2021 International Conference on Advanced Learning Technologies (ICALT) | 978-1-6654-4106-3/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICALT52272.2021.00037

Modeling students' flow experience through data logs in gamified educational systems

Wilk Oliveira, Seiji Isotani
University of São Paulo
São Carlos, Brazil
{wilk.oliveira, sisotani}@usp.br

Olena Pastushenko, Tomáš Hruška
Brno University of Technology
Brno, Czech Republic
{ipastushenko, hruska}@fit.vut.cz

Juho Hamari
Tampere University
Tampere, Finland
juho.hamari@tuni.fi

***Abstract*—User modeling in gamified educational systems is a contemporary challenge. In particular, modeling the students' flow experience (*i.e.*, challenge-skill balance, action-awareness merging, clear goals, unambiguous feedback, total concentration on the task at hand, sense of control, loss of self-consciousness, transformation of time, and *autotelic* experience) during a gamified system usage is highly challenging. It is because measurement' instruments usually are invasive, removing the users from the flow experience and/or cannot be applied massively (*e.g.*, participant observation, questionnaires or electroencephalogram). We faced this challenge by conducting a data-driven study (N = 23), where we used a robust statistical method (*i.e.*, partial least squares path modeling) to model the students' flow experience, based on their interaction data (*e.g.*, number of mouse clicks) in a gamified educational system. The main results indicate a relationship between the interaction logs and four flow experience dimensions. Our finds contribute to the area of gamified educational systems, through the students' flow experience modeling. Finally, based on our results, we also provided a series of recommendations for future studies.**

***Index Terms*—Gamified educational systems, Flow Theory, Flow experience, Students' experience, User modeling**

I. Introduction

In recent years, the number of different types of educational systems (*e.g.*, Massive Open Online Courses (MOOCs) [1], intelligent tutoring systems (ITS) [2], gamified educational systems [3], and others) has grown, attracting the attention of teachers/instructors and students around the world. That is causing the increase of the number of students using this type of systems [4]. Therefore it is necessary to invest in new methods to improve the student experience [5]. One of the commonly used methods to improve the quality of such educational systems is gamification ("The use of game elements in non-game contexts" [6]) [7].

On the one hand, the design of online gamified educational systems can help improve the teaching and learning process [8]. On the other hand, the large number of students using the same system at the same time tends to hinder some tasks, such as understanding students' behavior and assessing their experience (*e.g.*, engagement, motivation, and flow) during the system usage [9]. This is highlighting the importance of modeling students' experience in gamified educational systems through their data logs [10].

Faced with this challenge, recent research has attempted to take advantage of the big amounts of data logs generated during users interaction with educational systems to model students' experience [11], [12]. One of the most complex parameters to be analyzed in such data sets is the flow experience [13]. Flow is a deep engagement experience, composed of nine associated dimensions [13]: *i)* challenge-skill balance, *ii)* action-awareness merging, *iii)* clear goals, *iv)* unambiguous feedback, *v)* total concentration on the task, *vi)* sense of control, *vii)* loss of self-consciousness, *viii)* transformation of time and *ix) autotelic* experience. When a student is in a state of flow, they also tend to have a high learning experience (*i.e.*, flow state positively affects the learning process) [5].

This paper addresses the described challenge by presenting the results of a data-driven study with a sample composed of 23 university students. For this research we used structural equation modeling (*i.e.*, partial least squares path modeling [14]) to associate the students' flow experience in a gamified system with their interaction data logs. Afterwards, we answer the following research question: **Does possible the students' flow experience in a gamified educational system be modeled based on their interaction data logs?**

The study's main results indicate a correlational model between the group of data logs and four different flow experience dimensions (*i.e.*, unambiguous feedback, clear goals, loss of self-consciousness, and action-awareness merging). Thus, our study is a step towards modeling the students' flow experience in gamified educational systems based on the data logs. It also contributes to the development of computational approaches for providing automatic students' flow experience identification in this kind of system. Based on the achieved results, we proposed a series of recommendations for new studies in the field.

II. Related Works

To identify the main related works, we analyzed the systematic literature review about Flow Theory and educational technologies conducted by Oliveira *et al.* [15], the literature review about Flow Theory and game based systems conducted by Perttula *et al.* [16], and the literature review about Flow

The authors would like to thank the grant provided by São Paulo Research Foundation (FAPESP), Project: 2018/07688-1.

978-1-6654-4106-3/21/$31.00 ©2021 IEEE
DOI 10.1109/ICALT52272.2021.00037

Theory and gamification conducted by Oliveira *et al.* [17]. Initially, studies that aim to model the students' flow experience in educational systems using data logs are relatively recent [15]–[17]. The first studies were published in 2014 and used statistical analysis [18]. After that, new studies used ontology [19] and electroencephalogram [20] aiming to relate students' flow experience and their data logs. However, in these studies the flow experience was implemented only as challenge-skill balance.

Most recent papers are proposing and evaluating theoretical models that relate the students' flow experience in educational systems with different data logs [10], as well as conducting qualitative studies with the same objective [21]. Finally, there are studies which conduct similar experiments using machine learning methods to model the students' flow experience [22].

Analysis of the existing research indicates that one of the remaining challenges is the need to conduct different experiments in various contexts (*e.g.*, gamified educational systems), as well as data analysis using different techniques. As far as we know, **our study is the first to model the students' flow experience in gamified educational systems through structural equation modeling considering the nine original flow experience dimensions**.

III. Study Design

The main goal of this study is to model students' flow experience in a gamified educational system through data logs (*i.e.*, the student interaction data logs during the system usage). To achieve this goal, we choose a data-drive method (*i.e.*, a research based on users' data analysis) [23].

A. Research question and hypothesis

Based on the study goal, the following research question (RQ) was defined:

- **RQ**: Does possible the students' flow experience in a gamified educational system be modeled based on their interaction data logs?

Since a large number of students started to use online educational platforms in recent years, as well as due to the large amount of data generated by these interactions, numerous studies have sought to use this data to analyze students' experience [24]. In particular, concerning the flow, some recent studies have shown that there may be a direct relationship between different dimensions of the students' flow experience and the data logs [10], [21], [22]. Therefore, in this study, **we hypothesized that is possible to model students' flow experience through data logs in gamified educational systems**.

B. Materials and procedure

To conduct this study, we used the gamified educational system "bombsQuery"[1] [25], which is a tool for teaching the basics of JavaScript/jQuery. It is a gamified system with 11 different missions, each one devoted to a different topic. Each mission has some theory and examples and a free text area where students need to insert their proposed solutions. The playful goal of the missions is to clear the minefield from all bombs. If the student's solution was wrong, they have an unlimited amount of attempts to correct it. However, if their answer was correct, the next level starts. The students can always come back to any of the already solved levels. This might be useful if they want to check the accepted answer for inspiration or go through the theory once again [26]. The tool was chosen because it allowed the implementation of a module to collect the students' data logs. Moreover, it has already been validated and used by other researchers [26]. Figure 1 illustrates an example for the mission.

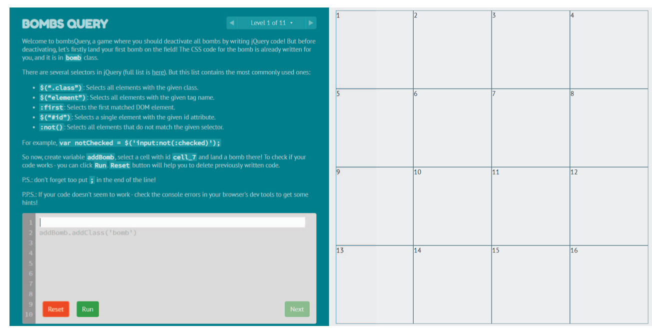

Fig. 1. An example of the mission in the gamified educational system bombsQuery

To collect the students' data logs, we implemented a new module in the tool (described below). Data logs were collected based on the theoretical model proposed by Oliveira *et al.* [10]. The theoretical model proposed by Oliveira *et al.* [10] presents a series of data logs theoretically associated with the nine flow experience dimensions. The module proposes nine different data logs that can be related to the nine flow experience dimensions. The collected data logs are: **ArtAF**: average students' response time after a feedback; **NumCOB**: number of mouse clicks; **ProWS**: proportion of wrong steps/responses; **RF**: received feedback; **TotUSV**: total unique session views; **UsdTFS**: used time to finish a step/mission; and **ActTS**: active time in the system.

To analyze the students' flow experience during working on the assignment, we used the short flow state scale (short FSS) proposed by Jackson and Mars [27]. This scale was chosen because it was previously validated by Hamari and Koivisto [28] to be used gamified settings, as well as being the most popular scale in studies in the area of educational technologies [15]. As the data collection was done after performing a quick activity (with less than an hour), following the recommendation of the "The Manual for the Flow Scales" [29], we chose to use the short scale composed of nine questions (one for each dimension of the flow experience) presented in a five-points Likert scale. To ensure the quality of the responses, inspired by recent studies [30], we have included an "attention-check" question (*i.e.*, if you are filling out the form carefully, answer 3*) to eliminate responses from students who were not paying

[1] https://lirael.github.io/bombsQuery/task.html

due attention when answering the questions. This study was organized in four different general steps: *i)* selection of the gamified system, *ii)* students' invitation, *iii)* data collection, and *iv)* data analysis.

C. Participants

Our participants were 31 bachelor students of Brno University of Technology (Czech Republic), who volunteered to participate in the experiment. Five responses were excluded because students spent less than 5 minutes on the assignment, which is an indication that they haven't really used the system. Three responses were excluded because the students answered incorrectly the attention-check question. We, therefore, included 23 participants (mean age = 21.54 years old, SD = 1.33; 6 women, 13 men, 0 non-binary, 4 preferred not to disclose gender). To participate in the study, students received a link to the questionnaires and the assignment, and they could work on it online, at their pace and preferred time.

IV. Results

In order to define the best strategy to analyse our data, we analysed the data normality. As recommended by Wohlin [31], we used the Shapiro-Wilk test to check it. The tests showed that data is within a non-normal distribution. Thus, we measured the internal reliability for the scale (for the overall flow experience), using Cronbach's alpha, thus obtain α = 0.621 (despite the low alpha value, this can occur because the measured experiences on the scale behave independently). Next, we measured the discriminant validity for the analyses. The results are shown in Table I.

To answer the RQ, we modeled the students' interaction logs (as latent variables) and their flow experience in the gamified educational system. Partial Least Squares Path Modeling (PLS-PM) analysis [14] was used to observe the relation between the students' data logs and their flow experience. PLS-PM was used because it is a reliable method for estimate cause-effect relationship models with latent variable [14]. At the same time, this method can be selected to the exploratory research and to studies with small sample sizes (as such our case) [32]. We used the software SmartPLS[2] to run the analyses. Table II present the PLS-PM matrix and Figure 2 present the research path model with the results.

A. Discussion

In this study, we used PLS-PM to model the user flow experience in the gamified educational system using gathered data logs. The created model presented a significant relationship between the data logs and four different flow experience dimensions (see Table II): unambiguous feedback (β -0.435), clear goals (β -0.530), loss of self-consciousness (β -0.707), and action-awareness merging (β -0.283).

Initially, the data logs have a negative relationship (β -0.435) with the unambiguous feedback. In this dimension, according to Oliveira *et al*. [10], when a student takes a long time to complete an activity after receiving feedback, they possibly received ambiguous feedback. Thus, the less time the student spends in the system, or the lesser the number of received feedback, the unambiguous feedback experience tends to be less. On the other hand, this result has not yet been identified in previous studies and needs to be confirmed [18], [21], [22].

[2]https://www.smartpls.com/

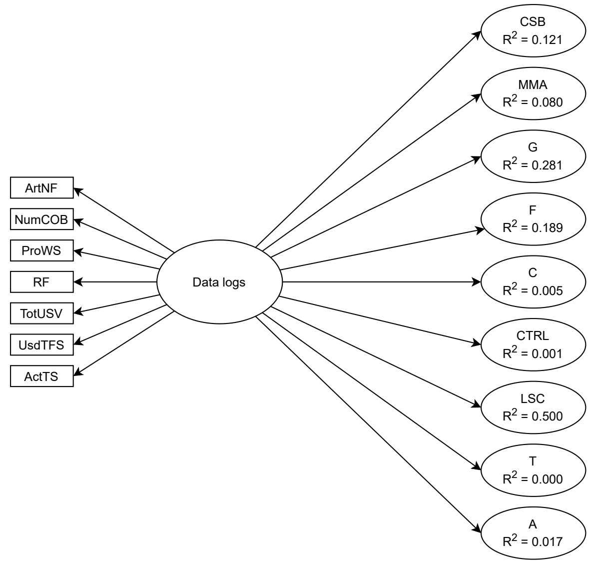

Fig. 2. Research path model

We also identified a negative relationship between the data logs model and the the clear goals dimension (β -0.530). This relationship can be explained based on the previous relationship, because, once a student has not received unambiguous feedback, they will also possibly not be able to clearly understand the objectives of the activity. This result can also help to explain the results identified in the qualitative study conducted by Oliveira *et al*. [21]. Their study identified that the average of correct steps affected the sense of "clear goals".

The highest relationship (also negative) occurred between the data logs and loss of self-consciousness dimension (β -0.707). According to Jackson *et al*. [29], when an individual is no longer concerned with what others think of them, self-consciousness has been lost. This statement may be key to interpreting the results as if there is a trend in data logs (*e.g.*, the proportion of wrong steps/responses, average students' response time after feedback, and active time in the system), is low, students can be concerned with what others think of them, and then, to have a low loss of self-consciousness.

The last relationship in the model in represented by the correlation between data logs and action-awareness merging dimension (β -0.283), an experience comes about through a total absorption in what one is doing [29]. This relationship can also be explained according to the same explanation as the previous experience. Our results demonstrate a tendency regarding a relationship/pattern between students' flow experience and their data logs in a gamified educational system. Therefore, following the trend of previous studies. However, the relationships identified in our study are different from the

TABLE I
DISCRIMINANT VALIDITY (COMPLETE BOOTSTRAPPING, SAMPLE=5000)

	A	C	CSB	CTRL	Datalogs	F	G	LSC	MMA	T
A	1.000									
C	-0.112	1.000								
CSB	-0.135	0.030	1.000							
CTRL	0.399	0.171	0.051	1.000						
Datalogs	0.128	0.068	-0.348	0.035	1.000					
F	0.017	0.369	0.361	0.228	-0.435	1.000				
G	0.157	0.145	0.239	0.090	-0.530	0.536	1.000			
LSC	-0.014	0.064	0.181	0.072	-0.707	0.311	0.303	1.000		
MMA	0.193	-0.130	0.586	0.294	-0.283	0.150	0.182	0.039	1.000	
T	0.644	0.209	0.002	0.138	-0.015	-0.043	0.113	0.246	-0.027	1.000

Key: CSB: challenge-skill balance, MMA: action-awareness merging, G: clear goals, F: unambiguous feedback, C: total concentration on the task at hand, CTRL: sense of control, LSC: loss of self-consciousness, T: transformation of time, and A: *autotelic* experience

TABLE II
PLS-PM MATRIX FOR DATA LOGS AND FLOW EXPERIENCE DIMENSIONS

					CI	
	β	M	SD	P	2.5%	97.5%
DL → A	0.128	0.058	0.248	0.605	-0.604	0.397
DL → C	0.068	0.141	0.220	0.756	-0.233	0.534
DL → CSB	-0.348	-0.384	0.190	0.067	-0.755	-0.034
DL → CTRL	0.035	0.010	0.201	0.862	-0.496	0.372
DL → F	-0.435**	-0.436	0.153	0.005	-0.707	-0.097
DL → G	-0.530**	-0.526	0.145	0.000	-0.756	-0.227
DL → LSC	-0.707*	-0.584	0.279	0.011	-0.908	0.034
DL → MMA	-0.283*	-0.341	0.134	0.036	-0.602	-0.101
DL → T	-0.015	-0.026	0.135	0.913	-0.284	0.232

Key: DL: data logs, CSB: challenge-skill balance, MMA: action-awareness merging, G: clear goals, F: unambiguous feedback, C: total concentration on the task at hand, CTRL: sense of control, LSC: loss of self-consciousness, T: transformation of time, and A: *autotelic* experience, β: regression coefficient, M: meam, SD: standard deviation, P: *p-value*, CI: confidence interval, * p<0.5, ** p<0.005

relationships observed in some other studies.

This result may indicate that the relationship between data logs and flow experience can be different according to the type of system, participants' age, and other factors (since each previous study was conducted in different settings). Another way of thinking is related to the number of participants (especially in our study). The sample size needs to be increased to also increase the confidence in the results. Regardless, our results are promising for modeling the students' flow experience in gamified educational systems based on data logs, while highlighting the need for further research.

B. Limitations

The study presented in this paper has some limitations, which we seek to mitigate. The experience measured in the study (*i.e.*, flow experience) is a complex parameter to be measured. To mitigate this limitation, we use only previously validated methods (*i.e.*, the short FSS validated by Hamari and Koivisto [28] for the gamification domain and theoretical model proposed by Oliveira [10] to collect data logs in educational systems). At the same time, to ensure the quality of responses and to avoid external threats (*e.g.*, lack of attention from students), we insert an "attention checking question" within the scale and used other methods (*e.g.*, remove responses from students who used the system for less than five minutes) to avoid data set inconsistencies. Another important limitation is related to our small sample size (*i.e.*, 23 students). To mitigate this limitation, we use a robust statistical method capable of accurately analyzing data from small samples (*i.e.*, PLS-PM) [14]. However, we highlight the importance of replicating the experiment with larger samples to provide a greater results generalization, and we are sure that this paper would serve as an excellent basis for such future research.

C. Ways forward

Based on our results, it is possible to provide some recommendations for future studies. Comparing our results with results of other studies [18], [21], [22], we can conclude that the relationship of each flow experience dimension with the different data logs can be changed according to the context (*i.e.*, with the type of educational system or even with the type of data analysis). Therefore, we **recommend that future studies conduct similar studies in different types of educational environments (*e.g.*, MOOCs, ITS, educational games, and others)**. In the same way, **we also recommend analyzing the data through different techniques (*e.g.*, qualitative analysis, data mining and machine learning techniques)**, seeking to carry out the experiments with larger samples, to increase the generalization of the results.

In our study, we considered the entry model as a set of different variables (*i.e.*, data logs). However, we do not model each data log individually with each flow experience dimension. Thus, we recommend that future studies can model the relationship of each data log (individually) with the students' flow experience dimensions. In our study, our input data (data logs) were defined based on the study by Oliveira *et al*. [10] However, not all data from the theoretical model was considered in our study. Thus, **we recommend that future studies also include the other data logs proposed in the theoretical model**. Last but not least, **we recommend that further research improve the inputs by analysing at whether gamification data (*e.g.*, number of points, badges, and leader-boards (alone)) affects students' flow experience**.

V. Concluding Remarks

Modeling students' flow experience in gamified educational systems is a contemporary challenge. In this study, we used PLS-PM to model the flow experience of the students through their data logs in a gamified educational system. Our results demonstrate a correlation between the interaction logs and four flow experience dimensions, moving towards modeling the students' flow experience in educational games using data logs. Future research is planned to replicate this experiment with larger numbers of participants, using new data analysis methods, such as data mining and machine learning.

Notes

Previous studies of this project have been published: Oliveira *et al*. [15] conducted a systematic literature review about Flow Theory and Educational Technologies; Oliveira [33] presented the project overview; Oliveira *et al*. [10] proposed a theoretical model relating students' data logs and their flow experience in educational systems; and Oliveira *et al*. [21] conducted a qualitative study analysing students' data logs and their flow experience in an educational systems.

References

[1] A. Bozkurt, E. Akgün-Özbek, and O. Zawacki-Richter, "Trends and patterns in massive open online courses: Review and content analysis of research on moocs (2008-2015)," *International Review of Research in Open and Distributed Learning: IRRODL*, vol. 18, no. 5, pp. 118–147, 2017.

[2] E. Mousavinasab, N. Zarifsanaiey, S. R. Niakan Kalhori, M. Rakhshan, L. Keikha, and M. Ghazi Saeedi, "Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods," *Interactive Learning Environments*, pp. 1–22, 2018.

[3] J. Koivisto and J. Hamari, "The rise of motivational information systems: A review of gamification research," *International Journal of Information Management*, vol. 45, pp. 191–210, 2019.

[4] C. Jack and S. Higgins, "Embedding educational technologies in early years education," *Research in learning technology*, vol. 27, 2019.

[5] I. Buil, S. Catalán, and E. Martínez, "The influence of flow on learning outcomes: An empirical study on the use of clickers," *British Journal of Educational Technology*, vol. 50, no. 1, pp. 428–439, 2019.

[6] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, "From game design elements to gamefulness: defining gamification," in *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*. ACM, 2011, pp. 9–15.

[7] C. Hursen and C. Bas, "Use of gamification applications in science education." *International Journal of emerging technologies in Learning*, vol. 14, no. 1, 2019.

[8] S. Bai, K. F. Hew, and B. Huang, "Is gamification "bullshit"? evidence from a meta-analysis and synthesis of qualitative data in educational contexts," *Educational Research Review*, p. 100322, 2020.

[9] L. Shi, A. I. Cristea, A. M. Toda, and W. Oliveira, "Exploring navigation styles in a futurelearn mooc," in *International Conference on Intelligent Tutoring Systems*. Springer, 2020, pp. 45–55.

[10] W. Oliveira, A. Toda, P. Palomino, L. Rodrigues, S. Isotani, and L. Shi, "Towards automatic flow experience identification in educational systems: A theory-driven approach," in *Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts*. ACM, 2019, pp. 581–588.

[11] L. Shi, A. I. Cristea, A. M. Toda, and W. Oliveira, "Social engagement versus learning engagement an exploratory study of futurelearn learners," in *2019 IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*. IEEE, 2019, pp. 476–483.

[12] ——, "Revealing the hidden patterns: A comparative study on profiling subpopulations of mooc students," *International Conference on Information Systems Development*, 2020.

[13] M. Csikszentmihalyi, *Finding flow: The psychology of engagement with everyday life*. Basic Books, 1997.

[14] J. F. Hair Jr, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications, 2016.

[15] W. Oliveira, I. I. Bittencourt, S. Isotani, D. Dermeval, L. B. Marques, and I. F. Silveira, "Flow theory to promote learning in educational systems: Is it really relevant?" *Brazilian Journal of Computers in Education*, vol. 26, no. 02, p. 29, 2018.

[16] A. Perttula, K. Kiili, A. Lindstedt, and P. Tuomi, "Flow experience in game based learning–a systematic literature review," *International Journal of Serious Games*, vol. 4, no. 1, pp. 57–72, 2017.

[17] W. Oliveira, O. Pastushenko, L. Rodruigues, A. M. Toda, P. T. Palomino, J. Hamari, and S. Isotani, "Does gamification affect flow experience? a systematic literature review," in *GamiFIN Conference 2021: Proceedings of the 5th International GamiFIN Conference*, 2021, pp. 1–10.

[18] P.-M. Lee, S.-Y. Jheng, and T.-C. Hsiao, "Towards automatically detecting whether student is in flow," in *International Conference on Intelligent Tutoring Systems*. Springer, 2014, pp. 11–18.

[19] G. C. Challco, F. R. Andrade, S. S. Borges, I. I. Bittencourt, and S. Isotani, "Toward a unified modeling of learner's growth process and flow theory," *Journal of Educational Technology & Society*, vol. 19, no. 2, 2016.

[20] F. De Kock, *The Neuropsychological Measure (EEG) of Flow Under Conditions of Peak Performance*. Unisa, 2014. [Online]. Available: https://books.google.com.br/books?id=qKDFrQEACAAJ

[21] W. Oliveira, L. Rodrigues, A. Toda, P. Palomino, L. Shi, and S. Isotani, "Towards automatic flow experience identification in educational systems: A qualitative study," in *Brazilian Symposium on Computers in Education*, vol. 31, 2020.

[22] Y. C. Semerci and D. Goularas, "Evaluation of students' flow state in an e-learning environment through activity and performance using deep learning techniques," *Journal of Educational Computing Research*, p. 0735633120979836, 2020.

[23] V. Dhar, "Data science and prediction," *Communications of the ACM*, vol. 56, no. 12, pp. 64–73, 2013.

[24] J. López-Zambrano, J. A. Lara, and C. Romero, "Towards portability of models for predicting students' final performance in university courses starting from moodle logs," *Applied Sciences*, vol. 10, no. 1, p. 354, 2020.

[25] O. Pastushenko, T. Hruška, and J. Zendulka, "Increasing students' motivation by using virtual learning environments based on gamification mechanics: Implementation and evaluation of gamified assignments for students," in *Proceedings of the Sixth International Conference on Technological Ecosystems for Enhancing Multiculturality*, 2018, pp. 755–760.

[26] O. Pastushenko, W. Oliveira, S. Isotani, and T. Hruška, "A methodology for multimodal learning analytics and flow experience identification within gamified assignments," in *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–9.

[27] S. A. Jackson and R. C. Eklund, "Assessing flow in physical activity: The flow state scale–2 and dispositional flow scale–2," *Journal of Sport and Exercise Psychology*, vol. 24, no. 2, pp. 133–150, 2002.

[28] J. Hamari and J. Koivisto, "Measuring flow in gamification: Dispositional flow scale-2," *Computers in Human Behavior*, vol. 40, pp. 133–143, 2014.

[29] S. Jackson, B. Eklund, and A. Martin, "The flow manual the manual for the flow scales manual. sampler set," *Mind*, pp. 1–85, 2011.

[30] R. Orji, G. F. Tondello, and L. E. Nacke, "Personalizing persuasive strategies in gameful systems to gamification user types," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018, pp. 1–14.

[31] C. Wohlin, P. Runeson, M. Höst, M. C. Ohlsson, B. Regnell, and A. Wesslén, *Experimentation in software engineering*. Springer Science & Business Media, 2012.

[32] J. Henseler, C. M. Ringle, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," in *New challenges to international marketing*. Emerald Group Publishing Limited, 2009.

[33] W. Oliveira, "Towards automatic flow experience identification in educational systems: A human-computer interaction approach," in *Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts*, 2019, pp. 41–46.