Higher Education Student's Self-Efficacy Beliefs During and Post Pandemic: an Explorative Learning Analytics Study

Satu Aksovaara,[1] Tommi Kärkkäinen,[2]
Minna Silvennoinen[1]

[1] Jamk University of Applied Sciences, Professional Teacher Education, Jyväskylä, Finland
satu.aksovaara@jamk.fi, minna.silvennoinen@jamk.fi
[2] Tommi Kärkkäinen, University of Jyväskylä, Faculty of Information Technology, Educational Technology and Cognitive Science, Jyväskylä, Finland
tommi.karkkainen@jyu.fi

The COVID-19 era massively accelerated digitalization of higher education and afterwards higher education institutions have partially reverted to their pre-pandemic modes of operation. In this study, we applied learning analytics to gain understanding of higher education students' experiences. We analyzed data on their self-efficacy beliefs and teamwork experiences. Data from 654 students were collected from two temporally distinct, identical courses, first at the beginning of the COVID-19 pandemic in fall 2020 and then after lockdowns ended in 2023. Our findings reveal a significant increase in self-efficacy post-pandemic, indicating that pandemic period may have influenced higher education students' self-efficacy beliefs. A moderately positive relationship between the students' self-efficacy and their self-assessed team contributions was found. These insights deepen understanding of higher education students' study experiences and support the development of evidence-based educational practices applying learning analytics. The results highlight the need for higher education institutions to consider the development of students' self-efficacy when designing collaborative learning processes, as supporting self-efficacy improves the study experience and presumably has an impact on teamwork.

Keywords:
COVID-19, higher education, self-efficacy, self-assessment, learning analytics

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.4.2024.5
ISBN 978-961-286-871-0

1 Introduction

Higher education is undergoing digital transformation, while responding to both future workforce and technological demands (Gaebel et al., 2021). Digitalized education has increasingly required students to be self-directed (Song & Hill, 2007). In 2020 the COVID-19 pandemic catalyzed a massive shift towards online learning, leaving students to navigate their educational paths in isolation. Students were forced to develop new learning strategies to succeed as their contact with teachers and peers diminished, and opportunities for interaction and feedback became less frequent (Holzer et al., 2021; Koh & Daniel, 2022). There is a paradoxical dual impact enhanced by the pandemic on the student's lives.

As the world entered the post-COVID era, educational institutions began gradually reverting to their pre-pandemic modes of operation without, however, completely returning to the old way (e.g. Zancajo et al., 2022). Indeed, studies have shown that COVID-19 changed higher education students' learning strategies to a more continuous habit, improving their efficiency (Gonzalez et al., 2020; Martin et al., 2023). The pandemic accelerated the digitalization of education significantly, which led to a decline in student well-being (Holzer et al., 2021; Schmits et al., 2021). This decrease led higher education institutions to invest into student well-being more heavily than before (Sarasjärvi et al., 2022; Van de Velde et al., 2021). Within an era of transformation, this shift in the learning paradigm necessitates research-based knowledge to understand students' experiences thoroughly, which is essential to implement meaningful, learner-centered education. There is a need for studies investigating students' resilience, changes in learning requirements, and abilities and regulation during COVID-19 and in post-pandemic era (Holzer et al., 2021; Müller et al., 2021).

The digital transformation has opened new avenues to examine learning processes and student's experiences through learning analytics, which refers to the collection, analysis, and reporting of educational data on learners and their environments to better understand and optimize learning (Long & Siemens, 2011). For example, data from student's learning paths can be used to explore study experiences during learning processes (Ifenthaler et al., 2017; Heilala et al., 2020). In recent years, learning analytics has attracted significant interest in the field of higher education, as it is expected to contribute to the development of high-quality, learner-centered education (Axelsen et al., 2020; Nunn et al., 2016; Oliva-Cordova, 2021) by informing decisions related to learning processes through insights into learners' behaviors and preferences (Jayashanka et al., 2019). However, to assess study experiences and their changes in higher education, relevant data must be collected and analyzed, for example, by gathering information on students' experiences through self-assessments (Aksovaara et al., 2024).

Study experience is an important indicator of a successful learning process, with a positive correlation with both academic achievement and learning outcomes (Elliott & Shin, 2002; Goh et al., 2017; Heilala et al., 2020). Study experience in higher education results from many factors, including individual traits (e.g., self-efficacy, competence beliefs, and motivation), relational aspects (e.g., interactions with peers and instructors), and participatory perspectives (e.g., opportunities to influence and personalize learning processes) (Goh et al., 2017; Jääskelä et al., 2021). Self-efficacy refers to individuals' beliefs in their own abilities to succeed in specific tasks or activities (Bandura, 1993) and has emerged as an important construct in research over the last 30 years. Self-efficacy is known to play a predictive and mediating role in relation to students' achievements, motivation, and learning (Parpala & Lindblom-Ylänne, 2012). Self-efficacy significantly impacts on students learning outcomes by increasing the ambitions in goal setting and positively affecting self-regulation of learning and study performance (e.g., Coutinho & Neuman, 2008; Kryshko et al., 202; Papinczak et al., 2008; Pintrich, 2003; Prat-Sala & Redford, 2010, 2).

In this study, we applied explorative learning analytics to gain understanding of higher education students' experiences. We analyzed data on students' self-efficacy beliefs and teamwork experiences. Data was collected from two identical implementations at the very beginning of the COVID-19 pandemic in fall 2020 and after educational practices had stabilized to their post-pandemic form in 2023. We consider the following research questions:

RQ1 How has the COVID-19 era affected higher education students' self-efficacy?

RQ2 How does self-efficacy relate to higher education students' self-assessed contributions on teamwork?

2 Methods and analysis

The research context was a two ECTS blended learning course, which is a mandatory course for first- and second-year undergraduates studying at a university of applied sciences (UAS). Our focus is on the collaborative phase (Phase 2; see Figure 1). This phase occurs between two asynchronous, online learning phases (Phases 1 and 3) of the course. The study was approved by the research review board of the UAS institution under study.

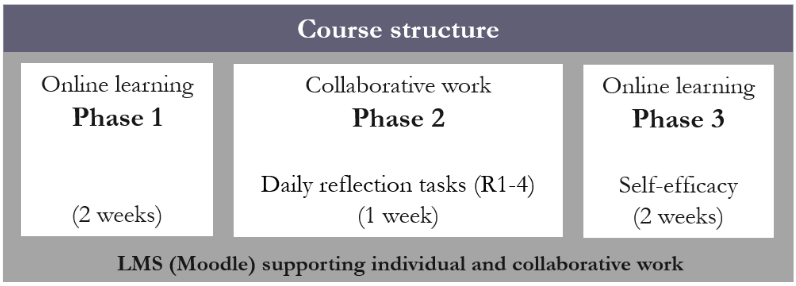

Figure 1: Course structure
Source: Own

2.1 Data collection and participants

Data collection was carried out across two identical implementations of the course. The structurally identical collaborative processes guiding self-directed teamwork and studying were built on the Moodle platform in both implementations and they included identical learning tasks and reflections. The first course implementation (A) took place in fall 2020 at the beginning of the COVID-19 pandemic, and the second (B) in 2023 after the pandemic had subsided. Participants (N = 654) represented a diverse range of educational fields, and the gender distribution among the 654 participants was nearly even, with males constituting 55% (194) and females 45% (159) implementation A. Implementation B maintained a similar balance, with males at 54% (162) and females at 46% (137). The collection of research data was seamlessly integrated into the course workflow in Moodle. During the learning tasks, the students reflected on their own actions within a team, four times during the collaborative working week, at the end of each day (see Figure 1). This enabled understanding of the daily variations of students' experiences. In addition, the students' evaluated their self-efficacy beliefs as part of the learning task within Phase 3 (see Figure 1).

2.2 Measures

The self-efficacy scale by Parpala & Lindblom-Ylänne (2012) is an effective instrument for measuring self-efficacy in higher education, whose reliability and validity have been tested. The scale consists of five statements (see Table 1), where the agreement level is measured using a five-point Likert scale (1=Fully disagree, 2=Somewhat disagree, 3=Neutral, 4=Somewhat agree and 5=Fully agree). Based on students' responses to these five statements, the mean variable for self-efficacy beliefs (SES) was calculated (Cronbach's alpha .893). The SES scores derived from this calculation represent the students' overall self-efficacy beliefs, with higher scores denoting stronger convictions in their academic abilities.

Table 1: The statements of self-efficacy beliefs and Cronbach's alpha values

Statements of self-efficacy beliefs	Cronbach's Alpha
I expect to be successful in my studies.	.863
I am confident that I can understand even the most difficult things related to my studies.	.875
I am sure that I can understand the basic concepts in my field.	.880
I believe I will succeed in my studies.	.864
I am sure I can learn the skills required for my field well.	.863

During daily learning tasks (R1-R4, see Figure 1), students reflected on their own activity and contributions within a team using two selected statements. An overall self-assessed mean variable (SAA) was calculated by combining the responses of the individual statements (SAA1 & SAA2) (see Table 2).

Table 2: Mean variables for self-assessed own activity

Variable	Statements reflecting activity and contributions	Items	Mean	Std. Dev.
SAA1	"I was an active team member."	4	4.01	0.585
SAA2	"My actions benefitted the team's work."	4	4.30	0.544
reSAA	Overall self-assessed contribution to teamwork from SAA1 & SAA2	8	4.13	0.510

3 Results

As defined by Chatti et al. (2012), data mining, social network analysis, information visualization, and statistical techniques belong to the methodological landscape of learning analytics. Here, we confine ourselves to statistical methods, more precisely to comparisons and correlation analysis, where the tests were conducted using the IBM SPSS v. 28.0 in a pseudonymized form.

Concerning RQ1, we start our investigation of the impact of the COVID-19 pandemic on students' self-efficacy beliefs by comparing the SES profiles between implementations A and B (see Table 3). The starting point is that in both instances, SES was always rated high, above four on a one-to-five scale.

Table 3: SES at the beginning of (A) and after (B) COVID-19

SES	N	Mean	Std. Dev.	Mean Rank	Sum of Ranks
A	353	4.11	.618	278.84	98,432.00
B	301	4.43	.562	384.56	115,753.00

Initial analyses confirmed the non-normal distribution of SES data, as evidenced by the Shapiro-Wilk tests (statistic = .914, df = 654, $p < .001$). Consequently, Mann-Whitney U test was used to assess the differences between the SES datasets in A and B. The results of this test were profound, showing a significant disparity in SES between A and B ($U = 35951.000$, $Z = -7.187$, $p < .001$), with the mean ranks indicating a higher SES in implementation B, as detailed in Table 5. This difference is not only statistically significant but also of medium to large practical importance (Cohen's $d = .593$), as depicted in Figure 2.

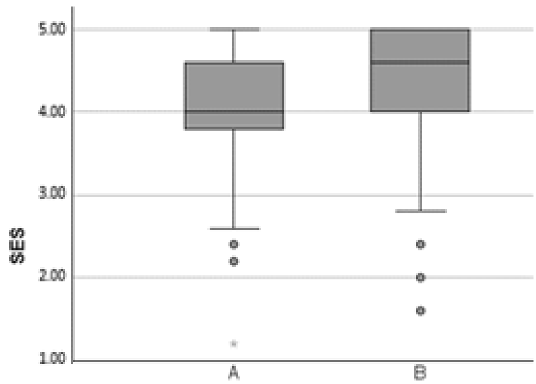

Figure 2: Boxplots of SES for instances A and B

Source: Own

In addressing RQ2, a correlation analysis was conducted. Self-efficacy SES and self-assessed own contribution SAA both demonstrate relatively even distributions around their means of 4.2560 (SD = 0.61277) and 4.1270 (SD = 0.50993). Initial analyses confirmed the non-normal distribution of both SES and SAA. Consequently, the nonparametric Spearman's rho was used in the correlation analysis, revealing a moderate positive relationship between SES and SAA ($\varrho = .444$, $p < .001$, two-tailed). It can be concluded that there is an association between SES and SAA, such that higher self-efficacy indicates higher self-assessed contribution. Nonetheless, the correlation is not so significant that the value of one variable could be predicted by the other.

When comparing early and post-pandemic measures separately, the correlation between SES and SAA was consistently positive (A: $\varrho = .465$, $p < .001$; B: $\varrho = .337$, $p < .001$), though it decreased slightly post-pandemic. The same holds true for the individual aspects of the self-assessed contribution; namely, for the Spearman's rhos between SES and SAA1/SAA2 (SAA1 in A: $\varrho = .392$, $p < .001$ and in B: $\varrho = .252$, $p < .001$; SAA2 in A: $\varrho = .451$, $p < .001$ and in B: $\varrho = .336$, $p < .001$). Again, in both cases, the moderate correlation decreases slightly in the post-pandemic case. This means that factors other than self-efficacy, whose level was found to be very high in case B, explain more of the variability of the self-assessed contribution. To this end, interesting negative correlations between the second statement (SAA2 “My actions benefitted the team's work.”) and its standard deviation (SAA2_SD) were found: in A: $\varrho = -.398$, $p < .001$ and in B: $\varrho = -.384$, $p < .001$. This means that lower variability of the self-assessed benefit was associated with the higher overall level. Again, this association was slightly stronger at the beginning of the COVID-19 period than in 2023.

4 Discussion and conclusions

In this study, learning analytics provided a data-driven exploration to understand the study experiences (see e.g. Heilala et al., 2020; Jääskelä et al., 2021; Silvola et al., 2021). The data collection was integrated into students' daily reflections of their own activity and contributions within a team enabling daily based tracking of their experiences. This data-driven approach provides opportunities for more learner-centered teaching and learning design (Cohen, 2018; Neelen & Kirschner, 2020), by enriching our understanding of students' varying experiences during collaborative, blended learning processes. Increasingly, learning analytics are being utilized to enable personalized learning and improve learning experiences with cost effective manners (Wong et al., 2023). Integrating data collection into the reflection process additionally supports the student's workflow and it has been shown how continuous reflection enables maintaining the student's activity, which is on the other hand known to improve the learning curve (Millar et al., 2021). Enabling the seamless integration and tailoring of analytics to students' varying learning processes can be identified as an area for further development.

The role of digitalization increased during COVID–19 and was a significant catalyst for changes that have profoundly impacted educational environments, even triggering a paradigm shift in how teaching and learning are organized (Gaebel et al., 2021; Holzer et al., 2021). The results of the present study offer insights into higher education students' self-efficacy at the beginning of and after the COVID-19 pandemic and the relationship between self-efficacy beliefs and student's reflections of their own activity and contributions within a team.

Even if the level of self-efficacy was high in general, it was found that the post-pandemic self-efficacy was significantly higher than it was at the beginning of the pandemic era. The results indicate that the COVID-19 era might have impacted on students' self-efficacy beliefs. Theories supporting this view may relate to the understanding that self-efficacy positively influences metacognitive learning strategies and academic performance (Hayat et al., 2020). It is known that the pandemic brought significant changes to study routines, including remote learning which necessitated more independent studying. Our results may indicate that the increased role and amount of online learning during the COVID-19 period in general has built up their confidence in relation to self-regulated learning and engagement (Gonzalez et al., 2020; Martin et al., 2023; Mou, 2023). Students might have also developed new learning strategies to succeed (Holzer et al., 2021; Koh & Daniel, 2022).

Our results also showed a moderate positive relationship between the students' self-efficacy and their self-assessed own activity and contributions in teamwork, suggesting that student's self-efficacy beliefs might offer an indicator of their abilities to contribute to team outcomes. This finding is in line with the results from studies on professional skills development through collaborative learning (including teamwork), where self-efficacy was the only significant predictor of the learning results (Yadav et al., 2021). Self-efficacy is strengthened through positive feedback and experiences of success (see Bandura 1997), which improves study experiences and the development of skills. The results are related to the students' self-efficacy having a predictive and mediating role in relation to their achievements, motivation, and learning (see, e.g., Dinther et al., 2011). Therefore, it is necessary for higher education institutions to pay more attention to the development of students' self-efficacy when designing collaborative learning processes and offer support strategies for building student's self-confidence. Supporting self-efficacy could improve the quality of teamwork and vice versa.

The COVID-19 pandemic and the era of digital transformation have prompted higher education institutions to develop peer learning solutions as student well-being has declined. Collaborative learning and studying in small groups are increasingly emphasized in both higher education and in workplace learning (Guo et al., 2020). However, collaborative learning is a complex, multidimensional phenomenon influenced by several factors. Therefore, it is beneficial to gain a deeper understanding of the interplay between the various student related elements affecting team dynamics and contributions. Future research should also continue to explore the effects of other psychological factors, e.g., motivation, on collaborative learning dynamics using larger datasets (see also Charalambous et al., 2021; Hannam University & Shin, 2018). Higher education institutions should pay more attention to creating curriculums that bolster students' well-being and academic success (van

Dinther et al., 2011). In this, the information produced by analytics about the student experience is a key constituent.

It is crucial to connect learning analytics to the reflection process so that understanding the student experience is possible dynamically and during learning processes within its varying phases. Knowledge of this up-to-date experience would also enable the provision of up-to-date guidance and targeted support to the student. A more diverse and in-depth examination of the learning experience would benefit from large datasets, from which integrated learning analytics could be used to identify factors influencing students' experiences.

References

Aksovaara, S., Määttä, S., Kärkkäinen, T., & Silvennoinen, M. (2024). Improving Learning Design Using Learning Analytics in Relation to Study Experience. Submitted for publication, Seminar.net, Special Issue for MEC 2023, In review.

Axelsen, M., Redmond, P., Heinrich, E., & Henderson, M. (2020). The evolving field of learning analytics research in higher education. Australasian Journal of Educational Technology, 36(2), 1–7. https://doi.org/10.14742/ajet.6266

Bandura, A. (1993). Perceived Self-Efficacy in Cognitive Development and Functioning. Educational Psychologist, 28(2), 117–148.

Charalambous, M., Hodge, J. A., & Ippolito, K. (2021). Statistically significant learning experiences: Towards building self-efficacy of undergraduate statistics learners through team-based learning. Educational Action Research, 29(2), 226–244. https://doi.org/10.1080/09650792.2020.1782240

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. International Journal of Technology Enhanced Learning, 4(5–6), 318–331. https://doi.org/10.1504/IJTEL.2012.051815

Cohen, J. A. (2018). Evidence based learning design – the opportunities afforded by learning analytics. Development and Learning in Organizations: An International Journal, 32(4), 10. https://doi.org/10.1108/dlo-10-2017-0084

Coutinho, S. A., & Neuman, G. (2008). A model of metacognition, achievement goal orientation, learning style and self-efficacy. Learning Environments Research, 11(2), 131–151. https://doi.org/10.1007/s10984-008-9042-7

Elliott, K. M., & Shin, D. (2002). Student Satisfaction: An alternative approach to assessing this important concept. Journal of Higher Education Policy and Management, 24(2), 197–209. https://doi.org/10.1080/1360080022000013518

Gaebel, M., Zhang, T., Stoeber, H., & Morrisroe, A. (2021). Digitally Enhanced Learning and Teaching in European Higher Education Institutions. Survey Report. European University Association.

Goh, C., Leong, C., Kasmin, K., Hii, P., & Tan, O. (2017). Students' Experiences, Learning Outcomes and Satisfaction in e-Learning. Journal of E-Learning and Knowledge Society, 13(2). https://www.learntechlib.org/p/188116/

Gonzalez, T., de la Rubia, M. A., Hincz, K. P., Comas-Lopez, M., Subirats, L., Fort, S., & Sacha, G. M. (2020). Influence of COVID-19 confinement on students' performance in higher education. PLOS ONE, 15(10), e0239490. https://doi.org/10.1371/journal.pone.0239490

Guo, P., Saab, N., Post, L. S., & Admiraal, W. (2020). A review of project-based learning in higher education: Student outcomes and measures. International Journal of Educational Research, 102, 101586. https://doi.org/10.1016/j.ijer.2020.101586

Hannam University, & Shin, M.-H. (2018). Effects of Project-based Learning on Students' Motivation and Self-efficacy. English Teaching, 73(1), 95–114. https://doi.org/10.15858/engtea.73.1.201803.95

Heilala, V., Jääskelä, P., Kärkkäinen, T., & Saarela, M. (2020). Understanding the Study Experiences of Students in Low Agency Profile: Towards a Smart Education Approach. In A. El Moussati, K. Kpalma, M. Ghaouth Belkasmi, M. Saber, & S. Guégan (Eds.), Advances in Smart Technologies Applications and Case Studies (Vol. 684, pp. 498–508). Springer International Publishing. https://doi.org/10.1007/978-3-030-53187-4_54

Holzer, J., Lüftenegger, M., Korlat, S., Pelikan, E., Salmela-Aro, K., Spiel, C., & Schober, B. (2021). Higher Education in Times of COVID-19: University Students' Basic Need Satisfaction, Self-Regulated Learning, and Well-Being. AERA Open, 7, 233285842110031. https://doi.org/10.1177/23328584211003164

Ifenthaler, Dirk, Gibson, David, & Dobozy, Eva. (2017). The synergistic and dynamic relationship between learning design and learning analytics. ASCILITE 2017, 1:5, 112–116.

Jääskelä, P., Heilala, V., Kärkkäinen, T., & Häkkinen, P. (2021). Student agency analytics: Learning analytics as a tool for analysing student agency in higher education. Behaviour & Information Technology, 40(8), 790–808. https://doi.org/10.1080/0144929X.2020.1725130

Jayashanka, R., Hewagamage, K. P., & Hettiarachchi, E. (2019). An Intelligent Interactive Visualizer to Improve Blended Learning in Higher Education. 2019 Twelfth International Conference on Ubi-Media Computing (Ubi-Media), 69–73. https://doi.org/10.1109/Ubi-Media.2019.00022

Koh, J. H. L., & Daniel, B. K. (2022). Shifting online during COVID-19: A systematic review of teaching and learning strategies and their outcomes. International Journal of Educational Technology in Higher Education, 19(1), 56. https://doi.org/10.1186/s41239-022-00361-7

Kryshko, O., Fleischer, J., Grunschel, C., & Leutner, D. (2022). Self-efficacy for motivational regulation and satisfaction with academic studies in STEM undergraduates: The mediating role of study motivation. Learning and Individual Differences, 93, 102096. https://doi.org/10.1016/j.lindif.2021.102096

Long, P., & Siemens, G. (2011). What is learning analytics. Proceedings of the 1st International Conference Learning Analytics and Knowledge, LAK, 11.

Martin, A. J., Ginns, P., & Collie, R. J. (2023). University students in COVID-19 lockdown: The role of adaptability and fluid reasoning in supporting their academic motivation and engagement. Learning and Instruction, 83, 101712. https://doi.org/10.1016/j.learninstruc.2022.101712

Millar, S.-K., Spencer, K., Stewart, T., & Dong, M. (2021). Learning Curves in COVID-19: Student Strategies in the 'new normal'? Frontiers in Education, 6, 641262. https://doi.org/10.3389/feduc.2021.641262

Mou, T.-Y. (2023). Online learning in the time of the COVID-19 crisis: Implications for the self-regulated learning of university design students. Active Learning in Higher Education, 24(2), 185–205. https://doi.org/10.1177/14697874211051226

Müller, F. H., Thomas, A. E., Carmignola, M., Dittrich, A.-K., Eckes, A., Großmann, N., Martinek, D., Wilde, M., & Bieg, S. (2021). University Students' Basic Psychological Needs, Motivation, and Vitality Before and During COVID-19: A Self-Determination Theory Approach. Frontiers in Psychology, 12. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2021.775804

Neelen, M., & Kirschner, P. A. (2020). Evidence-informed Learning Design: Creating Training to Improve Performance. KoganPage. https://books.google.fi/books?id=fyutxAEACAAJ

Nunn, S., Avella, J. T., Kanai, T., & Kebritchi, M. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. Online Learning, 20(2). https://doi.org/10.24059/olj.v20i2.790

Oliva-Cordova, L. M. (2021). Learning Analytics to Support Teaching Skills: A Systematic Literature Review. IEEE Access, 9, 58351–58363. https://doi.org/10.1109/ACCESS.2021.3070294

Papinczak, T., Young, L., Groves, M., & Haynes, M. (2008). Effects of a Metacognitive Intervention on Students' Approaches to Learning and Self-Efficacy in a First Year Medical Course. Advances in Health Sciences Education, 13(2), 213–232. https://doi.org/10.1007/s10459-006-9036-0

Parpala, A., & Lindblom-Ylänne, S. (2012). Using a research instrument for developing quality at the university. Quality in Higher Education, 18(3), 313–328. https://doi.org/10.1080/13538322.2012.733493

Pintrich, P. R. (2003). A Motivational Science Perspective on the Role of Student Motivation in Learning and Teaching Contexts. Journal of Educational Psychology, 95(4), 667–686. https://doi.org/10.1037/0022-0663.95.4.667

Prat-Sala, M., & Redford, Paul. (2010). The interplay between motivation, self-efficacy, and approaches to studying. British Journal of Educational Psychology, 80(2), 283–305. https://doi.org/10.1348/000709909X480563

Sarasjärvi, K. K., Vuolanto, P. H., Solin, P. C. M., Appelqvist-Schmidlechner, K. L., Tamminen, N. M., Elovainio, M., & Therman, S. (2022). Subjective mental well-being among higher education students in Finland during the first wave of COVID-19. Scandinavian Journal of Public Health, 50(6), 765–771. https://doi.org/10.1177/14034948221075433

Schmits, E., Dekeyser, S., Klein, O., Luminet, O., Yzerbyt, V., & Glowacz, F. (2021). Psychological Distress among Students in Higher Education: One Year after the Beginning of the COVID-19 Pandemic. International Journal of Environmental Research and Public Health, 18(14), 7445. https://doi.org/10.3390/ijerph18147445

Silvola, A., Näykki, P., Kaveri, A., & Muukkonen, H. (2021). Expectations for Supporting Student Engagement with Learning Analytics: An Academic Path Perspective. Computers & Education, 168, 104192. https://doi.org/10.1016/j.compedu.2021.104192

Song, L., & Hill, J. R. (2007). A conceptual model for understanding self-directed learning in online environments. Journal of Interactive Online Learning, 6(1), 27–42.

Van de Velde, S., Buffel, V., Bracke, P., Van Hal, G., Somogyi, N. M., Willems, B., Wouters, E., & for the C19 ISWS consortium#. (2021). The COVID-19 International Student Well-being Study. Scandinavian Journal of Public Health, 49(1), 114–122. https://doi.org/10.1177/1403494820981186

van Dinther, M., Dochy, F., & Segers, M. (2011). Factors affecting students' self-efficacy in higher education. Educational Research Review, 6(2), 95–108. https://doi.org/10.1016/j.edurev.2010.10.003

Wong, B. T., Li, K. C., & Cheung, S. K. S. (2023). An analysis of learning analytics in personalised learning. Journal of Computing in Higher Education, 35(3), 371–390. https://doi.org/10.1007/s12528-022-09324-3

Yadav, A., Mayfield, C., Moudgalya, S. K., Kussmaul, C., & Hu, H. H. (2021). Collaborative learning, self-efficacy, and student performance in cs1 pogil. 775–781.

Zancajo, A., Verger, A., & Bolea, P. (2022). Digitalization and beyond: The effects of Covid-19 on post-pandemic educational policy and delivery in Europe. Policy and Society, 41(1), 111–128. https://doi.org/10.1093/polsoc/puab016