Rethinking Student Support in Education 5.0: Emerging Technologies and Computational Thinking as Forces for Transformation

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Abstract

Student support in higher education has evolved from primarily face-to-face academic assistance to more structured models that integrate technology and computational thinking (CT). This study examined how emerging Education 5.0 dynamics shaped student support programs at Latin American higher education institutions between 2020 and 2024. We used a qualitative, comparative longitudinal approach and a multiple-case design to analyze institutional characteristics and strategies at the onset of the COVID-19 pandemic and in 2024. The findings indicate a shift from reactive support toward more proactive, technology-enabled approaches that aim to identify student needs, offer tailored guidance, and promote well-being. They also highlight five challenges: integrating technology into support programs; establishing effective processes for identifying and responding to students' risk factors and needs; strengthening institutional capacity to provide personalized support; ensuring equitable and inclusive access across complex contexts; and examining the social effects of these programs through frameworks that connect technology, well-being, and equity. The study offers insights for decision-makers, university administrators, researchers, and student support professionals seeking to develop more inclusive and effective support models.

Keywords: Computational thinking; student support; emerging technologies; educational innovation.

INTRODUCTION

Integrating emerging technologies associated with Education 5.0 into higher education student support systems requires a strategic balance between innovation and a human-centered approach. This integration is changing how institutions support students through more personalized, proactive, and well-being-focused services. The COVID-19 pandemic

accelerated this shift, as universities rapidly moved from in-person instruction to virtual learning environments (Rashid & Yadav, 2020). This transition demonstrated how digital tools and e-learning platforms could sustain teaching and support services, while also exposing substantial inequalities in access to technology (Alex, 2022). In a period marked by uncertainty and isolation, institutions had to reconsider how to protect students' emotional and psychological well-being while helping them continue their studies under difficult conditions.

During this period, technology-enabled student support became an important way to address the academic, emotional, and social challenges created by the crisis. These services helped students overcome obstacles and continue their studies while strengthening resilience and autonomy. Faculty members, counselors, and educational leaders also had to adapt quickly, finding ways to sustain student engagement, motivation, and well-being. This response highlighted the value of flexible, responsive, and student-centered support, including timely counseling when needed (Harris, 2020). Institutions also began adopting technologies that now feature in discussions of Education 5.0, including artificial intelligence for personalized learning, big data analysis to identify performance patterns, machine-learning tutoring systems, augmented and virtual reality, and the Internet of Things (IoT) for connected learning environments (Ahmad et al., 2023). These technologies can be designed around computational thinking principles, such as decomposing problems, identifying patterns, and developing procedures for intervention. Computational thinking is therefore relevant both as a student competency and as a framework for designing structured, adaptive institutional support.

Although early implementations were limited, technologies adopted during the pandemic helped higher education institutions respond to rapidly changing conditions. They also informed support strategies that were more responsive to students' varied circumstances (Raaper & Brown, 2020). Initial responses created a basis for more systematic approaches to student support. Computational thinking can help institutions organize complex support needs by identifying patterns, designing adaptive responses, and developing technologies that improve the university experience. Educational tools that strengthen self-regulation, socioemotional skills, and resilience offer one example (Flores et al., 2022). Together, these developments have created new ways to connect the academic, emotional, and social dimensions of student support through more personalized and proactive interactions.

This study examines how emerging Education 5.0 dynamics shaped student support programs at Latin American higher education institutions between 2020 and 2024. The article has four sections. The first introduces the research problem and reviews three themes: the development of student support, its complexity and connection to structured methods, and computational thinking as a framework for designing support tools. The second section explains the methodology, and the third presents the findings. The final section discusses the results and their theoretical and practical implications, then presents the conclusions, limitations, and directions for future research. The study considers how Education 5.0 innovations affected higher education during this period and how computational thinking can help organize complex support needs and inform more adaptive, data-informed approaches.

THEORETICAL FRAMEWORK

1.1. An evolving view of student support

Student support has developed from a largely corrective service for academic difficulties into a more structured and preventive part of students' academic and personal development. This shift reflects a broader understanding of university life and the need to address academic, psychosocial, cultural, and career-related needs. Kaur (2016) argues that student support services are more effective when integrated into an institution's structure rather than treated as a marginal resource. Cronin et al. (2021) report that students may avoid seeking help when services seem culturally inaccessible or poorly suited to their needs. Schwallie-Giddis et al. (2004) likewise emphasize the importance of culturally responsive support that recognizes students' diverse backgrounds and experiences. These perspectives position student support as an institutional strategy for promoting well-being, persistence, and academic success.

Before the pandemic, student support in higher education was already changing in response to technological and social developments. The year 2020 marked a turning point: institutions rapidly expanded and adapted services to meet new educational needs. Online learning platforms and learning-management systems helped maintain academic continuity, monitor performance, and provide support remotely. Asbahr et al. (2024) describe how these efforts contributed to a more inclusive understanding of university resilience during the crisis. Digital systems also created opportunities to identify risk behaviors, understood here as behaviors associated with a greater likelihood of adverse outcomes for students' health or well-being, including absenteeism, poor academic performance, and mental-health difficulties (Campbell et al., 2020). Early identification can help institutions respond before difficulties disrupt students' academic progress (Wanke et al., 2020). Artificial intelligence and learning-management systems can support the analysis of behavioral and academic patterns, although their use requires appropriate safeguards (Al-Sulami et al., 2023). Together, these developments have encouraged more structured support models that use analytical methods, including computational thinking, to identify needs and tailor interventions.

Student support has increasingly become a focus of institutional innovation, with a shift toward more coherent, proactive, and student-centered models. Computational thinking offers a framework for organizing complex support challenges through problem decomposition, abstraction, pattern recognition, and the design of procedures. González-Pérez et al. (2023) explain that Education 4.0 maturity models oriented toward Society 5.0 emphasize a balance among technological, pedagogical, and social dimensions. Applied to student support, this perspective can inform inclusive and adaptive systems that align technology, teaching practices, and student needs. Massaty et al. (2024) report that integrating artificial intelligence into education may support computational thinking and students' self-efficacy. These findings suggest that intelligent technologies could help personalize academic support and create opportunities for students to make decisions and solve problems. Luckin et al. (2016) also argue that educational technologies should be designed around people and ethical decision-making. This principle means that artificial intelligence should serve supportive, inclusive, and respectful learning environments, rather than only make institutional processes more efficient. In Education 5.0, institutions can use intelligent systems to strengthen responsible and sustainable student support models while preserving the human relationships central to student well-being.

The complexity of student support and its connection to technology and structured methods

Student support in higher education is a complex process that must respond to multiple dimensions of university life. It involves professionals with different roles and students with diverse backgrounds, trajectories, and needs. Emotional, academic, institutional, and contextual factors can all affect students' well-being and persistence. Kaur (2016) notes that support is more effective when it forms an integral part of educational quality. Cronin et al. (2021) describe structural and cultural barriers that may prevent students from seeking help. In response, Plak et al. (2022) examine proactive approaches and early-warning systems that can help university counselors identify students who may need support. Schwallie-Giddis et al. (2004) emphasize culturally responsive practices tailored to different student groups. Addressing this complexity requires structured methods that respond to students' needs while considering the institutional and social conditions that shape them.

Designing structured approaches to student support requires attention to both human and technological factors. Digital tools can broaden access to educational resources, but their value depends on how institutions incorporate them into teaching and support services. Orozco Carrillo et al. (2023) examine educational tools intended to promote computational thinking among secondary students, with a focus on problem-solving, logical reasoning, and creativity. Their chapter addresses classroom learning rather than university counseling; it therefore informs the pedagogical use of technology but does not establish effects on counseling or student support services. Raaper and Brown (2020) discuss implications of campus closures for student support practice during COVID-19, while Kulikowski et al. (2021) examine academic teachers' motivation during remote teaching. Together, these studies point to the need to design technology-mediated support in response to student needs and institutional conditions.

The convergence of pedagogy, technology, and flexible methods calls for student support to be understood as a structured and adaptive institutional practice. Computational thinking offers a way to describe complex problems through decomposition, abstraction, pattern recognition, and procedure design. Denning and Tedre (2021) discuss computational thinking as a disciplinary approach to framing and solving problems, while Kalelioglu et al. (2016) review research on computational thinking frameworks. These sources provide conceptual grounds for applying structured reasoning in educational settings; they do not, by themselves, show that computational thinking improves counseling outcomes. Its role in student support should therefore be treated as a design perspective whose value must be evaluated in specific institutional contexts.

Computational thinking as a framework for designing student support tools

Computational thinking (CT) has become an important framework for addressing 21st-century challenges. It can help people understand, decompose, and solve problems in technological, social, scientific, and educational contexts. Denning and Tedre (2021) describe computational thinking as a way to address complexity across disciplines and contexts, extending beyond computer science. It can therefore be understood both as a student competency and as a framework for designing solutions in other fields. Ezeamuzie and Leung (2022) review empirical research on computational thinking and discuss skills such as analysis, abstraction, modeling, and complex problem-solving. George-Reyes (2023) examines the relationship between computational thinking and digital literacy in education.

For student support, this perspective may help institutions structure processes that respond more effectively to the needs of their communities.

Computational thinking can inform the design of technology-mediated student support, particularly when institutions need to organize information and respond to complex situations. In a field experiment, Plak et al. (2022) examined whether early-warning information could help university counselors identify students at risk of dropping out and provide timely support. Kalelioglu et al. (2016) reviewed computational thinking frameworks, while Denning and Tedre (2021) discuss computational thinking as a disciplinary approach to formulating problems and designing solutions. Together, these sources support the use of structured analytical methods in student support design. They do not establish that computational systems can assess students' emotional states; any such use would require separate validation and safeguards.

Computational thinking can be a learning objective and a design framework for complex educational challenges, including student support. Brennan and Resnick (2012) describe computational concepts, practices, and perspectives that can inform how computational thinking is studied and assessed. Lodi and Martini (2021) discuss connections between computational thinking, pedagogy, and formal reasoning. Vázquez-Parra et al. (2024) report a positive association between university students' perceived development of complex thinking and their openness to using artificial-intelligence tools in education and future work. Their findings concern complex thinking and technology adoption; they do not directly address virtual reality or student support interventions. Taken together, these sources suggest that computational thinking can help structure responses to complex educational problems and inform more adaptive approaches to student support.

METHOD

This study used a qualitative, comparative longitudinal approach to examine how emerging Education 5.0 dynamics shaped student support programs at three Spanish-speaking higher education institutions in Latin America between 2020 and 2024. The analysis focused on two points in time: 2020, during the COVID-19 education emergency, and 2024, when institutions were consolidating new educational practices associated with the transition to Society 5.0.

A multiple-case study design enabled an in-depth, context-sensitive analysis of each institution's programs, practices, and organizational characteristics. It also supported comparisons across the three institutions and between the two time points. This approach was used to identify continuities, changes, and innovations while taking account of each institution's sociocultural, technological, and organizational context.

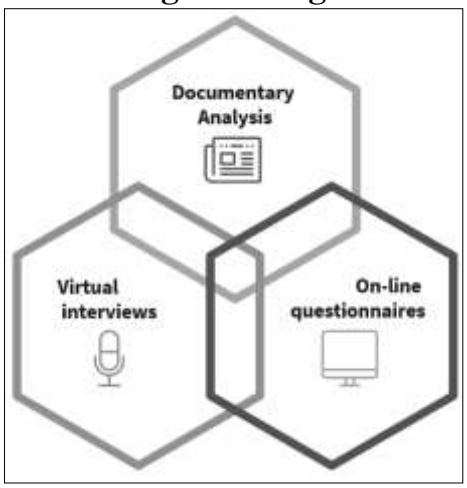
The three data-collection methods are described below:

Data were collected using three complementary methods: (a) documentary content analysis of institutional plans, management reports, student-well-being guidelines, and support protocols from both periods (Morgan, 2022); (b) semi-structured interviews with institutional leaders, counselors, faculty members, and students involved in the programs (Gray et al., 2020); and (c) open-ended online questionnaires administered to a purposive sample of students who had participated in student support services.

These methods were used to triangulate the data and develop a broad understanding of the study topic. Figure 1 shows how each method contributed a distinct perspective and how

the three sources informed the analysis. Comparing information across sources and participants strengthened the credibility of the findings.

Fig. 1. Methodological triangulation strategy.



Data collection procedures

The study used systematic procedures to collect data and support the credibility and interpretive depth of the findings. The methodological strategy triangulated three complementary methods: documentary analysis, semi-structured online questionnaires, and virtual interviews. The following subsections describe each method.

Documentary analysis

Documentary analysis focused on information available through the official online resources of the selected institutions. Documents were reviewed according to predefined inclusion and exclusion criteria. This process provided a contextualized account of how each institution organized its student support programs and related policies.

The procedure was developed in the following stages:

a. identification of sources
b. selection of documents according to established criteria
c. systematic downloading and archiving
d. data organization
e. preliminary analysis
f. coding and categorization
g. interpretation and validation.

Online Questionnaires

A semi-structured questionnaire was designed and applied to three higher education institutions selected under the following inclusion criteria:

The institutions were selected using three inclusion criteria: (a) an ascending position in the Webometrics rankings; (b) Spanish as the language of instruction; and (c) location in Latin America.

Questionnaire administration followed these stages:

a. Initial contact
b. Questionnaire distribution and informed consent
c. Follow-up and response to questions
d. Data collection

e. Preliminary analysis
f. Validation of findings

Virtual interviews

Semi-structured interviews were conducted online with institutional leaders from different geographic regions. The interviews gathered first-hand information about student support programs and the social, cultural, and organizational contexts in which they operated. A protocol was used to guide the process through the following stages:

a. Planning and design
b. Selection of participants
c. Contact and informed consent
d. Scheduling
e. Technical preparation and logistics
f. Conducting the interview
g. Transcription
h. Coding
i. Analysis and validation of results

Data analysis strategy

Data analysis involved two complementary phases. First, an inductive thematic analysis was used to identify categories emerging from participants' accounts in semi-structured interviews and open-ended questionnaires. This approach helped identify patterns of meaning, shared experiences, and differences in student support programs across the two periods (2020 and 2024).

Second, multiple correspondence analysis (MCA) was used to explore relationships among categorical variables and represent associations among categories in a principal-component space (Merchán-Sanmartín et al., 2022). The analysis used a matrix based on the coding frequencies of the identified categories to compare their positions and relevance in 2020 and 2024. The resulting visualization helped identify changes in student support priorities, including a stronger focus on well-being, prevention, and personalized support.

The two phases were integrated during interpretation, providing complementary perspectives on the data and supporting a more comprehensive analysis of the study topic.

RESULTS

This section presents findings from the analysis of student support programs at three Latin American higher education institutions at two points in time: 2020 and 2024. The findings show both continuities and changes in the structure, priorities, and components of these programs.

The analysis combined two methods. Inductive thematic analysis was used to develop categories from institutional participants' accounts. Multiple correspondence analysis was used to compare the two periods and identify relationships among the variables.

Together, these methods helped identify changes between the two periods and highlight institutional priorities related to student well-being, personalized support, and digital technology.

Focus of student support programs in 2020

In 2020, the student support programs examined focused on three areas: academic performance; psychoeducational and social support; and professional development. Table 1 summarizes the variables and components associated with each area.

Table 1. Variables and components of student support programs

Support area	Variable	Components
Academic performance	Academic performance	- Monitoring of academic performance - Attrition - Retention - Tutoring and reinforcement
	Internal processes	- Academic and administrative processes - Scholarships - Incentives and recognition - Government programs - Internationalization - Student mobility
Psychoeducational and social support	Transition and adjustment	- Adaptation to university life - Incoming-student profile - Interviews - life project
	Psychosocial support and holistic well-being	- Support networks: (family, partner, peers, teachers)
		- Psychological support - Healthy habits - Prevention - Self-care - Crisis management
	Healthy habits	- Quality of life and basic needs - Coexistence - Diversity
	Integration and representative groups	- Student participation groups - Culture and art - Strategic alliances
Professional development	Professional orientation	- Vocational orientation - Professional orientation - Skills for professional and academic success
	Work environment preparation	- Access to the world of work - Social skills - Development funds - Entrepreneurship - Personal Finance - Peer mentoring

Component analysis

The 2020 programs addressed academic performance through two variables: monitoring academic progress and managing academic and administrative processes. These areas

informed institutional strategies, policies, programs, and tools intended to help students navigate their studies.

The programs also linked academic performance with emotional health through a psychoeducational support area. Its variables included transition and adjustment, psychosocial support and holistic well-being, healthy habits, and participation in representative groups. Before 2020, institutions had developed approaches to support personal growth and meaningful relationships, informed decision-making, balanced lifestyles, and physical and mental health.

A third area focused on professional development and the skills students need for their future careers (Almazova et al., 2020). The programs emphasized career guidance and preparation for the workplace. These components aimed to help students identify their interests and professional goals, consider academic pathways, build confidence in their career decisions, and plan for professional development during higher education.

Multiple correspondence analysis of student support programs, 2020–2024

Multiple correspondence analysis (MCA) was used to identify patterns in the data by examining associations among categories of variables (Hjellbrekke, 2018). The analysis compared variables identified in student support programs in 2020 and 2024, using a matrix of frequencies and proportions. It also represented distances among categories in a Euclidean space. In 2024, the variables included risk-behavior identification, internal processes, emergency channels, transition to university, and workplace preparation. In 2020, the most prominent variables were healthy habits, participation in representative groups, psychosocial support, and holistic well-being. Career guidance and academic performance appeared in both periods.

Table 2 presents the frequencies and proportions of the categories in the dataset. These values were used to calculate distances among categories and support comparisons across the two periods.

Table 2. Frequencies and proportions

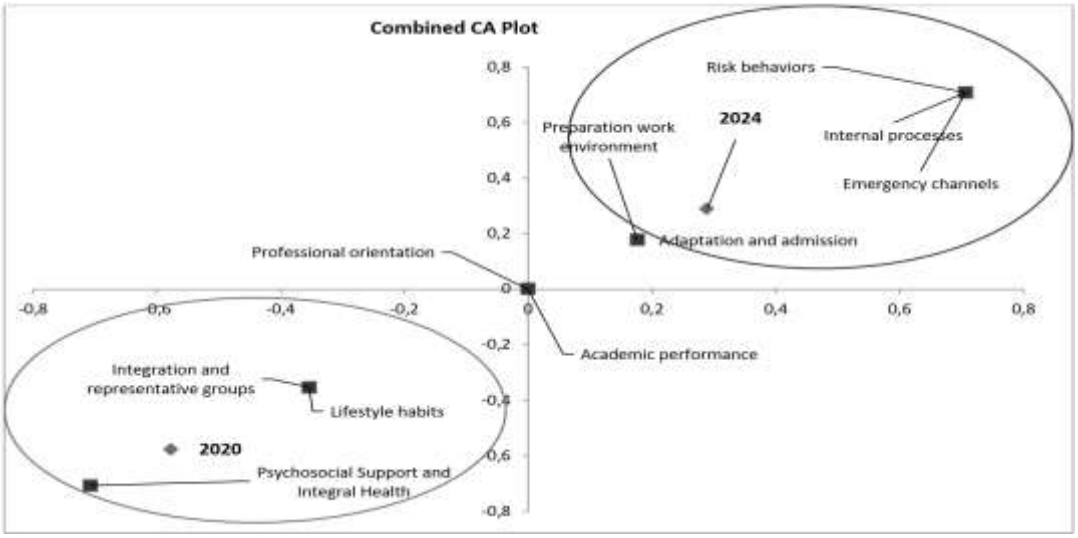
Variable	***2020 n***	***2020 %***	***2024 n***	***2024 %***	***Total n***	***Total %***	***Z test***	***Chi-square p***
Transition and adjustment	1	11%	3	16.7 %	4	14.8 %	0.702	0.779
Integration and representative groups	2	22%	2	11.1 %	4	14.8 %	0.444	
Work environment preparation	1	11%	3	16.7 %	4	14.8 %	0.194	
Psychological and psychosocial support	2	22%	1	5.6 %	3	11.1 %	0.194	
Professional orientation	1	11%	2	11.1 %	3	11.1 %	1.000	
Academic performance	1	11%	2	11.1 %	3	11.1 %	1.000	
Emergency channels	0	0%	2	11.1 %	2	7.4 %	0.299	
Healthy habits	1	11%	1	5.6 %	2	7.4 %	0.603	

Variable	*2020 n*	*2020 %*	*2024 n*	*2024 %*	*Total n*	*Total %*	*Z test*	*Chi-square p*
Internal processes	0	0%	1	5.6 %	1	3.7 %	0.721	
Risk behaviors	0	0%	1	5.6 %	1	3.7 %	0.721	
Total	**9**	**100.0%**	**18**	**100.0%**	**27**	**100.0%**		

Figure 2 presents the correspondence map for the two time points. The variables appear as points in a two-dimensional space; the distance between points represents their association in the analysis (Ogunsakin et al., 2021). Points that are closer together indicate a stronger association, while points farther apart indicate a weaker association.

The p value associated with this analysis was .799. This value does not meet a conventional threshold for statistical significance ($p < .05$), so the relationships shown in the map should be interpreted as exploratory rather than conclusive.

Fig. 2. Multiple correspondence analysis: comparison of student support priorities in Latin American institutions, 2020 and 2024

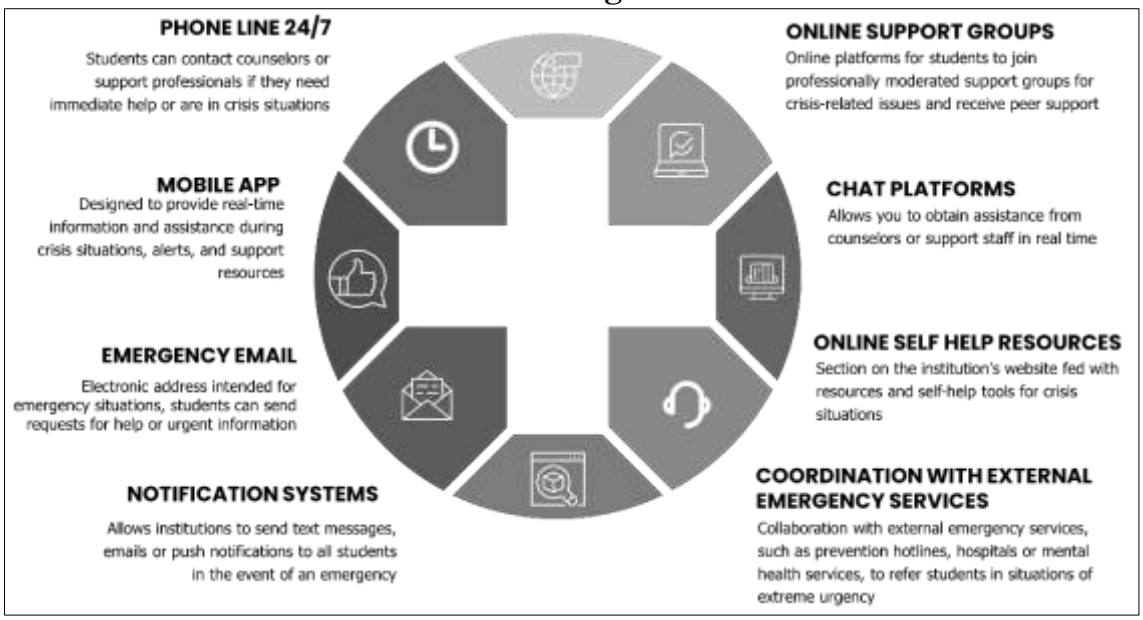


Innovations in student support programs in Education 5.0

In 2024, the student support programs examined included emergency communication channels that used artificial intelligence (AI), machine learning (ML), and 5G technologies. These channels were designed to help students obtain timely access to support during academic or personal crises, including mental-health challenges and financial difficulties (Agasisti et al., 2020). They also provided a way to contact trained professionals who could offer guidance, connect students with relevant services, and help them navigate difficulties. These communication channels may support student safety and well-being and strengthen connections between institutions and students. Their inclusion also illustrates how student support programs can adapt to changing needs while extending beyond academic concerns.

The analysis identified several tools and technical resources used to communicate with students in urgent situations. Figure 3 summarizes these channels and their intended role in supporting student safety and well-being.

Fig. 3. Communication channels for student emergencies using Education 5.0 technologies



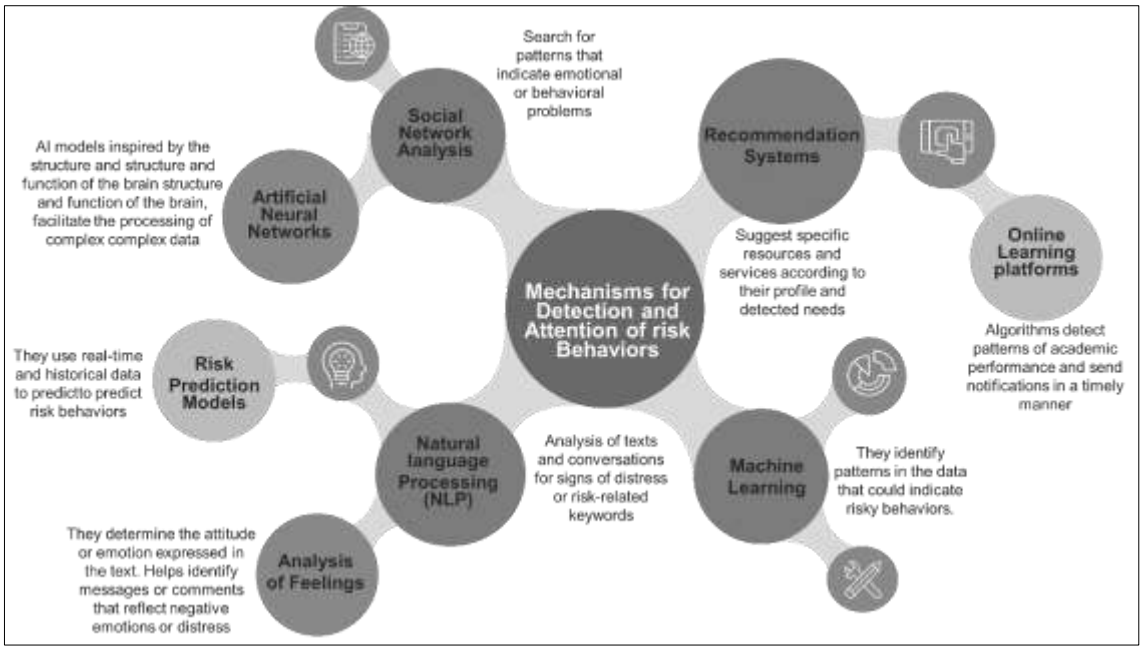
The analysis also identified mechanisms for detecting and responding to risk behaviors. These mechanisms rely on early identification and intervention, using tools such as data analysis, algorithms, and artificial intelligence (Zawacki-Richter et al., 2019). Computational thinking provides a framework for describing how these tools can decompose problems, identify behavioral patterns, and model possible responses. Related research has examined university students' digital health literacy and online information-seeking during the COVID-19 pandemic (Dadaczynski et al., 2021).

The mechanisms identified in the study monitored indicators that may signal risk, including poor academic performance, social isolation, signs of emotional distress, and limited participation in academic or extracurricular activities.

Mechanisms for identifying and responding to risk behaviors represent a preventive approach to student well-being. They may help institutions respond before a concern escalates, supporting safer learning environments (Luan et al., 2020). Depending on the circumstances, student support programs may offer individualized guidance, connect students with counselors or mentors, provide mental-health resources, organize peer-support groups, or refer students to external health services.

Figure 4 presents examples of mechanisms identified in the data analysis for detecting and responding to risk behaviors. It summarizes the technological and artificial-intelligence tools that the participating institutions reported using for this purpose.

Fig. 4. Mechanisms for identifying and responding to risk behaviors



DISCUSSION

This study examined how student support programs at three Latin American higher education institutions changed between 2020 and 2024. The findings indicate a shift from approaches focused mainly on general well-being and emotional support toward more structured and personalized models. This change reflects the digital transformation of education and a broader understanding of the institutional role of student support in promoting persistence, development, and inclusion.

A central contribution of this study is its use of computational thinking as a framework for examining student support tools. Brennan and Resnick (2012) describe computational concepts, practices, and perspectives that can inform how computational thinking is studied and assessed. In this study, problem decomposition, abstraction, pattern recognition, and algorithmic modeling were used to interpret mechanisms identified in the cases, including emergency channels, alert systems, and predictive models of student risk. Plak et al. (2022) provide empirical evidence about early-warning information in university counseling. These sources inform the interpretation of the cases; the study's findings remain specific to the institutions examined.

Figure 2 presents the multiple correspondence analysis and shows how the positions of selected student support dimensions differed between 2020 and 2024. Categories associated with general well-being and holistic health appear in different positions from institutional components related to prevention, adaptability, and personalized support. The map offers an exploratory view of these relationships and illustrates how computational thinking concepts, such as organizing variables and identifying patterns, can inform the analysis of student support systems.

The findings also show the growing relevance of Society 5.0 principles to student support. González-Pérez et al. (2023) describe Education 4.0 maturity models oriented toward Society 5.0 as integrating technological, pedagogical, and social dimensions. The institutional changes observed in this study are consistent with that emphasis. Participants described the use of artificial intelligence, data analysis, and process automation to monitor academic

performance and provide more tailored support. These findings suggest that technology guided by computational thinking principles and a person-centered approach may inform how institutions respond to students' varied needs.

These changes also raise concerns. Institutions differ in their pace of implementation, students have unequal access to digital platforms, staff training varies, and the use of sensitive data presents ethical challenges. Luckin et al. (2016) argue that educational technologies should support ethical decision-making and student well-being. Institutions therefore need to prepare staff in digital skills, computational thinking, and educational data analysis, while ensuring that automated tools remain contextualized and subject to appropriate human oversight.

The findings support treating student support as a strategic educational practice that requires clear theoretical and methodological foundations. Computational thinking can help organize information and decisions, but institutions must adapt its use to their contexts and students' needs. Technology can contribute to inclusive and ethically responsible support when it complements, rather than replaces, human guidance.

CONCLUSION

The comparison of student support programs in 2020 and 2024 showed changes in how the participating institutions approached student needs. Before 2020, the programs focused mainly on academic performance, with less attention to emotional well-being and career development. The COVID-19 crisis prompted institutions to broaden this focus and respond to students' emotional, social, and technological needs.

After 2020, the institutions incorporated more technological tools into student support, including artificial intelligence, data analytics, and adaptive platforms. The programs used these tools to identify possible risk behaviors, tailor support, and better understand student needs. Computational thinking provided a framework for organizing these processes through decomposition, modeling, and pattern analysis. The findings describe the practices observed in the participating institutions during the study period; they do not establish that these technologies caused improvements in student outcomes.

Looking ahead from the 2024 study period, technology and human interaction will both remain relevant to sustainable and ethical student support. Personalized communication, professional guidance, and emotional support continue to matter for students' academic and psychosocial well-being. Institutions should provide ongoing training for support staff in digital competencies, computational thinking, and ethical practice. Further work can also document and share approaches to using computational thinking in student support services.

Future research could design, implement, and evaluate student guidance systems informed by computational thinking principles. Such studies could examine how systems that use academic, emotional, and social information can provide appropriate, personalized responses while protecting students' privacy and autonomy. Researchers should evaluate these approaches in specific higher education contexts and include safeguards and human review in their design.

Collaboration among researchers and higher education institutions can strengthen the evidence base for student support, inform staff development, and help institutions identify the services students need to progress through university.

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