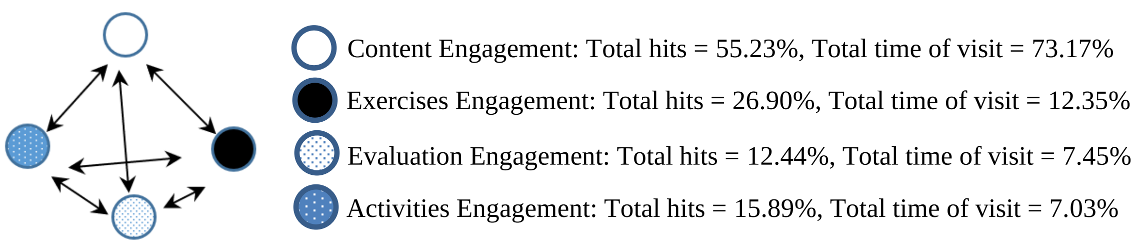


FIGURE 2. The HOTS enhancement framework using learning analytics for Beta Group.

The interaction between each engagement type was calculated using Sequential Analysis, based on the overall percentage of navigation from one engagement type to another, as illustrated in Table 2.

TABLE 2. Percentage of interactions between each engagement for Beta Group.

Interaction between Engagement			Percentage, %
Content	⟷	Exercises	35.67
Exercises	⟷	Evaluation	1.74
Evaluation	⟷	Activities	1.25
Activities	⟷	Content	17.54
Activities	⟷	Exercises	40.18
Content	⟷	Evaluation	3.62

Again, the data indicates that 82.13 per cent of the engagement required to cultivate mathematical HOTS was composed of content and exercises engagement. Nonetheless, the total time spent by the samples on content, exercises, and activities exceeded the time spent on evaluation; 92.55 per cent of the time spent on engagement accounted for content, exercises, and activities.

To construct a mathematical HOTS cultivation model based on the collected analytical data, a number of samples were individually analysed for their engagement frequency and duration. As previously reported, this analytical data was normally distributed, so Pearson's correlation was used instead of Spearman's correlation test to examine their correlation. However, the test conducted showed that the samples' mathematical HOTS cultivation (based on their scores) was related to their frequency of engagement with content, exercises and activities. The results of Pearson's correlation between the scores and visit frequency and the content (hits) are shown in Table 3.

TABLE 3. Correlation of score and hits with content, exercises, and activities.

	r	Sig.
Score - Content	.552	.003
Score - Exercises	.616	.001
Score - Activities	.543	.004

To understand how engagement led to the HOTS improvement, linear regression testing was conducted with the data, as shown in Table 4.

TABLE 4. Result of regression testing.

	B	SD	Beta	t	Sig.
Constant	-8.01	16.62	.00	-.48	.634
Exercises *f*	1.71	.56	.41	.61	.006
Activities *f*	1.58	.40	.48	3.98	.001
Content *f*	.43	.19	.32	2.32	.030

The outcome demonstrates that attendance at each of these three engagements contributed to the development of the samples' HOTS. To evaluate the reliability of this result, the model summary of the regression test is shown in Table 5.

TABLE 5. The model summary.

R	R^2
.85	.69

The correlation coefficient of 0.85, indicates a high degree of correlation, 69 per cent of it which can be explained. The ANOVA result, as presented in Table 6, indicates that the model predicted the variable with statistical significance.

TABLE 6. ANOVA of the model.

Model	Sum of Squares	F	Sig.
Regression	1851.56	16.16	.000
Residual	840.35		
Total	2691.91		

CONCLUSION

We believe that the implementation of a technology-enhanced learning environments with the appropriate learning strategies will increase the mathematical proficiency of school students in the HOTS domain. In this study, we were successful in developing technology-enhanced learning environments that incorporated constructivism learning strategies. Sixty samples were used to test the effectiveness constructivism in cultivating mathematical HOTS. On the basis of their statistical significance, technology-enhanced learning environments were deemed suitable for use in Malaysian schools to foster and improve HOTS. Through sequential analysis of more than 10,000 data logs collected by the learning analytics technology embedded in the technology-enhanced learning environments, three engagements (content, exercises, and activities) were revealed to be essential for the development of mathematical HOTS. These three activities contributed to a 69% improvement in the samples' mathematical HOTS, as demonstrated by the additional statistical analysis.

ACKNOWLEDGMENTS

Authors would like to thank Ministry of Higher Education and Universiti Teknologi Malaysia for sponsoring this research through UTM Fundamental Research (UTMFR) grant with Project Number Q.J130000.2553.21H23.

REFERENCES

1. Ramlee N, Rosli MS, Saleh NS. Mathematical HOTS cultivation via online learning environment and 5E inquiry model: Cognitive impact and the learning activities. Int J Emerg Technol Learn. 2019;14(24).
2. Mustapha S, Rosli MS, Saleh NS. Online learning environment to enhance HOTS in mathematics using Polya's problem solving model. In: Journal of Physics: Conference Series. Institute of Physics Publishing; 2019.
3. Rosli MS, Aris B, Ahmad MH. Online intellectual transformation system. Contemp Eng Sci. 2015;8(1–4):39–47.
4. Shapiro WL, Roskos K, Cartwright GP. Technology: Technology-Enhanced Learning Environments. Chang Mag High Learn. 1995 Nov;27(6):67–9.
5. Uysal MP. Evaluation of learning environments for object-oriented programming: measuring cognitive load with a novel measurement technique. Interact Learn Environ. 2016 Oct 2;24(7):1590–609.
6. Kongaut C, Bohlin E. Investigating mobile broadband adoption and usage: A case of smartphones in Sweden. Telemat Informatics [Internet]. 2016;33(3):742–52. Available from: https://www.sciencedirect.com/science/article/pii/S0736585315301131
7. Hannafin MJ, Land SM. The foundations and assumptions of technology-enhanced student-centered learning. Vol. 25, Science. 1997.
8. Rosli MS, Saleh NS. Technology enhanced learning acceptance among university students during Covid-19: Integrating the full spectrum of Self-Determination Theory and self-efficacy into the Technology Acceptance Model. Curr Psychol [Internet]. 2022 Mar 25; Available from: https://link.springer.com/10.1007/s12144-022-02996-1
9. Carroll F, Kop R. Colouring the gaps in learning design: Aesthetics and the visual in learning. Int J Distance Educ Technol. 2016 Jan 1;14(1):92–103.
10. Ahmad AR, Soon NK, Md Yusoff R, Kamri KA. The acceptance of mobile learning innovation and initiative at higher education institutions. In: Proceedings of the 25th International Business Information Management Association Conference - Innovation Vision 2020: From Regional Development Sustainability to Global Economic Growth, IBIMA 2015 [Internet]. 2015. p. 133–45. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-

84947561691&partnerID=40&md5=9f1c5a1a827530cd9f0e869f3023640d
11. Rosli MS, Saleh NS, Md. Ali A, Abu Bakar S, Mohd Tahir L. A Systematic Review of the Technology Acceptance Model for the Sustainability of Higher Education during the COVID-19 Pandemic and Identified Research Gaps. Sustainability [Internet]. 2022;14(18). Available from: https://www.mdpi.com/2071-1050/14/18/11389
12. Gregory A, Ronan M. Insights into the development of strategy from a complexity perspective. Vol. 66, Journal of the Operational Research Society. Palgrave Macmillan Ltd.; 2015. p. 627–36.
13. Lau KHV. Computer-based teaching module design: Principles derived from learning theories. Med Educ. 2014 Mar;48(3):247–54.
14. Chetty J, Barlow-Jones G. Novice students and computer programming: Toward constructivist pedagogy. Mediterr J Soc Sci. 2014;5(14):240–51.
15. Baharom MM, Atan NA, Rosli MS, Yusof S, Hamid MZA. Integration of science learning apps based on Inquiry Based Science Education (IBSE) in enhancing students Science Process Skills (SPS). Int J Interact Mob Technol. 2020;14(9):95–109.
16. Perry S, Bridges SM, Burrow MF. A review of the use of simulation in dental education. Vol. 10, Simulation in Healthcare. Lippincott Williams and Wilkins; 2015. p. 31–7.
17. Wilkinson A. Decoding learning in law: Collaborative action towards the reshaping of university teaching and learning. EMI Educ Media Int. 2014;51(2):124–34.
18. Aris B, Gharbaghi A, Ahmad MH, Rosli MS. A check list for evaluating persuasive features of mathematics courseware. Int Educ Stud. 2013;6(9):125–34.
19. Matuk CF, Linn MC, Eylon BS. Technology to support teachers using evidence from student work to customize technology-enhanced inquiry units. Instr Sci. 2015 Mar 1;43(2):229–57.
20. Cober R, Tan E, Slotta J, So HJ, Könings KD. Teachers as participatory designers: two case studies with technology-enhanced learning environments. Instr Sci. 2015 Mar 1;43(2):203–28.
21. van Dijk AM, Lazonder AW. Scaffolding students' use of learner-generated content in a technology-enhanced inquiry learning environment. Interact Learn Environ. 2016 Jan 2;24(1):194–204.
22. Al-Zoubi K, Wainer G. Distributed simulation of DEVS and Cell-DEVS models using the RISE middleware. Simul Model Pract Theory. 2015 Jun 1;55:27–45.
23. Lebrun Y, Adam E, Mandiau R, Kolski C. A model for managing interactions between tangible and virtual agents on an RFID interactive tabletop: Case study in traffic simulation. J Comput Syst Sci [Internet]. 2015;81(3):585–98. Available from: http://dx.doi.org/10.1016/j.jcss.2014.11.011
24. Galloway KR, Malakpa Z, Bretz SL. Investigating Affective Experiences in the Undergraduate Chemistry Laboratory: Students' Perceptions of Control and Responsibility. J Chem Educ [Internet]. 2016 Feb 9;93(2):227–38. Available from: https://doi.org/10.1021/acs.jchemed.5b00737
25. Honebein PC, Honebein CH. Effectiveness, efficiency, and appeal: pick any two? The influence of learning domains and learning outcomes on designer judgments of useful instructional methods. Educ Technol Res Dev. 2015 Dec 1;63(6):937–55.
26. Hettiarachchi E, Huertas MA, Guerrero-Roldán A-E. Improving student performance in high cognitive level courses by using formative e-assessment. Vol. 7, Int. J. Technology Enhanced Learning. 2015.
27. Takacs ZK, Swart EK, Bus AG. Benefits and Pitfalls of Multimedia and Interactive Features in Technology-Enhanced Storybooks: A Meta-Analysis. Rev Educ Res. 2015 Dec 1;85(4):698–739.
28. Kamri KA, Md Yusoff R, Ahmad MF, Mohd Ali AS, Attan MN, Ishak MS, et al. A systematic literature review on civic engagement form among youth: Online participation. Int J Psychosoc Rehabil [Internet]. 2019;23(3):573 – 586. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85081573721&doi=10.37200%2FIJPR%2FV23I3%2FPR190347&partnerID=40&md5=77f0126eb4688830a44a5fc0d9bc756b
29. Johar SS. The impact of emotional intelligence competencies on self-esteem among public servants. Indian J Public Heal Res Dev [Internet]. 2019;10(6):1598 – 1603. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85071192837&doi=10.5958%2F0976-5506.2019.01524.9&partnerID=40&md5=f6662935e998a82e6ab341ef3f32e739
30. Kamri KA, Isa K, Yahya A, Ahmad AR, Md Yusoff R. Factors influencing alumni donations at Malaysian public universities. In: Proceedings of the 28th International Business Information Management Association Conference - Vision 2020: Innovation Management, Development Sustainability, and Competitive Economic Growth [Internet]. 2016. p. 278 – 286. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013948484&partnerID=40&md5=bfc11d749aade77d33ae541dce29ab0c

31. Huang H, Gartner G, Klettner S, Schmidt M. Considering affective responses towards environments for enhancing location based services. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing; 2014. p. 93–6.
32. Bannert M, Sonnenberg C, Mengelkamp C, Pieger E. Short- and long-term effects of students' self-directed metacognitive prompts on navigation behavior and learning performance. Comput Human Behav. 2015 Jun 22;52:293–306.
33. Kornmann J, Kammerer Y, Anjewierden A, Zettler I, Trautwein U, Gerjets P. How children navigate a multiperspective hypermedia environment: The role of spatial working memory capacity. Comput Human Behav. 2016 Feb 1;55:145–58.
34. Aesaert K, Van Nijlen D, Vanderlinde R, Tondeur J, Devlieger I, Van Braak J. The contribution of pupil, classroom and school level characteristics to primary school pupils' ICT competences: A performance-based approach. Comput Educ. 2015 Sep 1;87:55–69.
35. Waring HZ. Promoting self-discovery in the language classroom. IRAL - Int Rev Appl Linguist Lang Teach. 2015 Mar 1;53(1):61–85.
36. Rusk F, Pörn M, Sahlström F, Slotte-Lüttge A. Perspectives on using video recordings in conversation analytical studies on learning in interaction. Int J Res Method Educ. 2015 Jan 2;38(1):39–55.
37. Xing W, Guo R, Lowrance N, Kochtanek T. Decision Support Based on Time-Series Analytics: A Cluster Methodology. In: Yamamoto S, editor. Human Interface and the Management of Information Information and Knowledge in Applications and Services. Cham: Springer International Publishing; 2014. p. 217–25.
38. Endert A, Fox S, Maiti D, Leman S, North C. The Semantics of Clustering: Analysis of User-Generated Spatializations of Text Documents. In: Proceedings of the International Working Conference on Advanced Visual Interfaces [Internet]. New York, NY, USA: Association for Computing Machinery; 2012. p. 555–62. (AVI '12). Available from: https://doi.org/10.1145/2254556.2254660
39. Kandogan E. Just-in-time interactive analytics: Guiding visual exploration of data. IBM J Res Dev. 2015 Mar 1;59(2–3).
40. Goldenberg D, Galván A. The use of functional and effective connectivity techniques to understand the developing brain. Vol. 12, Developmental Cognitive Neuroscience. Elsevier Ltd; 2015. p. 155–64.
41. Wu SY, Hou HT. How cognitive styles affect the learning behaviors of online problem-solving based discussion activity: A lag sequential analysis. J Educ Comput Res. 2015 Apr 4;52(2):277–98.
42. Wu KC. Affective surfing in the visualized interface of a digital library for children. Inf Process Manag. 2015;51(4):373–90.
43. Wu S-Y, Chen SY, Hou H-T. A Study of Users' Reactions to a Mixed Online Discussion Model: A Lag Sequential Analysis Approach. Int J Human–Computer Interact [Internet]. 2015;31(3):180–92. Available from: https://doi.org/10.1080/10447318.2014.986637
44. Hou HT, Chang KE, Sung YT. Applying lag sequential analysis to detect visual behavioural patterns of online learning activities. Br J Educ Technol. 2010 Mar;41(2).