Digital Learning Environments and Student Satisfaction: A Learning Analytics Perspective

Sarmīte Mickeviča and Signe Bāliņa
University of Latvia, Riga, Latvia

sarmite.mickevica@hotmail.com
signe.balina@lu.lv

Abstract: Higher education is increasingly characterised by heterogeneous student populations, digitally mediated learning environments, and the growing use of artificial intelligence (AI). This study examines how student complexity, digital readiness, learning-environment preferences, and perceived employability may inform the development of AI-enabled Student Relationship Management (SRM). The conceptual framework integrates relationship marketing, the Industrial Marketing and Purchasing (IMP) network perspective, the Nordic School's value co-creation logic, and learning analytics. Using EUROSTUDENT 8 data, the study combines a comparative descriptive analysis of six European higher education systems with exploratory correlation analysis across all countries for which comparable indicators are available. The findings reveal a pronounced "working student" profile among mature learners, characterised by substantial employment alongside continued academic commitments. Digital access and self-assessed professional digital skills are comparatively well-established across age groups, while high digital readiness shows no meaningful association with high perceived employability. Most importantly, greater online-learning intensity does not automatically produce stronger alignment with student preferences. Higher employment intensity is associated with stronger preferences for online learning, yet some mature student groups experience more online provision than they would ideally prefer. The findings therefore highlight a critical distinction between digitalisation and flexibility. AI-enabled SRM may contribute by supporting adaptive alignment between institutional delivery models, student circumstances, and differentiated support needs rather than by increasing digital intensity alone. The study contributes to educational technology and relationship-management literature by demonstrating that the strategic necessity of AI-enabled SRM arises primarily from growing student complexity and institutional adaptability challenges rather than from deficiencies in baseline digital readiness.

Keywords: Learning Analytics; Digital Learning Environments; Higher Education; Student Relationship Management; Digital Readiness; Student Heterogeneity

1. Introduction

Higher education is increasingly transforming from institution-centred systems into interconnected, data-driven digital ecosystems (Benavides et al., 2020). Within these ecosystems, AI applications are expanding across areas including prediction, assessment and evaluation, personalised support, intelligent tutoring, and student-learning management (Crompton & Burke, 2023; Bond et al., 2024). From a relationship-marketing and network perspective, universities no longer operate as isolated educational providers, but as actors embedded within complex value co-creation systems involving students, employers, digital platforms, and institutional stakeholders. Within a public service logic framework, higher education institutions function primarily as value facilitators, providing structural and digital resources that students, as active value creators, integrate into their everyday practices to generate value-in-use (Grönroos, 2019).

At the macro level, higher education ecosystems are becoming increasingly heterogeneous due to shifting student demographics, including the growing participation of non-traditional, working, and lifelong learners, as well as increasing international mobility (OECD, 2019; Hauschildt, Vögtle & Gwosć, 2018; Hauschildt, 2024). At the same time, digital transformation has expanded the use of online learning environments, digital administration, and learning analytics (Benavides et al., 2020; Darvishi et al., 2024; Gašević et al., 2022). Together, these developments challenge traditional "one-size-fits-all" approaches and increase the need for flexible, personalised, and data-driven student support and institutional management.

Recent systematic reviews show that AI research in higher education remains largely organised around specific applications, including learning, teaching, assessment, administration, profiling, prediction, adaptive systems and personalisation (Chiu et al., 2023; Crompton & Burke, 2023; Bond et al., 2024). Existing AI research frequently focuses on profiling, automation, and dropout prediction (Zawacki-Richter et al., 2019), while comparatively less attention has been devoted to how student heterogeneity, digital readiness, learning-environment preferences, and employability perceptions can inform the development of AI-enabled SRM from a networked ecosystem perspective. Chiu et al. (2023) specifically call for a more holistic perspective on the role of AI in education, while recent evidence also indicates comparatively limited attention to administrative and institutional applications of AI in higher education (Crompton & Burke, 2023; Bond et al., 2024). Taken together

with the SRM literature (Gholami et al., 2018; Rigo et al., 2016), this suggests an underdeveloped connection between AI-enabled capabilities and broader SRM perspectives.

This study aims to examine patterns of student heterogeneity, digital readiness, learning-environment preferences, and perceived employability across European higher education systems and to explore their implications for the development of adaptive AI-enabled SRM. Drawing on comparative EUROSTUDENT 8 data and integrating relationship-marketing theory, ecosystem perspectives, and learning analytics, the study contributes to the understanding the strategic role of AI-enabled SRM in digitally transformed higher education institutions.

2. Theoretical Foundation

2.1 Relationship Marketing and Value Co-creation

Relationship marketing theory provides a theoretical foundation for understanding how universities manage interactions with students and other stakeholders. The Nordic School and the Industrial Marketing and Purchasing (IMP) Group are particularly relevant for analysing relationship management within higher education ecosystems.

The Nordic School emphasises interaction and value co-creation as central to long-term relationships. Within public service logic, organisations act primarily as value facilitators, while beneficiaries create value-in-use by integrating available resources into their own contexts (Grönroos, 2019; Gummesson, 2008; Payne & Frow, 2017). When applied to higher education, this framework positions students as active value creators rather than passive recipients, integrating institutional resources into their learning and work-life circumstances. From this perspective, AI-enabled SRM may support value co-creation by helping institutions align communication, services, and support with heterogeneous student profiles and constraints.

2.2 Higher Education as a Networked Ecosystem

Complementing the Nordic School perspective, the IMP Group conceptualises organisations as actors embedded within complex relationship networks rather than isolated entities (Håkansson & Snehota, 2006). Value creation therefore occurs within interconnected systems involving multiple stakeholders.

This network perspective can be extended through the concept of ecosystems, where interactions are structured across interdependent actors, technologies, and institutional processes. Universities increasingly operate within digitally enabled ecosystems involving students, employers, government institutions, and technology providers, reflecting the broader digital transformation of higher education (Benavides et al., 2020).

Following Adner (2017), ecosystems consist of interrelated actors, activities, positions, and links that collectively create value. Within higher education, these include teaching, learning, recruitment, support services, and institutional coordination processes. In this structure, students occupy a dual role as both customers and co-creators of educational value and knowledge.

AI functions within this ecosystem as an integrating mechanism capable of strengthening coordination, interaction, and data exchange across institutional networks. Consequently, AI-enabled SRM can be understood not merely as a technological tool, but as a relationship-management mechanism operating across interconnected higher education ecosystems.

2.3 Learning Analytics and the Evolution from CRM to AI-Enabled SRM

Learning analytics concerns the measurement, collection, analysis, and reporting of data about learners and their contexts to understand and optimise learning and learning environments (Siemens, 2012). In higher education, learning analytics has developed from descriptive indicators and dashboards towards prediction, intervention, personalised feedback, and institutional decision support (Gašević et al., 2022). Importantly, learning analytics models and insights are highly context-sensitive, reinforcing the need to move beyond “one-size-fits-all” approaches (Gašević et al., 2016).

Learning analytics and AI are also sociotechnical rather than neutral systems. Their design and implementation may create risks related to surveillance, reductionism, power asymmetries, and limited transparency if appropriate safeguards are absent (Buckingham Shum & Luckin, 2019; Mouta et al., 2024; Selwyn, 2019).

Nevertheless, learning analytics can provide an analytical foundation for AI-enabled SRM by identifying patterns relevant to student engagement, support needs, and institutional decision-making.

The evolution from Customer Relationship Management (CRM) towards Student Relationship Management (SRM) reflects a transition from transactional administration to student-centred relationship management. While higher education CRM has often focused on administrative functions (Rigo et al., 2016), SRM emphasises engagement, support, and long-term relationships (Gholami et al., 2018). AI may extend these capabilities through prediction, personalised support, AI-assisted interaction, and adaptive systems. Recent reviews identify prediction, AI assistants, intelligent tutoring, assessment, student-learning management, and personalisation among major AI applications in higher education (Crompton & Burke, 2023; Bond et al., 2024).

Building on these theoretical perspectives, this study conceptualises AI-enabled SRM as an integrated ecosystem capability comprising three interconnected components: strategic, operational, and analytical.

- The **strategic component** concerns adaptive value co-creation and institutional responsiveness to heterogeneous student needs. Drawing on the Nordic School and IMP Group perspectives, it focuses on aligning institutional resources, study pathways, and support with differentiated student profiles and circumstances (Grönroos, 2019; Håkansson & Snehota, 2006).
- The **operational component** concerns digitally mediated interaction and service delivery. AI-enabled SRM may extend beyond administrative automation through AI-assisted communication, personalised interaction, and adaptive student-support services (Rigo et al., 2016; Gholami et al., 2018; Crompton & Burke, 2023).
- The **analytical component** concerns learning analytics, prediction, and proactive support. It enables the identification of patterns related to engagement, academic risk, and potential dropout, supporting earlier institutional intervention and data-informed decision-making (Siemens, 2012; Gašević et al., 2022; Bond et al., 2024).

Overall, AI-enabled SRM can be conceptualised as a strategic ecosystem capability integrating relationships, institutional processes, data, and technology to support more adaptive, discipline-sensitive, and student-centred higher education management (Gholami et al., 2020). Within this framework, digitalisation functions not merely as a technological instrument, but as a strategic capability enabling institutional flexibility, responsiveness, and competitiveness within increasingly globalised and heterogeneous higher education ecosystems.

3. Methodology

3.1 Research Design and Data Source

This study employs a non-experimental comparative quantitative design based on secondary EUROSTUDENT 8 data (2021–2024), combining descriptive comparison and exploratory correlation analysis. It does not evaluate the implementation or effectiveness of an active AI-enabled SRM system. Instead, it examines patterns of student heterogeneity, digital readiness, time constraints, learning-environment preferences, and perceived employability that may inform the development of adaptive student-support models. The analysis is informed by a learning analytics perspective and draws on the EUROSTUDENT modules “Digitalisation”, “Time Budget”, “Assessment of Studies and Performance”, and “Equipment at Home”.

The exploratory correlation analysis uses all EUROSTUDENT 8 countries for which comparable indicators are available, examining aggregated macro-level associations rather than individual-level relationships. This broader analytical scope captures substantial cross-national variation in student characteristics and study conditions. The approach is consistent with learning analytics research emphasising the importance of context in which learning and technology use occur (Gašević et al., 2016). For detailed descriptive comparison and visualisation, six higher education systems were selected as an illustrative subset: Estonia (EE), Finland (FI), Lithuania (LT), Latvia (LV), the Netherlands (NL), and Poland (PL). This subset is used for contextual interpretation rather than statistical generalisation.

3.2 Analytical Framework and Selected Variables

The selected indicators are interpreted in relation to the three AI-enabled SRM dimensions developed in Section 2: operational, analytical, and strategic. These are not treated as directly measured constructs. The operational dimension is reflected in digital-service provision and alignment between actual and preferred study modes; the analytical dimension in student heterogeneity, time allocation, digital readiness, and perceived employability;

and the strategic dimension in the interpretation of these patterns in relation to potential adaptive institutional responses.

The empirical analysis is organised around four domains.

- **Student Complexity**. Age groups, fields of study based on ISCED-F 2013 classifications (UNESCO Institute for Statistics, 2015), and time allocation between taught studies, personal study, and paid employment.
- **Digital Readiness**. Self-assessed professional digital skills and access to essential digital infrastructure, including a computer and reliable internet connection.
- **Learning Environment Alignment**. Comparison between actual and preferred online and in-person study modes and satisfaction with digitally available services.
- **Perceived Employability.** Self-assessed preparedness for national and international labour markets, interpreted as perceived labour-market readiness rather than an objective employment outcome.

3.3 Data Analysis Procedures

Data were analysed using descriptive statistics, comparative analysis, and exploratory correlations.

- **Descriptive and Visual Analysis.** Cross-country comparisons and visualisations focus on the six-country subset. Student time budgets across age groups were presented using stacked bar charts. Learning-environment alignment was assessed by comparing reported actual and preferred online and in-person study modes, with differences interpreted as indicators of alignment or mismatch. Scatter plots were used to visualise these relationships.
- **Correlation Analysis.** Pearson correlations were calculated across aggregated country-by-age-group observations for all countries with comparable data. The analysis yielded $N = 92$ observations for time-budget, study-preference, and digital-readiness analyses ($df = 90$), and $N = 88$ for digital-readiness and employability analyses ($df = 86$). Fisher's r-to-z transformation was used to calculate 95% confidence intervals (CI). Given the aggregated structure of the data, correlations are interpreted as exploratory macro-level associations and do not imply causal or individual-level relationships.

4. Results and Comparative Analysis

4.1 Student Complexity and the 'Working Student' Model

EUROSTUDENT 8 data reveal substantial heterogeneity in students' time allocation between taught studies, personal study, and paid employment. Across the six-country subset, employment intensity increases considerably with age. In LV, students aged under 22 spend approximately 14 hours per week in paid employment, compared with approximately 23 hours among older age groups. Mature students (30+) in LV and PL spend 31.9 and 35.9 hours per week in paid employment, respectively, while maintaining substantial study commitments. In contrast, FI shows lower employment intensity among mature students (21.4 hours per week).

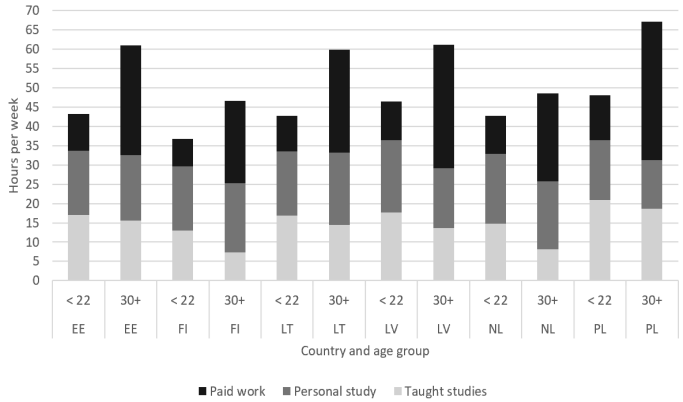


Figure 1: Weekly time-budget distribution of younger (<22) and mature (30+) students across the six-country comparative subset.

Figure 1 shows that mature students combine substantially higher employment intensity with continued academic commitments. In several systems, their combined weekly workload exceeds 57 hours. Differences by

field of study further contribute to student heterogeneity, with Medicine and Dental Studies showing particularly high study-time intensity and ICT students exhibiting comparatively high employment participation. These patterns indicate a pronounced "working student" profile among mature learners and highlight substantial variation in student time constraints.

4.2 Student Digital Readiness and Digital Capital

EUROSTUDENT 8 indicates a generally high baseline of digital capital across participating higher education systems. Cross-country mean values are high for self-assessed professional digital skills (4.3), access to computers (4.8), desks (4.6), sufficient internet connections (4.5), and quiet places to study (4.1) (Schirmer, 2024). Although country-level variation remains, these results indicate that most student populations have broadly favourable access to the skills and resources required for digitally enabled study.

Within the six-country subset, 59.7% of students aged under 22 (*SD* = 0.039) and 57.0% of students aged 30+ (*SD* = 0.027) assess their professional digital skills as "completely sufficient". In LV, the corresponding share is 58.6%, compared with 66.9% in EE and 64.7% in NL. These patterns are consistent with arguments that traditional assumptions concerning a generational digital divide and the technological superiority of so-called "digital natives" may be becoming less applicable in contemporary higher education contexts (Janschitz & Penker, 2022).

The exploratory correlation analysis across all available EUROSTUDENT 8 country-by-age-group observations indicates generally weak associations between student time allocation and self-assessed professional digital skills ($N = 92$, $df = 90$). The share of students reporting their digital skills as "completely sufficient" shows a weak negative association with time spent in taught studies ($r = -.142$, $p = .178$, 95% CI [-.337, .065]), a negligible positive association with personal study time ($r = .101$, $p = .337$, 95% CI [-.106, .300]), and a weak positive association with paid employment ($r = .250$, $p = .016$, 95% CI [.048, .433]). Similarly, the share reporting their digital skills as "not sufficient at all" is weakly associated with taught studies ($r = .048$, $p = .648$, 95% CI [-.158, .251]), personal study time ($r = -.224$, $p = .032$, 95% CI [-.410, -.020]), and paid employment ($r = -.035$, $p = .740$, 95% CI [-.238, .171]). By contrast, paid employment is moderately negatively associated with personal study time ($r = -.525$, $p < .001$, 95% CI [-.659, -.358]), indicating that increasing employment intensity is more clearly associated with time-allocation pressure than with lower perceived digital readiness. Overall, the results suggest that workload intensity and self-assessed digital readiness represent relatively distinct dimensions of student experience.

4.3 Learning Environment Alignment and Institutional Digital Provision

Actual and preferred online and in-person study modes vary substantially across countries and age groups. LV and FI are among the more online-oriented systems in the six-country subset, but greater online intensity does not necessarily correspond to stronger alignment with student preferences.

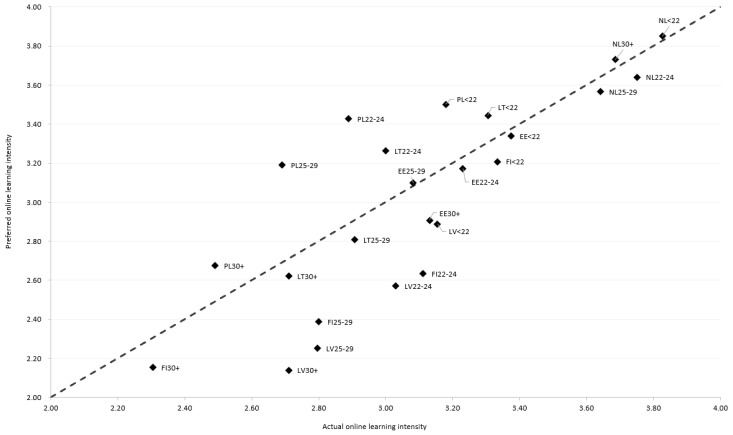


Figure 2: Alignment between actual and preferred online and in-person study modes across countries and age groups. The five-point scale ranges from predominantly online learning (1) to predominantly in-person learning (5). Points below the diagonal indicate more online learning than preferred; points above indicate a preference for more online learning than currently experienced.

Figure 2 shows that younger age groups generally lie closer to the alignment line, while several mature groups, particularly in LV and FI, display greater mismatches. Some mature groups therefore experience more online learning than they would ideally prefer.

Employment intensity is also associated with learning-environment preferences. Across country-by-age-group observations (N = 92), paid employment shows a strong positive association with a preference for completely online learning (r = .677, p < .001, 95% CI [.548, .774]) and a moderate negative association with a preference for predominantly in-person study (r = -.466, p < .001, 95% CI [-.612, -.289]). Thus, higher employment intensity is associated with stronger demand for online flexibility, while the alignment analysis shows that more online provision does not necessarily produce better alignment.

A second analytical component concerns students' satisfaction with the digital availability of institutional services. Descriptive results indicate substantial variation across service categories. Within the six-country comparative subset, satisfaction with the digital availability of online examinations is particularly high in LV (79%), with similarly high levels observed in EE and LT. Descriptively, however, satisfaction appears to vary considerably across different types of digitally available services, with counselling receiving comparatively lower positive evaluations than several transactional services.

4.4 Student Digital Readiness and Perceived Employability

Perceived labour-market preparedness varies across the six-country subset: NL shows comparatively high international preparedness, EE exhibits stronger national preparedness, while LV and LT report more moderate international preparedness. The exploratory correlation analysis (N = 88, df = 86) shows no meaningful association between "completely sufficient" self-assessed digital skills and high perceived employability. Associations are non-significant for both national (r = .034, p = .751, 95% CI [-.176, .242]) and international labour markets (r = -.080, p = .459, 95% CI [-.285, .132]). These findings indicate that high self-assessed digital readiness is not systematically associated with high perceived labour-market preparedness at the aggregated country-by-age-group level.

5. Discussion

The findings of this study indicate that the student experience in digitally enabled higher education cannot be interpreted independently of broader patterns of employment, time allocation, and study behaviour. The six-country comparison reveals a pronounced "working student" profile among mature learners, particularly in LV and PL, where substantial paid employment is combined with continued academic commitments. This pattern reinforces the limitations of uniform student-support models and is consistent with learning analytics research arguing that educational interventions should remain sensitive to contextual and learner heterogeneity rather than relying on "one-size-fits-all" approaches (Gašević et al., 2016).

Importantly, the findings suggest that flexibility and digitalisation should not be treated as synonymous concepts. Greater digital delivery does not automatically translate into stronger alignment with student preferences. Although working students demonstrate stronger preferences for online-oriented and flexible learning arrangements, mature student groups in several ecosystems – particularly LV and FI – also exhibit signs of potential digital overprovision, where actual online-learning intensity exceeds preferred levels. This indicates that effective digital transformation depends not on maximising online delivery itself, but on maintaining alignment between institutional delivery models and heterogeneous student preferences.

The findings further suggest that this alignment challenge cannot be explained simply by insufficient student digital readiness. Basic digital access and self-assessed professional digital skills are comparatively well-established across the analysed systems and age groups, consistent with the broader concept of digital capital as a combination of skills, access, and resources enabling participation in digitally mediated environments (Ragnedda et al., 2020). Moreover, high self-assessed digital readiness shows no meaningful association with high perceived labour-market preparedness. Digital competence may therefore be interpreted primarily as an enabling condition for participation in digitally transformed higher education rather than as a sufficient explanation of differences in student experience or perceived employability.

From an AI-enabled SRM perspective, these findings shift the strategic emphasis from increasing digital intensity towards adaptive alignment. The potential value of AI-enabled SRM lies not primarily in expanding the volume of digital interaction, but in helping institutions identify heterogeneous student profiles, recognise differing time constraints and learning preferences, and adjust communication and support accordingly. In this sense, AI-

enabled SRM may provide a mechanism for translating digitalisation into flexibility rather than treating the two as equivalent. Strategically, it may support alignment between institutional delivery models and differentiated student needs; operationally, AI-assisted communication and advising may extend the availability and responsiveness of support; analytically, learning analytics may help identify patterns requiring institutional attention. However, the present study does not evaluate the effectiveness of these AI-enabled mechanisms themselves. Rather, it identifies contextual conditions that may inform their future design and empirical validation.

At the same time, adaptive support should not be equated with automated decision-making. Learning analytics and AI systems are not neutral infrastructures; their design and implementation may embed institutional assumptions, reinforce existing inequalities, or reduce complex student experiences to simplified predictive categories (Buckingham Shum & Luckin, 2019; Mouta et al., 2024). Recent evidence also suggests that AI-supported performance does not necessarily translate into equivalent independent performance once assistance is removed, highlighting the importance of preserving learner agency and human judgement (Darvishi et al., 2024). AI-enabled SRM should therefore be implemented as a support mechanism rather than a deterministic management system, supported by clear governance concerning data privacy, transparency, accountability, equity, and ongoing evaluation.

Taken together, the findings suggest that the strategic challenge of digital transformation in higher education is shifting from basic technological access towards institutional adaptability. The key issue is not simply whether higher education becomes more digital, but whether digital provision remains aligned with heterogeneous student needs and circumstances. The distinction between digitalisation and flexibility is therefore central: greater digital intensity does not automatically produce better alignment with student preferences, whereas adaptive institutional capacity may be more important than technological intensity itself. Within this context, AI-enabled SRM represents a potential strategic mechanism for supporting more responsive and student-centred higher education while preserving meaningful student choice, agency, and human oversight.

6. Conclusions

This study empirically examined student and learning-environment conditions that may inform the future development of AI-enabled SRM by analysing student complexity, digital readiness, learning-environment preferences, and perceived employability. By integrating a learning analytics perspective with the IMP Group network perspective and the Nordic School's value co-creation logic, the study demonstrates the limitations of uniform "one-size-fits-all" approaches within increasingly heterogeneous higher education environments.

First, the findings reveal that student complexity is increasingly shaped by the emergence of the "working student" model. Mature students frequently combine substantial employment commitments with ongoing academic workloads, creating significant time-pressure conditions that increase the demand for flexible and online-oriented study arrangements. These patterns reinforce the need for student-support models that are responsive to heterogeneous life circumstances rather than relying on traditional full-time student assumptions.

Second, the analysis indicates that basic digital access and self-assessed professional digital skills are comparatively well-established across the analysed systems and age groups. High digital readiness is not systematically associated with high perceived labour-market preparedness, suggesting that digital competence functions primarily as an enabling condition for participation in digitally transformed higher education rather than as a sufficient explanation of differences in perceived employability.

Third, and most importantly, the findings demonstrate that digitalisation and flexibility should not be treated as synonymous concepts. Greater online-learning intensity does not automatically produce stronger alignment with student preferences. While higher employment intensity is associated with a stronger preference for online learning, some mature student groups already experience more online provision than they would ideally prefer. Effective flexibility therefore depends on the alignment between institutional delivery models and heterogeneous student needs rather than on maximising digital delivery itself.

From an AI-enabled SRM perspective, these findings suggest that the strategic value of AI may lie less in increasing digital intensity or administrative automation and more in supporting adaptive alignment. AI-enabled SRM may help institutions identify differentiated student profiles, recognise varying time constraints and learning preferences, and provide more responsive communication, advising, and support. However, the present study does not evaluate the effectiveness of such AI-enabled mechanisms and therefore treats them as potential institutional capabilities requiring further empirical validation.

Given that the study relies on aggregated cross-country and country-by-age-group indicators, it does not establish causal or individual-level relationships. Future research should therefore validate the proposed AI-enabled SRM framework using micro-level institutional data and student-level studies, with particular attention to adaptive support, student engagement, perceived employability, transparency, student agency, and the effectiveness of AI-enabled interventions.

Ethics Declaration

This study is based on secondary analysis of aggregated, anonymised, and publicly available data obtained from the EUROSTUDENT 8 database. The research did not involve direct interaction with human participants, primary data collection, or the processing of identifiable personal information. Consequently, formal approval from an institutional ethics committee was not required.

AI Declaration

During the preparation of this paper, AI tools (large language models) were used to support language refinement, academic proofreading, and technical clarification of selected data-processing procedures using Microsoft Excel. These tools were not used for autonomous data analysis, interpretation of findings, or the generation of scientific conclusions.

All conceptual development, empirical interpretation, analytical reasoning, and final conclusions represent the original work and responsibility of the authors.

References

Adner, R. (2017) 'Ecosystem as structure: An actionable construct for strategy', *Journal of Management*, 43(1), pp. 39–58. Available at: https://doi.org/10.1177/0149206316678451.

Benavides, L.M.C., Arias, J.A.T., Serna, M.D.A., Bedoya, J.W.B. and Burgos, D. (2020) 'Digital transformation in higher education institutions: A systematic literature review', *Sensors*, 20(11), p. 3291. Available at: https://doi.org/10.3390/s20113291.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S.W. and Siemens, G. (2024) 'A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour', *International Journal of Educational Technology in Higher Education*, 21, p. 4. Available at: https://doi.org/10.1186/s41239-023-00436-z.

Buckingham Shum, S.J. and Luckin, R. (2019) 'Learning analytics and AI: Politics, pedagogy and practices', *British Journal of Educational Technology*, 50(6), pp. 2785–2793. Available at: https://doi.org/10.1111/bjet.12880.

Chiu, T.K.F., Xia, Q., Zhou, X., Chai, C.S. and Cheng, M. (2023) 'Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education', *Computers and Education: Artificial Intelligence*, 4, p. 100118. Available at: https://doi.org/10.1016/j.caeai.2022.100118.

Crompton, H. and Burke, D. (2023) 'Artificial intelligence in higher education: The state of the field', *International Journal of Educational Technology in Higher Education*, 20, p. 22. Available at: https://doi.org/10.1186/s41239-023-00392-8.

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D. and Siemens, G. (2024) 'Impact of AI assistance on student agency', *Computers & Education*, 210, p. 104967. Available at: https://doi.org/10.1016/j.compedu.2023.104967.

Gašević, D., Dawson, S., Rogers, T. and Gasevic, D. (2016) 'Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success', *The Internet and Higher Education*, 28, pp. 68–84. Available at: https://doi.org/10.1016/j.iheduc.2015.10.002.

Gašević, D., Tsai, Y.-S. and Drachsler, H. (2022) 'Learning analytics in higher education – Stakeholders, strategy and scale', *The Internet and Higher Education*, 52, p. 100833. Available at: https://doi.org/10.1016/j.iheduc.2021.100833.

Gašević, D., Siemens, G. and Sadiq, S. (2023) 'Empowering learners for the age of artificial intelligence', *Computers and Education: Artificial Intelligence*, 4, p. 100130. Available at: https://doi.org/10.1016/j.caeai.2023.100130.

Gholami, H., Saman, M.Z.M., Mardani, A., Streimikiene, D., Sharif, S. and Zakuan, N. (2018) 'Proposed analytic framework for student relationship management based on a systematic review of CRM systems literature', *Sustainability*, 10(4), p. 1237. Available at: https://doi.org/10.3390/su10041237.

Gholami, H., Zakuan, N., Saman, M.Z.M., Sharif, S. and Kohar, U.H.A. (2020) 'Conceptualizing and operationalizing the student relationship management strategy: Towards a more sustainable-based platform', *Journal of Cleaner Production*, 244, p. 118707. Available at: https://doi.org/10.1016/j.jclepro.2019.118707.

Grönroos, C. (2019) 'Reforming public services: Does service logic have anything to offer?', *Public Management Review*, 21(5), pp. 775–788. Available at: https://doi.org/10.1080/14719037.2018.1529879.

Gummesson, E. (2008) *Total relationship marketing*. 3rd edn. Oxford: Butterworth-Heinemann.

Hauschildt, K., Vögtle, E.M. and Gwosć, C. (2018) *EUROSTUDENT VI overview and selected findings: Social and economic conditions of student life in Europe*. Bielefeld: W. Bertelsmann Verlag. Available at: https://doi.org/10.3278/104-274w.

Hauschildt, K. (ed.) (2024) *Social and economic conditions of student life in Europe: EUROSTUDENT 8 Synopsis of indicators 2021–2024*. Bielefeld: wbv Publikation. Available at: https://doi.org/10.3278/6001920ew.

Håkansson, H. and Snehota, I. (2006) 'No business is an island: The network concept of business strategy', *Scandinavian Journal of Management*, 22(3), pp. 256–270. Available at: https://doi.org/10.1016/j.scaman.2006.10.005.

Janschitz, G. and Penker, M. (2022) 'How digital are "digital natives" actually? Developing an instrument to measure the degree of digitalisation of university students – the DDS-Index', *Bulletin of Sociological Methodology/Bulletin de Méthodologie Sociologique*, 153(1), pp. 127–159. Available at: https://doi.org/10.1177/07591063211061760.

Mouta, A., Pinto-Llorente, A.M. and Torrecilla-Sánchez, E.M. (2024) 'Uncovering blind spots in education ethics: Insights from a systematic literature review on artificial intelligence in education', *International Journal of Artificial Intelligence in Education*, 34, pp. 1166–1205. Available at: https://doi.org/10.1007/s40593-023-00384-9.

OECD (2019) *Benchmarking higher education system performance*. Paris: OECD Publishing. Available at: https://doi.org/10.1787/be5514d7-en.

Payne, A. and Frow, P. (2017) 'Relationship marketing: Looking backwards towards the future', *Journal of Services Marketing*, 31(1), pp. 11–15. Available at: https://doi.org/10.1108/JSM-11-2016-0380.

Ragnedda, M., Ruiu, M.L. and Addeo, F. (2020) 'Measuring digital capital: An empirical investigation', *New Media & Society*, 22(5), pp. 793–816. Available at: https://doi.org/10.1177/1461444819869604.

Rigo, G.-E., Pedron, C.D., Caldeira, M. and Araújo, C.C.S. (2016) 'CRM adoption in a higher education institution', *Journal of Information Systems and Technology Management*, 13(1), pp. 45–60. Available at: https://doi.org/10.4301/S1807-17752016000100003.

Schirmer, H. (2024) *Digitalisation of teaching, learning, and student life*. EUROSTUDENT 8 Topical Module Report. Hannover: Deutsches Zentrum für Hochschul- und Wissenschaftsforschung (DZHW).

Selwyn, N. (2019) 'What's the problem with learning analytics?', *Journal of Learning Analytics*, 6(3), pp. 11–19. Available at: https://doi.org/10.18608/jla.2019.63.3.

Siemens, G. (2012) 'Learning analytics: Envisioning a research discipline and a domain of practice', in *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*. New York: ACM, pp. 4–8. Available at: https://doi.org/10.1145/2330601.2330605.

UNESCO Institute for Statistics (2015) *International standard classification of education: Fields of education and training 2013 (ISCED-F 2013)*. Montreal: UNESCO Institute for Statistics.

Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019) 'Systematic review of research on artificial intelligence applications in higher education – where are the educators?', *International Journal of Educational Technology in Higher Education*, 16(1), p. 39. Available at: https://doi.org/10.1186/s41239-019-0171-0.