

# Measuring and supporting self-regulated learning in blended learning contexts

Esteban Villalobos<sup>1,\*</sup>, Mar Pérez-Sanagustin<sup>1</sup>, André Tricot<sup>2</sup> and Julien Broisin<sup>1</sup>

<sup>1</sup>IRIT, Université de Toulouse, CNRS, Toulouse INP, UT3, Toulouse, France

<sup>2</sup>Université Paul-Valéry Montpellier 3, EPSYLON

## Abstract

Despite the positive effects of Blended Learning (BL), several studies have shown that students require high levels of self-regulation to succeed in these types of practices. Still, there is little understanding of how students organize their learning in BL authentic contexts. This paper presents the objectives and current status of a project that seeks to understand how students' Self-regulated Learning (SRL) strategies manifest themselves in BL contexts holistically and how to foster it through technological solutions. The contributions of this project will be three-fold. First, we aim to develop novel analytical and technological solutions to understand better the dynamics of how self-regulated learning unveils in BL contexts. Second is the development of a dashboard-based support tool for students and teachers. And third, we will provide evaluations of the analytical framework and support tool in authentic BL contexts. We expect that these contributions will provide the community with a better understanding of the dynamics of SRL in BL.

## Keywords

Self-regulated Learning, Blended Learning, Learning Analytics

## 1. Introduction

In the last few years, we have seen Blended Learning (BL) approaches becoming more varied and commonly applied [1]. This methodology consists in combining online and traditional in-person activities [2]. Nonetheless, while BL has been shown to have positive effects on learning, many students often have problems regulating their study [3, 4, 2]. This has prompted a growing interest in finding out how to understand and support students' self-regulation abilities in BL.

Self-regulated Learning (SRL) is defined as a complex process that combines meta-cognitive, motivational, and emotional processes [5]. Recent literature shows that students' SRL ability is a good predictor of their behavior and success in a course [6]. However, most studies on SRL have been conducted in online contexts and little is known about how these processes manifest in BL [3]. Recent works show that students' SRL manifests differently depending on pedagogical decisions, such as the learning context and course modality [3, 7, 8, 9]. For example, Matcha et al. [9] compared students' strate-

gies in a BL course, in a Flipped Classroom (FC), and in Massive Open Online Courses (MOOCs), showing that students used similar strategies in BL and FC modalities, but these differed from the tactics used in MOOCs. Moreover, [3] showed that BL students used SRL strategies less often than online students. Overall, there seems to be a strong connection between the course design, the learners' SRL ability profile, and the learning strategies in the course [9, 7].

To support students' SRL, researchers propose different mechanisms. One of these mechanisms is using dashboard-based tools. These tools provide learners with information about their progress. Although most of these tools have been designed and evaluated in online environments with encouraging results [10], only a few works show how students incorporate them into their learning strategies and have an impact on their behavior in BL courses [11, 12].

In order to give meaningful SRL support in BL it is important to understand how different external factors (e.g., the influence of the teacher or face-to-face classes) and internal factors (e.g., students' self-regulation abilities) affect learners in these contexts. These factors influence how students will interact with the learning material along the course. This represents a particular challenge in TEL, as it implies that strategies observed will be heavily influenced by the dynamics of the system in which the students operate [13, 14]. This points out the need to develop new holistic approaches to understand the SRL behavior of the students better.

This work is part of a 3-year thesis starting in October 2021, in which we expect to contribute to the TEL domain by addressing these gaps. Specifically, we propose: (1)

*Proceedings of the Doctoral Consortium of the Seventeenth European Conference on Technology Enhanced Learning, September 12–16, 2022, Toulouse, France.*

\*Corresponding author.

✉ esteban.villalobos@irit.fr (E. Villalobos);  
mar.perez-sanagustin@irit.fr (M. Pérez-Sanagustin);  
andre.tricot@univ-montp3.fr (A. Tricot); julien.broisin@irit.fr  
(J. Broisin)

📞 0000-0002-6026-3756 (E. Villalobos); 0000-0001-9854-9963

(M. Pérez-Sanagustin); 0000-0003-4005-7338 (A. Tricot);

0000-0001-8713-6282 (J. Broisin)

© 2022 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).



CEUR Workshop Proceedings (CEUR-WS.org)

studying new analytics techniques to understand the development of SRL strategies in BL holistically and (2) developing technological solutions to support SRL in BL.

## 2. Objectives and research questions

The general objective of this project is to investigate the SRL strategies used by learners in BL scenarios and to propose and evaluate a Learning Analytics (LA) technological solution based on user-centered dashboards (for teachers and students) to support those strategies that maximize learners' performance. Three main objectives are derived from this general objective:

- **Objective 1:** To propose an analytical framework to study in a holistic manner how students' SRL strategies manifest in BL contexts.
- **Objective 2:** To design a LA dashboard-based solution for teachers and students to support SRL in BL.
- **Objective 3:** To evaluate the impact of LA solution on students' learning strategies and teachers' decision-making in BL scenarios.

### 2.1. Measuring SRL in BL

Different methods have been proposed for studying how SRL manifests in different learning contexts, especially in online learning environments. These range from using self reported data [15] to detecting tactics and strategies by using the trace data collected from the course's LMS [16, 7, 17, 18, 9]. The latter has seen many contributions from the field of Learning Analytics (LA). Some examples of these analytical approaches have used techniques derived from temporal analysis and sequence mining [17, 16]. Some studies have also made the connection between these techniques and the SRL theory [16]. Fan et al. [16] suggests this theoretical backbone may allow us to overcome the limitations of the context-specific nature of LA to perform pedagogical interventions that go beyond course setting.

Most of these methods have been applied in online settings, and very few have been applied in Blended Learning settings. The currently applied methods are limited in capturing the impact of factors such as teacher interventions and face-to-face classes. In fact, current research applying existing methods in Blended Learning encounters difficulties in providing indicators on run-time, as well as in giving a temporal meaning to the collected data. From this, we derive the following research question:

- **RQ1:** How can pre-existing LA methods and techniques be adapted and combined with qualitative

methods to create an analytical framework for characterizing the dynamics of students' strategies in BL?

### 2.2. Supporting SRL in BL

Researchers have proposed different approaches to support students' SRL processes [19]. The most common approaches explored are educational prompts and integrated support systems [20]. These solutions transform raw data into 'actionable insights' to produce behavioral changes in the students [21]. So far, most of this prior work has been conducted in online settings, such in Massive Open Online Courses (MOOCs), in which students have low interaction with the teacher [20]. These studies suggest that dashboards could be an appropriate approach for supporting SRL strategies. In particular, the strategies of goal setting, strategic planning, time management, and monitoring have been shown to be more effective for promoting students' motivation and impact on course performance.

There are still very few studies looking at these solutions BL contexts (e.g., [22, 23]). These works in BL have two main limitations. First, the tools focus on supporting the students directly, usually overlooking the role of the teacher. Second, while some tools are based on theoretical models for SRL, there is still much to understand about their impact on students' SRL strategies. This poses the following research questions for the project:

- **RQ2:** How useful (interpretable, actionable, and comprehensive) are the existing indicators provided in the SRL-support dashboard for students and teachers?
- **RQ3:** How do SRL support tools influence students' strategies and teachers' decision-making in BL scenarios?

## 3. Project Methodology

Design Based Research (DBR) will be used as a methodological approach, which combines experiments in real-world settings with theoretical models [24]. The interventions will be based on the NoteMyProgress (NMP) tool [25], a Moodle plug-in that delivers dashboards with self-regulation indicators in the course to both students and teachers (see Figure 1). Three experimental cycles will be carried out to improve the tool and the analytical frameworks in an iterative way. After each cycle, the results will be published as part of the LASER project following an Open Science Framework.



Figure 1: Examples of visualizations in the NoteMyProgress plug-in

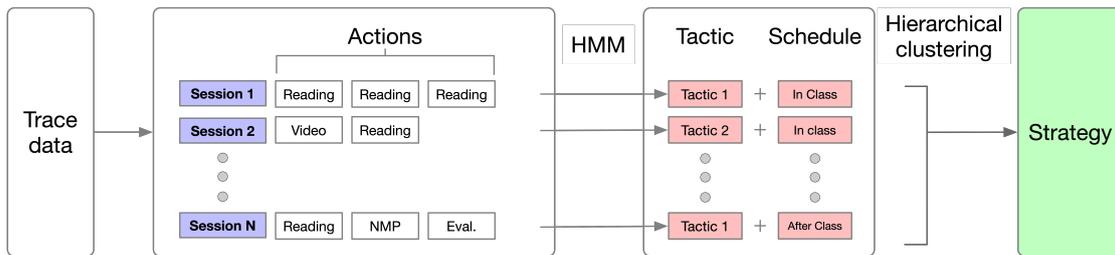


Figure 2: Analytical approach used to evaluate the first design cycle [26].

## 4. Current Results: First Design Cycle

The first cycle focused on studying students' behavior in BL. This cycle had three research questions:

1. How do students' learning tactics and strategies manifest along the BL course?
2. Does the NMP tool, designed to support students' SRL, have an effect on their learning tactics and strategies?
3. Is there a relationship between students' learning strategies, course performance, and SRL ability profile?

This intervention took place between September 2021 and January 2022. The study consisted on 241 students from two university courses. At the beginning of the course, students completed the informed consent for participation and a questionnaire to assess their level of SRL. Midway through the course (week 6), they were introduced to NMP and invited to refer to it to assess their study strategies [27]. At the end of the course, they were asked to complete a questionnaire on their sense-making of the tool [25].

The evaluation of one of these courses is detailed in [26]. Here, we extended an analytical approach proposed in Fincham et al. [17] and analyzed the results with respect to students' SRL ability profile, final performance,

and previous achievements. The approach consists of the following steps:

1. **Separating the activity of the students into sessions.** These correspond to a sequence of actions not separated by more than 30 minutes of inactivity.
2. **Detecting the underlying tactic of each session.** A tactic is defined as the underlying process that a student is applying in a given period of time [17]. We used a Hidden Markov Model (HMM) in order to detect students' tactics.
3. **Detecting students' strategies.** Under the analytical approach proposed by Fincham et al. [17], strategies are defined as sequences of tactics applied by the students. In order to include the context of the BL course, we included in this model the timing with respect to the face-to-face sessions.
4. **Analyzing relationships between strategies and students' profile.** We analyzed how different tactics and strategies applied by the students related to their SRL ability profile, course performance, and previous achievements.

We found that students' strategies were correlated with their previous achievements (GPA) and their self-reported Self-Regulation ability. We also found that the tactics used by the students varied across modalities and

Activity	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Final test - 1	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Final test - 2	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Final test - 3	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Final test - 4	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Final test - 5	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 3: Examples of the ‘Student planning and goal setting’ functionalities added to NMP

Levels	Basis points
3	50
<b>Débutant</b>	<b>Senior</b>
Description	Description
Points required: 0	Points required: 100

Figure 4: Example of the ‘Gamification’ functionalities added to NMP

were based on the pedagogical decisions of the course. In terms of the usage of NMP we found that even though some students incorporated the SRL support tool into their learning tactics, the use of the tool was relatively sparse. We also found that, even if the use of the tool was not mandatory, most of the students interacted with the indicators relating to Strategic Planning.

While this gives us some insight into the performance of the students in the course, this methodology still has some limitations. Mainly, since the methods applied are "memory-less", we are losing information on the temporal dynamics of the events. Also, this methodology only allows us to do a retrospective analysis of the course. This limits our capability to perform meaningful interventions on run-time.

## 5. Future work: Second Design Cycle

The second design cycle focuses on the role of the teacher in the BL course, as well as on students’ behavior when they use support for planning their course. This cycle will take place between September 2022 and January 2023. Based on the insights from the first cycle, new developments were made to NMP. We developed new functionalities of student planning and goal setting (see Figure 3), and gamification (see Figure 4).

We aim to evaluate this intervention based on the temporal dynamics of the students. Our goal is to understand how external factors (such as feedback and gamification) and internal factors (such as student planning) affect the students’ SRL behavior. Following the recent works by [14, 28, 29], we will study how context-dependent and context-independent indicators behaviors throughout the course and their potential to give meaningful information to students and teachers. In the short term, we will be following behavior-based indicators already studied in the literature to provide students feedback week to week. In the long term, we are looking to develop indicators based on point processes to capture more complex temporal behavior from the students. This study will be done in collaboration with the Millennium Nucleus Student Experience in Higher Education in Chile (NMEDSUP) to see how this work can be extended to different institutions and contexts.

## 6. Contribution to TEL domain

This work aims at advancing research in TEL, and in particular in the study of SRL in BL scenarios, with three contributions. Firstly, we expect to provide the community with an analytical framework for understanding the dynamics of SRL in BL in a holistic manner and taking into consideration temporal aspects. These tools will help

in analyzing data but also in proposing indicators that could serve researchers doing interventions on run-time. Second, we contribute with the NMP tool, a functional tool that both teachers and students could use to support SRL, and its evaluation in authentic contexts. The current version of the tool is already openly available<sup>1</sup>. And third, we expect to contribute with exemplary scenarios on how to apply our analytical framework in BL.

These contributions will have implications at the theoretical level, the analytical level, and the teaching practices level. We expect that our analytical framework and proposed tool can give the community greater insights into how to understand the different factors that affect the dynamics of SRL in BL. We hope that this allows the community to have a better understanding of how to support SRL in a holistic manner.

## Acknowledgments

This paper has been partially funded by the ANR LASER (156322). The authors acknowledge PROF-XXI, which is an Erasmus+ Capacity Building in the Field of Higher Education project funded by the European Commission (609767-EPP-1-2019-1-ES-EPPKA2-CBHE-JP). This publication reflects the views only of the authors and funders cannot be held responsible for any use which may be made of the information contained therein.

## References

- [1] K. Pelletier, M. McCormack, J. Reeves, J. Robert, N. Arbino, 2022 EDUCAUSE Horizon Report, Teaching and Learning Edition (2022) 58.
- [2] C. R. Graham, Blended learning systems: Definition, current trends, future directions, in: Handbook of blended learning: Global Perspectives, local designs, San Francisco, CA: Pfeiffer Publishing, Brigham Young University, USA, 2004.
- [3] J. Broadbent, Comparing online and blended learner's self-regulated learning strategies and academic performance, *The Internet and Higher Education* 33 (2017) 24–32. URL: <https://www.sciencedirect.com/science/article/pii/S1096751617300398>. doi:10.1016/j.iheduc.2017.01.004.
- [4] J. Broadbent, M. Fuller-Tyszkiewicz, Profiles in self-regulated learning and their correlates for online and blended learning students, *Educational Technology Research and Development* 66 (2018) 1435–1455. URL: <http://link.springer.com/10.1007/s11423-018-9595-9>. doi:10.1007/s11423-018-9595-9.
- [5] E. Panadero, A Review of Self-regulated Learning: Six Models and Four Directions for Research, *Frontiers in Psychology* 8 (2017) 422. URL: <http://journal.frontiersin.org/article/10.3389/fpsyg.2017.00422/full>. doi:10.3389/fpsyg.2017.00422.
- [6] J. Maldonado-Mahauad, M. Pérez-Sanagustín, P. M. Moreno-Marcos, C. Alario-Hoyos, P. J. Muñoz-Merino, C. Delgado-Kloos, Predicting Learners' Success in a Self-paced MOOC Through Sequence Patterns of Self-regulated Learning, in: V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachler, R. Elferink, M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning*, volume 11082, Springer International Publishing, Cham, 2018, pp. 355–369. URL: [http://link.springer.com/10.1007/978-3-319-98572-5\\_27](http://link.springer.com/10.1007/978-3-319-98572-5_27). doi:10.1007/978-3-319-98572-5\_27, series Title: Lecture Notes in Computer Science.
- [7] Y. Fan, W. Matcha, N. A. Uzir, Q. Wang, D. Gašević, Learning Analytics to Reveal Links Between Learning Design and Self-Regulated Learning, *International Journal of Artificial Intelligence in Education* 31 (2021) 980–1021. URL: <https://link.springer.com/10.1007/s40593-021-00249-z>. doi:10.1007/s40593-021-00249-z.
- [8] D. Gašević, N. Mirriahi, S. Dawson, S. Joksimović, Effects of instructional conditions and experience on the adoption of a learning tool, *Computers in Human Behavior* 67 (2017) 207–220. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0747563216307270>. doi:10.1016/j.chb.2016.10.026.
- [9] W. Matcha, D. Gašević, N. Ahmad Uzir, J. Jovanović, A. Pardo, L. Lim, J. Maldonado-Mahauad, S. Gentili, M. Pérez-Sanagustín, Y.-S. Tsai, Analytics of Learning Strategies: Role of Course Design and Delivery Modality, *Journal of Learning Analytics* 7 (2020) 45–71. URL: <https://learning-analytics.info/index.php/JLA/article/view/7008>. doi:10.18608/jla.2020.72.3.
- [10] R. Pérez-Álvarez, J. Maldonado, M. Pérez-Sanagustín, Tools to Support Self-Regulated Learning in Online Environments: Literature Review: 13th European Conference on Technology Enhanced Learning, EC-TEL 2018, Leeds, UK, September 3-5, 2018, Proceedings, 2018, pp. 16–30. doi:10.1007/978-3-319-98572-5\_2.
- [11] M. Pérez-Sanagustín, D. Sapunar-Opazo, R. Pérez-Álvarez, I. Hilliger, A. Bey, J. Maldonado-Mahauad, J. Baier, A MOOC-based flipped experience: Scaffolding SRL strategies improves learners' time management and engagement, *Computer Applications in Engineering Education* 29 (2021) 750–768. URL: <https://onlinelibrary.wiley.com/doi/10.1002/>

<sup>1</sup><https://gitlab.com/laser-anr/notemyprogress-plugin-in>

- cae.22337. doi:10.1002/cae.22337.
- [12] M. Yoon, J. Hill, D. Kim, Designing supports for promoting self-regulated learning in the flipped classroom, *Journal of Computing in Higher Education* 33 (2021) 398–418. URL: <https://link.springer.com/10.1007/s12528-021-09269-z>. doi:10.1007/s12528-021-09269-z.
- [13] S. Dawson, S. Joksimovic, O. Poquet, G. Siemens, Increasing the Impact of Learning Analytics, in: *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, ACM, Tempe AZ USA, 2019, pp. 446–455. URL: <https://dl.acm.org/doi/10.1145/3303772.3303784>. doi:10.1145/3303772.3303784.
- [14] J. Jovanović, M. Saqr, S. Joksimović, D. Gašević, Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success, *Computers & Education* 172 (2021) 104251. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0360131521001287>. doi:10.1016/j.compedu.2021.104251.
- [15] M. Zhou, P. H. Winne, Modeling academic achievement by self-reported versus traced goal orientation, *Learning and Instruction* 22 (2012) 413–419. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0959475212000217>. doi:10.1016/j.learninstruc.2012.03.004.
- [16] Y. Fan, J. Saint, S. Singh, J. Jovanovic, D. Gašević, A learning analytic approach to unveiling self-regulatory processes in learning tactics, in: *LAK21: 11th International Learning Analytics and Knowledge Conference*, ACM, Irvine CA USA, 2021, pp. 184–195. URL: <https://dl.acm.org/doi/10.1145/3448139.3448211>. doi:10.1145/3448139.3448211.
- [17] E. Fincham, D. Gašević, J. Jovanović, A. Pardo, From Study Tactics to Learning Strategies: An Analytical Method for Extracting Interpretable Representations, *IEEE Transactions on Learning Technologies* 12 (2019) 59–72. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85045204080&doi=10.1109%2FTLT.2018.2823317&partnerID=40&md5=84a758598f985bd200d40eab1fb0e45c>. doi:10.1109/TLT.2018.2823317.
- [18] D. Gasevic, J. Jovanovic, A. Pardo, S. Dawson, Detecting Learning Strategies with Analytics: Links with Self-reported Measures and Academic Performance, *Journal of Learning Analytics* 4 (2017). URL: <https://learning-analytics.info/index.php/JLA/article/view/5085>. doi:10.18608/jla.2017.42.10.
- [19] A. Devolder, J. van Braak, J. Tondeur, Supporting self-regulated learning in computer-based learning environments: systematic review of effects of scaffolding in the domain of science education: Scaffolding self-regulated learning with CBLES, *Journal of Computer Assisted Learning* 28 (2012) 557–573. URL: <https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2729.2011.00476.x>. doi:10.1111/j.1365-2729.2011.00476.x.
- [20] J. Wong, M. Baars, D. Davis, T. Van Der Zee, G.-J. Houben, F. Paas, Supporting Self-Regulated Learning in Online Learning Environments and MOOCs: A Systematic Review, *International Journal of Human-Computer Interaction* 35 (2019) 356–373. URL: <https://www.tandfonline.com/doi/full/10.1080/10447318.2018.1543084>. doi:10.1080/10447318.2018.1543084.
- [21] R. L. Jørnø, K. Gynther, What Constitutes an ‘Actionable Insight’ in Learning Analytics?, *Journal of Learning Analytics* 5 (2018). URL: <https://learning-analytics.info/index.php/JLA/article/view/5897>. doi:10.18608/jla.2018.53.13.
- [22] W.-J. Shyr, C.-H. Chen, Designing a technology-enhanced flipped learning system to facilitate students’ self-regulation and performance, *Journal of Computer Assisted Learning* 34 (2018) 53–62. URL: <https://onlinelibrary.wiley.com/doi/10.1111/jcal.12213>. doi:10.1111/jcal.12213.
- [23] C. Michel, E. Lavoué, S. George, M. Ji, Supporting Awareness and Self-Regulation In Project-Based Learning through Personalized Dashboards, *International Journal of Technology Enhanced Learning* 9 (2017) 204–226. URL: <https://hal.archives-ouvertes.fr/hal-01384211>. doi:10.1504/IJTEd.2017.084500.
- [24] P. Reimann, Design-Based Research, in: L. Markauskaite, P. Freebody, J. Irwin (Eds.), *Methodological Choice and Design: Scholarship, Policy and Practice in Social and Educational Research*, Methodos Series, Springer Netherlands, Dordrecht, 2011, pp. 37–50. URL: [https://doi.org/10.1007/978-90-481-8933-5\\_3](https://doi.org/10.1007/978-90-481-8933-5_3). doi:10.1007/978-90-481-8933-5\_3.
- [25] M. Pérez-Sanagustín, R. Pérez-Álvarez, J. Maldonado-Mahauad, E. Villalobos, C. Sanza, Designing a moodle plugin for promoting learners’ self-regulated learning in blended learning, in: *Proceedings of the Seventeenth European Conference on Technology-Enhanced Learning - EC-TEL ’22*, Toulouse, France, In press.
- [26] E. Villalobos, M. Pérez-Sanagustín, C. Sanza, A. Tricot, J. Broisin, Supporting self-regulated learning in bl: Exploring learners’ tactics and strategies, in: *Proceedings of the Seventeenth European Conference on Technology-Enhanced Learning - EC-TEL ’22*, Toulouse, France, In press.
- [27] P. R. Pintrich, E. V. D. Groot, Motivational and Self-Regulated Learning Components of Classroom Academic Performance (1990) 8.

- [28] J. Jovanovic, N. Mirriahi, D. Gašević, S. Dawson, A. Pardo, Predictive power of regularity of pre-class activities in a flipped classroom, *Computers & Education* 134 (2019) 156–168. URL: <https://www.sciencedirect.com/science/article/pii/S0360131519300405>. doi:10.1016/j.compedu.2019.02.011.
- [29] M. Saqr, J. Jovanovic, O. Viberg, D. Gašević, Is there order in the mess? A single paper meta-analysis approach to identification of predictors of success in learning analytics, *Studies in Higher Education* (2022) 1–22. URL: <https://www.tandfonline.com/doi/full/10.1080/03075079.2022.2061450>. doi:10.1080/03075079.2022.2061450.