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Digital divide as an explanatory variable for dropout in higher education

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Abstract
The digital divide is a multidimensional phenomenon that significantly affects access, learning, and retention in higher education. This study aimed to simulate the effects of digital inequality on student dropout rates in undergraduate programs. Using a System Dynamics methodology, a causal loop and a stock-and-flow model were developed and calibrated with empirical data from Colombia, including dropout rates, enrollment levels, household income, internet connectivity, and availability of digital devices. The model was validated structurally and behaviorally, and sensitivity analyses were conducted. Simulations were performed under three scenarios: variations in household income (affecting connectivity and equipment provision), changes in enrollment rates, and effectiveness of digital training programs. Results reveal that structural limitations, especially poor infrastructure and high dropout rates from training programs, are major drivers of student attrition related to the digital divide. The findings emphasize that dropout is not equally distributed but is shaped by socioeconomic and institutional factors. Addressing the digital divide requires systemic and policy-level interventions. This study contributes to Sustainable Development Goal 4 by offering a simulation-based approach to inform strategies that promote digital equity and reduce educational exclusion in higher education.

Keywords Digital skills, Information society, Access to information, Dropping out, Digital divide

Introduction

In the information age, the digital divide has become an increasingly relevant issue for policymakers, scholars, and the general public. This gap is characterized by inequality in digital skills training and limited or inefficient access and usage of Information Communication Technologies (ICTs). Van Dijk (2020) argued that the digital divide extends beyond a purely technical issue, as it deeply intertwines with social, economic, and educational factors that significantly impact people's access to opportunities and resources. Similarly, Hargittai (2002) and Selwyn (2004) emphasized the importance of considering variables such as age, sex, and technological experience when assessing digital skills and understanding the digital divide. They argued that this divide should not be understood solely in terms of ITcs access but rather as a multifaceted issue. Said that, digital skills are a crucial component, as mere access to technology holds little value without the necessary competencies to use it effectively (Acharya & Rana, 2024; Selwyn, 2004). These skills involve:

The confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competences related to cybersecurity), intellectual property related questions, problem solving and critical thinking (European Commission: Directorate-General for Education, Youth, Sport and Culture, 2019, p.10).

In this context, Gil de Zúñiga et al. (2022) applied the social capital theories of Bourdieu (1997) and Coleman (1997) to the use of the internet and social media, identifying new agents and spaces that produce social capital in digital contexts. Social capital, in essence, requires resources, such as trust, reciprocity, social support, and access to information, as well as the benefits that people obtain through their social, community, and family networks to achieve individual or collective goals (Cañón et al. 2024; Gil de Zúñiga et al., 2022). Although ICTs have facilitated the production of social capital, they have also given rise to new forms of social exclusion or fragmentation, commonly referred to as the digital divide (Ventrella & Cotnam-Kappel, 2024). As Aissaoui (2021) points out, this divide can be conceptualized at three distinct levels: the first related to access, the second to digital skills, and the third to the outcomes obtained through the use of technology. In this regard, research has disproportionately focused on the second level, neglecting fundamental issues such as access to infrastructure and its determining factors, as well as contextual outcomes. This article contributes to both perspectives by analyzing aspects such as access to infrastructure and the adjacent variables that need to be addressed to reduce the digital divide, as well as the contextual outcomes related to dropout in higher education.

The digital divide is, therefore, a multidimensional concept encompassing the development of digital skills, as well as the differential access to and use of ICTs. While internet coverage has improved substantially worldwide, inequality persists both between and within countries. In particular, the digital infrastructure in African, Latin American, and Caribbean nations remains inconsistent, leading to difficulties in access, slow connection speeds, and poor service quality (Cañón et al., 2024; Barragán et al., 2024; Afzal et al., 2023; Adrogue & García de Fanelli, 2018; Hargittai, 2002. The digital divide also includes infrastructural limitations that prevent users from fully utilizing the internet, benefiting from online resources, and improving their digital competences. Additionally, factors such as educational level, age, technological experience, socioeconomic conditions, and social environment influence an individual's ability to navigate the technological infrastructure effectively (Cañón et al., 2024; Heeks, 2022; Mubarak & Suomi, 2022; Hargittai, 2002; Norris, 2000); This situation is exacerbated in the global south, where these disparities are even greater (Han & Kumwenda, 2025). Moreover, the digital divide extends to people's capacity to use technology efficiently and effectively to engage in political, civic, democratic, educational, economic, and social spheres. A lack of these competences can marginalize citizens, reinforce dominant power structures, and perpetuate existing inequalities (Luan et al., 2023; Mubarak & Suomi, 2022; Youssef et al., 2022). In this sense, as underscored by Aissaoui (2021), there is a critical need for future research to explore how new digital inequalities emerge from technologies that fail to respond to diverse needs, especially in countries with fragile digital ecosystems.

For higher education institutions (HEIs), the digital divide presents a significant challenge, as it restricts equitable access, diminishes the benefits of technology, and reduces academic effectiveness (Greaves, 2024; Elrayah & Alshih, 2024; Bracco et al., 2022; Galpin et al., 2022; Banerjee, 2020). Addressing this issue requires HEIs to integrate digital leadership skills, intercultural competences, and self-efficacy development into their curricula, as this combination enhances employability rates in the contemporary labor market (Zhan et al., 2024; Hrynevych et al., 2021). The digital divide exacerbates student dropout in higher education, limiting the individual and social benefits of completing a university degree (Barragán & González, 2024; Guzmán et al., 2021).

In this context, our research was guided by the following question: How does the digital divide affect student dropout rates in undergraduate higher education programs? Accordingly, the objective of this article was to simulate the effect of the digital divide on student dropout rates in these programs.

Studies on student dropout and the digital divide play a crucial role in advancing SDG 4– Quality Education (United Nations, 2023), particularly in targets 4.3 and 4.4. Target 4.3 emphasizes equal access to quality technical, vocational, and tertiary education, while target 4.4 aims to substantially increase the number of youth and adults with relevant digital skills. Given that this study addresses inequalities in digital access and dropout rates in higher education, it contributes to the broader goal of ensuring inclusive and equitable education and promoting lifelong learning opportunities for all. By identifying structural barriers and behavioral causes of exclusion (Nedungadi et al., 2024), the research aligns with the global commitment to reduce educational disparities and foster digital equity in the context of post-pandemic hybrid learning environments.

To achieve this objective, the article was divided into four sections. First, we present the theoretical framework, followed by the research methodology. Next, we outlined the results of the study and, finally, we presented the discussion and conclusions.

Theoretical framework

Student dropout in higher education

Tinto (1975) and Roslan et al. (2025) define student dropout as the phenomenon in which students abandon their higher education studies before completion. In 2012, the ALFA GUIA DCI-ALA/2010/94 Project conceptualized dropout as a relational, interactive, dynamic event of an individual, social, and institutional nature, which alters the interactions among different educational stakeholders. This modification arises from the assessment of intrinsic and extrinsic expectations, offerings, and demands within the educational process. Given its contextual and complex nature, student dropout must be addressed through interdisciplinary approaches that incorporate multiple and complementary strategies (Grupo Análisis. Proyecto ALFA GUIA DCI-ALA/2010/94, 2012, p. 4).

Student dropout has a significant impact on the management, financial sustainability, and reputation of HEIs (Guzmán et al., 2023; Cosenz, 2022). This phenomenon results from the interplay of multiple factors which can be grouped into four interrelated categories: individual, academic, socioeconomic, and institutional (Barragán & González, 2024; Ministerio de Educación Nacional de Colombia, 2015). Figure 1 provides an overview of the key variables within these categories.

Source: Prepared by the authors based on Barragán and González (2024), Nkansah and Oldac (2024), Guzmán and Valencia (2024), Guzmán et al. (2023), Tinto (1975), and Ministerio de Educación Nacional de Colombia (2015). PresentationGO.com was used to produce the presentation's template.

Notably, the explanatory variable for student dropout, referred to as "access to technology and internet connectivity" (Cañón et al., 2024; Heeks, 2022) lies at the intersection of the socioeconomic, institutional, and academic categories. Additionally, it is also note-worthy that Nkansah and Oldac (2024) emphasized that the digital divide in HEIs is driven by individual, familial, institutional, and governmental factors, manifesting in a knowledge deficit and weak digital competencies.

Previous studies have identified key variables associated with the digital divide that contribute to student dropout in higher education, including: lack of access to technology, such as devices and a stable internet connection (Cañón et al., 2024; Elrayah & Alshiha, 2024; Wu & Yang, 2023); absence of digital competencies—students who are not proficient in handling digital tools face significant learning difficulties (Elrayah & Alshiha, 2024; Wu & Yang, 2023); adverse socioeconomic conditions—disadvantaged students have fewer financial resources to invest in technology and connectivity (Cañón et al., 2024; Elrayah & Alshiha, 2024; Sun et al., 2022); institutional support, including the availability of computer equipment, adequate facilities, and technological resources in HEIs—without sufficient academic support, these shortcomings can lead to student dropout (García et al., 2023; Okoye et al., 2022); family and social environment—home conditions and family support can encourage or hinder digital learning and skill development (Payne et al., 2022; Guzmán et al., 2021); poor quality of online learning, which, compared to face-to-face education, negatively affects academic success and student retention (García et al., 2023; Caprara & Caprara, 2022); the impact of the COVID-19 pandemic, which exacerbated these factors, accelerated the digital transition, and deepened educational inequality (Sitar-Tăut et al., 2024; Yu et al., 2023).

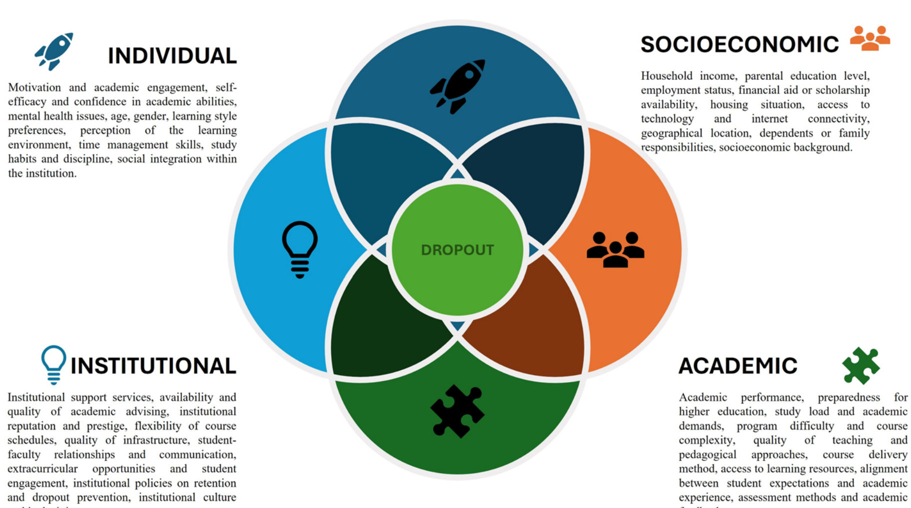

Fig. 1 Categories of factors that cause student dropout in higher education

Approaches to student dropout in higher education within the context of the digital age

Selwyn (2004) cautioned against oversimplifying the concept of the digital divide, emphasizing the importance of considering economic, cultural, and social capital as mediating factors. He argued that a more nuanced understanding requires sophisticated models that account for these complexities. In line with this perspective, analyzing the digital divide's role in student retention in higher education necessitates an approach grounded in theoretical models of student dropout, particularly within an equity framework (Silva et al., 2023). One of the earliest and most influential models in this area is Vincent Tinto's (1975) interaction model, which explains student retention and dropout based on social and academic integration. According to Tinto, academic integration refers to both academic performance and interaction with the HEIs' staff, while social integration refers to participation in extracurricular activities and peer interaction within the institution.

While the interaction model remains a foundational framework, it is not without critique. Samoila & Vrabie (2023) and Donoso and Schiefelbein (2007) have challenged its universal applicability. Given the changing nature of student dropout, it is essential to expand existing models and theories to account for the new variables introduced by the digital divide.

The digital age has introduced new challenges in diagnosing, addressing, and tracking student dropout in higher education (Oliveira et al., 2018). To effectively analyze this phenomenon, existing theoretical and empirical models must evolve, or new frameworks must emerge to better capture the underlying structures of the system (Bianchi, 2016). Below, we summarize three key approaches to student dropout that integrate both traditional variables—such as those outlined in Fig. 1—and factors related to the digital divide and technological access.

Theoretical approach to digital inequality in higher education

Inequality in higher education related to the digital divide encompasses disparities in access to, use of, and outcomes from digital resources and ICTs in teaching and learning processes (Troyan et al., 2023). This inequality stems from challenging sociocultural, political, and economic factors including globalization, socioeconomic disparities, the commodification of education, and ethical concerns surrounding technology use (Pashkov & Pashkova, 2022). Drawing on Bourdieu's (1997) theory of social capital, the digital divide reinforces existing inequalities by shaping the extent to which different social groups can access ICTs and develop digital skills (Cañón et al., 2024; Ventrella & Cotnam-Kappel, 2024; De Zúñiga et al., 2022).

Approach based on interaction

Although Bernard et al. (2014), Armstrong et al. (2018), and Choi and Kim (2018) did not adapt Tinto's (1975) model, their findings provide relevant insights, particularly in the context of digital technology-assisted learning environments. In these environments, student-teacher interactions and pedagogical models play a crucial role. A lack of meaningful interaction can negatively impact academic performance and motivation. It is worth noting that Bernard et al. (2014) further examined student dropout, attributing it to a limited engagement in academic activities due to restricted access to technology, which in turns reduces learning opportunities. They also emphasized deficiencies in instructional design that fail to foster the necessary interaction for effective learning experiences. Additionally, they argued that low motivation and a lack of autonomy hinder students' ability to self-regulate their learning.

Approach based on the acceptance and use of technology

Inequality is also closely linked to acceptance and use of technology by all stakeholders in the teaching-learning process. For technology to be widely accepted and adopted, educators must receive training in digital tools, pedagogy, and instructional design for virtual learning environments (Fernández-Batanero et al., 2021). Students' engagement with technological tools depends on various factors, including learning styles, family practices, generational differences, socioeconomic status, geographic location (rural versus urban), and gender (see Fig. 1). These characteristics shape how students respond to ICT-related challenges (Barragán & González, 2024; García et al., 2023; Mubarak et al., 2022; Guzmán et al., 2021; Banerjee, 2020). Furthermore, institutional policies and strategic plans in higher must acknowledge that digital transformation necessitates not only the integration of new technologies but also the adaptation of institutional processes. This requires equipping individuals with the necessary skills to effectively navigate and leverage these technologies (Chinkes & Julien, 2019, p. 24).

Implications of the digital divide for institutional policies and student dropout management in higher education

Bridging the digital divide requires HEIs to design institutional policies that translate into concrete plans, strategies, and actions aimed at building and maintaining the necessary infrastructure for digital transformation. This effort must ensure equitable access for the entire community to cutting-edge ICTs while fostering digital skills and competences among faculty, students, and staff (Chinkes & Julien, 2019; Ramírez-Montoya et al., 2022). Furthermore, student Retention and Timely Graduation (RTG) Plans should integrate emotional and social support mechanisms to mitigate the vulnerabilities exacerbated by the digital divide. The increasing digitalization of educational environments—whether face-to-face, blended, or fully virtual (García, 2021; Guzmán et al., 2021)—significantly influences academic and social interactions (Tinto, 1993), students' sense of belonging to their institution (Ministerio de Educación Nacional de Colombia, 2015), and their experiences of loneliness or isolation (Guzmán et al., 2021). To address these challenges, RTG plans should prioritize the development and reinforcement of online support networks, monitoring systems, tutoring, and counseling services (Barragán & González, 2024). Whether delivered synchronously or asynchronously, these initiatives can enhance students' emotional well-being and improve overall learning experience within the academic community.

The management of HEIs should adopt a preventive and proactive approach focused on monitoring at-risk students. This approach requires that the assessment, monitoring, and intervention of student dropout rates be informed by advanced theories and models. Additionally, it calls for the strategic coordination of technology, admissions, and student support services to effectively incorporate new explanatory variables for dropout, account for diverse student characteristics, implement early warning systems, and enhance university well-being initiatives. (Roslan et al., 2025; Amado-Mateus et al., 2024; Barragán & González, 2024; Guzmán & Valencia, 2024).

In this context, this research is particularly relevant as it employs real data analyzed through advanced scientific methods and specialized software.

Methodology

Design

To simulate the impact of the digital divide on student dropout rates in higher education undergraduate programs, this study employed the SD methodology, following the approach of Ramoni and Orlandoni (2022). SD enables the analysis and projection of system components' behavior over time while also identifying feedback loops among variables in complex situations (Cosenz, 2022). SD is grounded in models that enable a holistic understanding of complex systems by analyzing their components and interrelationships (Bala et al., 2017; Bianchi, 2016). This methodology allows the rationalization of system's structures, the identification of key interactions, and the prediction of component behavior—whether at the variable, subsystem, or system-wide level—when modifications occur (González, 2022; De Leo et al., 2020). Given the characteristics of SD and the recognition that student retention is a dynamic and continuously evolving process (Guzmán et al., 2023), this methodology is well-suited for modeling and simulating student dropout, focusing on general system aspects rather than individual cases. This implies that while the value of models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) is acknowledged, explaining users' acceptance and use of technology with a comprehensive approach (Venkatesh et al., 2003)—its individual and non-systemic scope is also recognized, which is the orientation of this article.

While alternative modeling approaches, such as agent-based modeling (ABM) or discrete event simulation (DES), could offer insights into individual-level behavior and operational processes, they are less suited for capturing the structural and systemic dynamics underlying educational inequality. ABM emphasizes micro-level heterogeneity and autonomous decision-making by individual agents, and DES focuses on process flow and event scheduling. In contrast, SD is specifically designed to model accumulations, delays, and feedback mechanisms, which are essential for understanding the cumulative effects of digital inequality on student dropout rates over time (Guzmán et al., 2023). This study does not aim to simulate isolated student behaviors but rather to examine how structural variables interact systemically and influence educational trajectories at scale (González, 2022; Guzmán et al., 2023).

Furthermore, the selection of SD aligns with recent applications of this methodology in educational contexts, where it has proven effective in modeling and evaluating policy interventions to improve retention and mitigate dropout (Bianchi & Salazar, 2022). Therefore, SD offers a robust and theoretically grounded framework for addressing the research question from a systems-thinking perspective, without sacrificing analytical depth or policy relevance.

Modeling process

The modeling process followed a two-stage approach based on model progression (Oliva, 2019). This progression systematically incorporated elements that enhanced the understanding of the system's behavior.

Stage 1: Design of the causal loop diagram.

The design of this diagram uncovered the dynamic hypotheses underlying the system (Cosenz, 2022; Aracil & Gordillo, 1997). In the diagram, arrows represent the influence of variables, while the accompanying signs indicate the nature of their relationship: a positive sign (+) denotes that an increase in one variable leads to an increase in the other, whereas a negative sign (-) signifies that an increase in one variable results in a decrease in the other. Causal relationships are modeled through feedback loops and validated in the simulation via the identification of the dominant loop, highlighting the system's inherent non-linearity.

Stage 2: Design of the stock-and-flow diagram.

This diagram represents the underlying physical structure of the system and allows the quantification of causal relationships between its variables. In other words, it serves as the simulation model (Cosenz, 2022; Schaffernicht, 2009; Aracil & Gordillo, 1997). The stock-and-flow diagram incorporates three types of variables: (1) Levels, which indicate the availability of a resource at a specific point in time; (2) flows, which represent increases or decreases in resource levels based on the implementation of improvement strategies or interventions; (3) Auxiliaries, which function as key drivers of system performance (Bianchi, 2016). Simulations based on this model allow for the analysis of various social scenarios or interventions (Bianchi & Salazar, 2022), helping to identify more effective strategies for improving retention rates in undergraduate programs (Guzmán et al., 2021, 2023).

The model was designed with a general approach, its parameterization and validation based on specific contextual data, following Landriscina's (2013) methodological recommendations on best practices in applied modeling. Thus, the model was adapted to the Colombian case, considering that the variables present in the research are monitored at a national level. For international applications, the training cycle can be adjusted to the specific circumstances of each nation.

Then, to parameterize the model, we used empirical data from official and institutional sources in Colombia. Specifically, the dropout and graduation rates were obtained from the SPADIES database (Sistema para la Prevención de la Deserción en las Instituciones de Educación Superior), managed by the Ministry of National Education. This source provides disaggregated historical information on student retention and dropout, which allowed us to establish realistic baseline values for key variables. Additionally, we incorporated data from the statistical bulletin of the Universidad de Bogotá Jorge Tadeo Lozano (2025), particularly to define reference values for enrollment rates, digital skills distribution, and training program completion. The data and their respective sources are detailed in Table 1. Moreover, we used data presented in the study by Cañón et al. (2024) to construct several graphical functions in the simulation model. These functions describe the dynamic behavior of critical variables such as the digital connectivity index and the availability of equipment at home. In SD, graphical functions allow the modeling of nonlinear relationships between variables over time. In our case, for example, a function was constructed to represent the relationship between household income levels and internet speed, based on empirical observations.

The digital divide is a multidimensional phenomenon that cannot be fully captured through isolated indicators. A composite index as Index of the digital divide (Table 1) allows for the simultaneous consideration of variables, providing a more comprehensive and comparative perspective. This approach helps identify cumulative inequalities and supports evidence-based decision-making especially in higher education, where the digital divide is closely linked to dropout rates and educational equity (Aissaoui, 2021; van Dijk, 2020).

The validation process of system dynamics models can be approached from various perspectives. As Schwaninger and Groesser (2020) point out, these approaches can be classified into three main categories: context validation, structure validation, and behavior validation. In the present study, validation focused on the latter two categories, aiming, on one hand, to assess the logical consistency of the model's internal architecture, and on the other, its ability to reproduce observable patterns of behavior in the educational context. This strategy made it possible to ensure both the structural soundness of the model and its explanatory relevance regarding the phenomena under study.

First, the structural validation of the model was carried out through an analysis of the feedback loops present in the causal loop diagram and their comparison with the behavior patterns obtained from the simulations. According to Schwaninger and Groesser (2020), this type of validation seeks to determine whether the internal logic of the model is consistent with the underlying structure of the phenomenon in the real world. To this end, a loop dominance analysis was conducted, which made it possible to identify the predominant feedback structures during different phases of the simulated behavior. Second, a behavior validation of the model was conducted by comparing the simulated results with historical data from the System for the Prevention of Dropout in Higher Education Institutions (SPADIES). This test aimed to verify whether the model was capable of replicating observable patterns in reality.

Based on the parameters outlined in Table 1, which define the structural boundaries and constraints of the system, the simulation process commenced with the construction of the reference mode, representing the baseline behavior and current dynamics of the system under study (Bala et al., 2017). This mode served as a benchmark scenario for validating the internal consistency and behavioral plausibility of the model.

Following this initial validation, a sensitivity analysis was performed to assess the model's responsiveness to variations in key input parameters. This procedure involved systematically modifying the values of critical variables within predefined ranges to examine their influence on the system's overall behavior and stability. The following variables were subjected to intervention:

- Enrollment rate (0.20 to 0.40).
- Graduation rate (0.20 to 0.40).
- Dropout rate due to other causes (0 to 0.20).
- Students with low digital skills rate (0 to 0.40).
- Program linkage rate (0.10 to 0.50).
- Dropout rate from training programs (0.60 to 1).
- Average level of family income (200 to 600).

The sensitivity analysis was based on Behavior Over Time Graphs, which enabled the visualization of system dynamics under multiple parameter scenarios. The analysis focused on the confidence intervals observed across simulation trajectories, allowing for the identification of system's performance over time. This approach provided robust insights into the model's sensitivity structure, informing the prioritization of policy levers and contributing to the design of evidence-based interventions.

Table 1 Variables included in the simulation model

Variable	Equation	Interpretation	Source
Accessing programs	$Program\ linkage\ rate\ \times\ Students\ with\ low\ digital\ skills$	Number of students with low digital skills accessing training programs.	Not apply
Average level of family income	420	Household income level, which affects access to technology and education.	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Digital connectivity index	$WITHLOOKUP$ $(Indexofthedigitaldivide, ([(0,0)-(1,1)],(0,0.03),(1,0)))$	Measures the quality of internet connectivity, considering speed and access to devices.	Not apply
Dropout due to the digital divide	$WITH\ LOOKUP\ (Index\ of\ the\ digital\ divide,\ ([(0{,}0)-(1{,}1)],(0{,}0.03),(1{,}0)))$	Number of students dropping out due to digital divide factors.	Cañón et al. (2024)
Dropout general rate	$\mathrm{Dropoutrateduetoothercauses}$ $+\mathrm{Dropoutfordigitaldivide}$	Overall student dropout rate considering digital and non-digital causes.	Not apply
Dropout rate due to other causes	0.0522	Dropout rate due to non-digital reasons (e.g., financial or academic issues).	SPADIES
Training programs dropout rate	0.8	Digital skills training programs dropout rate.	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Dropout	$Students\ enrolled\ \times\ Dropout\ general\ rate$	Total number of students who drop out of the higher education system.	Not apply
Training programs dropout	$Dropout\ training\ programs\ rate\ \times\ Students\ in\ training\ programs$	Number of students who abandon digital skills training programs.	Not apply
Enrollment	$Enrollment\ rate\ \times\ Students\ enrolled$	Number of new students entering at the IES	Not apply
Students with low digital skills enrollment	$Students\ enrolled\ \times\ Students\ with\ low\ digital\ skills\ rate$	Number of students with low digital skills who are newly enrolled.	Not apply
Enrollment rate	0.31	Rate at which students enroll at the IES	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Finishing programs	$Students\ in\ training\ programs\ \times\ Program\ success\ rate$	Number of students who complete digital skills training programs.	Not apply
Graduating	$Graduation\ rate\ \times\ Students\ enrolled$	Number of students graduating from higher education programs.	Not apply
Graduation rate	0.23	Percentage of enrolled students who successfully complete their programs.	SPADIES

Table 1 (continued)

Variable	Equation	Interpretation	Source
Index of the digital divide	$\frac{\text{Digital connectivity index} + \text{Infrastructure quality} + \text{Training program effectiveness}}{2}$	Measures disparities in access to digital resources and technological proficiency.	Not apply
Infrastructure quality	$WITHLOOKUP(Studentsenrolled, ([(0,0)-(3000,1)], (0,0), (100,0.05), (500,0.15), (1000,0.4), (2000,0.8), (3000,1)))$	Measures the quality of technological infrastructure supporting digital education.	Cañón et al. (2024)
Internet speed	$WITHLOOKUP(Averagelevelfamilyincome, ([(0,0)(4000,400)], (0,0), (500,50), (1000,200), (1500,250), (2416.19,400), (3052.02,400), (4000,400)))$	Internet speed available for students, affecting connectivity and digital engagement.	Cañón et al. (2024)
Program linkage rate	0.3	Percentage of students with low digital skills in training programs.	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Program success rate	$1 - Dropout\ training\ programs\ rate$	Percentage of students who successfully complete training programs.	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Provision of equipment at home	$WITHLOOKUP(Averagelevelfamilyincome, ([(0,0)-(4000,1)], (0,0), (1000,0.2), (2000,0.5), (4000,1)))$	Measures availability of digital devices at home, which impacts digital accessibility.	Cañón et al. (2024)
Students enrolled	$INTEG\,(Enrolling - Dropping\ Out - Graduating,)$	Total number of students currently enrolled at the IES	Not apply
Students in training programs	$INTEG\begin{pmatrix} Accessingprograms \\ -Droppingouttrainingprograms \\ -Finishingprograms \end{pmatrix}$	Total number of students who participate in digital skills training programs.	Not apply
Students with digital skills	$INTEG\,(Finishing\ programs,\ 0)$	Total number of students who have acquired sufficient digital skills.	Not apply
Students with low digital skills	$INTEG\begin{pmatrix} Enrollingstudentswithlowdigitalskills \\ -Accessingprograms \end{pmatrix}$	Total number of students who lack essential digital skills.	Not apply
Students with low digital skills rate	0.2	Percentage of students in higher education who lack essential digital skills.	Universidad de Bogotá Jorge Tadeo Lozano (2025)
Training program effectiveness	$\frac{Finishing\ programs}{Accessing\ programs}$	Measures the efficiency and success rate of digital skills training programs.	Not apply

Simulations

With the model calibrated, simulations were conducted across three distinct scenarios. The first scenario examined variations in household income; the second explored changes in the training programs implemented by higher education institutions (HEIs); and the third focused on student enrollment rates. Each simulation involved adjusting the parameters listed in Table 2, either increasing or decreasing them relative to the values defined in the reference model.

The results were analyzed using an inductive approach, which involved comparing the dynamic behavior observed in each scenario in order to identify emerging patterns, causal mechanisms, and critical thresholds. This methodological strategy enabled a nuanced understanding of how structural and policy-related variables interact to influence student dropout due to the digital divide.

Results

Causal loop diagram

The causal loop diagram captures the structural dynamics of student retention in higher education systems influenced by digital divide. It highlights the interaction of three reinforcing loops (R1, R2, R3) and two balancing loops (B1, B2) that collectively explain the behavior of student enrollment, dropout, and digital access.

The loop R1 represents a classic reinforcing mechanism, an increase in student enrollment leads to more students entering the system, including those with limited digital skills. These students are more likely to struggle within the academic environment, increasing the overall dropout rate and eventually weakening enrollment sustainability. In the case of the reinforcing loop R2, it becomes evident that an increase in student enrollment enhances the infrastructure quality of the HEI, as a larger student body allows for greater investment in technological infrastructure and digital platforms. Improved infrastructure contributes to a reduction in the digital divide index, thereby decreasing the number of students who drop out due to digital inequality. This, in turn, has a positive effect on overall enrollment, as it supports student retention and reduces attrition linked to technological barriers. Finally, for the R3 loop, a dynamic emerges that deepens the educational exclusion linked to the digital divide. As the number of students with low digital skills increases, so does the demand for training programs aimed at bridging this gap. However, the effectiveness of these programs becomes a critical factor. When training programs lack quality, relevance or sufficient resources, students are unable to develop the necessary skills, which in turn leads to increased dropout rates associated with the digital divide. This increases dropout rates and consequently decreases student enrollment (Fig. 2).

Table 2 Parameters of the simulation scenarios

Scenario	Variable	Value
1	Household income	350 USD and 1000 USD
2	Program Linkage Rate	0.50 and 0.80
	Dropout Training Programs Rate	0.30 and 0.50
3	Enrollment Rates	0.10 and 0.60

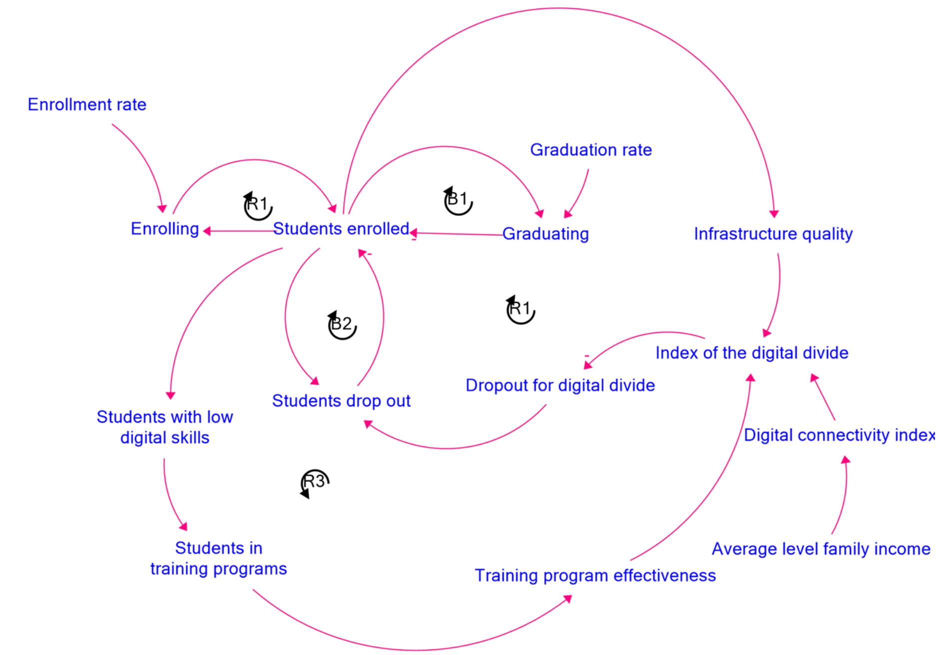

Fig. 2 Causal loop diagram

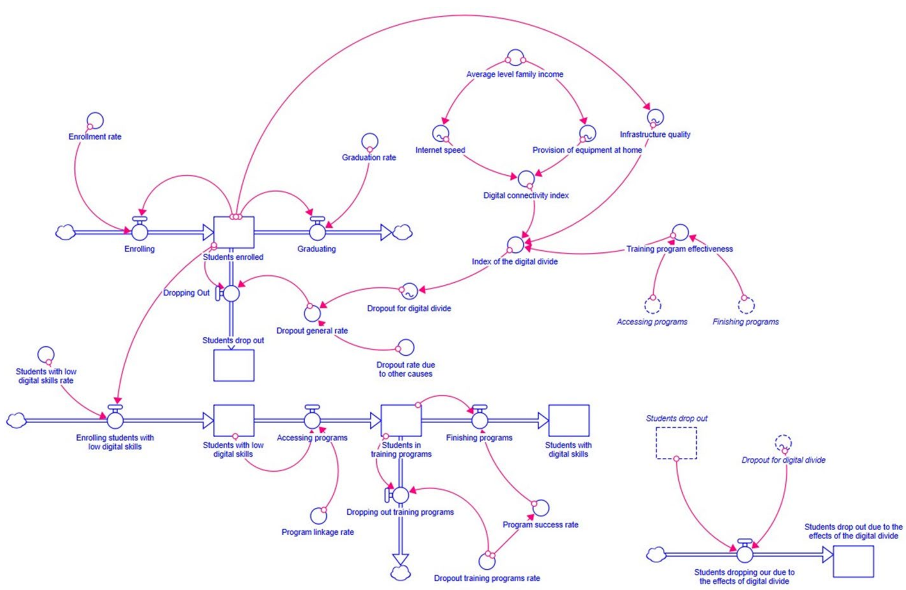

Fig. 3 Stock-and-flow diagram

Stock-and-flow diagram

Table 1 presents the variables, equations, and their interpretations used in the stock-and-flow diagram in Fig. 3. This diagram represents the mathematical model designed to simulate the impact of the digital divide on student retention in higher education undergraduate programs. Some variables in Table 1 were labeled as indices, as they serve as integrative metrics that encapsulate the combined effects of the variables depicted in Fig. 1, along with those related to the digital divide.

As part of the model's structural validation, a feedback loop analysis was conducted based on the CLD and compared with the emerging behavior patterns from the reference model simulations (see Fig. 5). A total of nine main loops were identified and categorized as reinforcing (R1 and R2) and balancing (B1 to B6). Each loop was evaluated by measuring the percentage impact of its key variables on the associated stocks (enrolled students and students in training programs), which enabled the determination of their relative weight within the system. The four loops initially proposed in the CLD were reflected in the loop dominance analysis.

Reinforcing loop R1, which links enrollment to the stock of enrolled students, exhibited the highest level of dominance, reaching a maximum impact of 41.6%. This dynamic represents a typical positive feedback structure observed in expanding educational systems: the higher the number of enrolled students, the greater the institutional visibility and legitimacy, which in turn encourages new enrollments and reinforces growth. In contrast, loop R2—although structurally complex with 11 variables and three stocks—showed low quantitative dominance (max. 1.42%). Nonetheless, its analytical value lies in its capacity to connect critical variables such as the effectiveness of training programs, the digital divide index, and dropout rates due to technological deficiencies. While currently exerting limited influence on simulated behavior, this loop offers a coherent representation of real-world systemic structures associated with the digital divide and highlights a high potential for policy intervention (Fig. 4).

Among the balancing loops, B2 (graduation) was the most dominant, with a negative impact of up to -30.8%, acting as an outflow valve in the higher education system. Loops B3 (access to training programs) and B4 (general dropout) also contributed significantly to system equilibrium, albeit to a lesser extent (-4.31% and − 9.2%, respectively). By contrast, loops such as B5 (completion of programs) and B6 (a long cycle involving nine variables) exhibited marginal dominance (below − 0.5%), suggesting that in the configuration of the reference model, no substantial corrective effects are being generated.

The comparison between these quantitative results and the structure of the CLD demonstrates that the model's internal logic is consistent with the theoretical structure of the phenomenon under study.

As a complementary stage to the structural validation, behavioral validation was conducted by comparing the simulated results with historical data obtained from the SPADIES. Figure 5a presents the comparison between simulated and actual values for the number of enrolled students across five consecutive academic periods, from the second semester of 2021 to the second semester of 2023. The results reveal a high degree of concordance between the curves, suggesting that the model adequately captures the historical evolution of the student population.

Additionally, Fig. 5b displays the values corresponding to the number of students who dropped out during each of the analyzed periods. In this case, although minor deviations can be observed between the simulated and actual data—particularly in the first semester of 2023—the overall trend remains aligned, replicating the characteristic peaks and troughs of the dropout phenomenon. Taken together, the results from this phase confirm that the model is not only structurally consistent with the systemic logic of the phenomenon (structural validation), but also behaviorally valid, as it successfully replicates the empirical trajectories reported in official sources with a high level of accuracy.

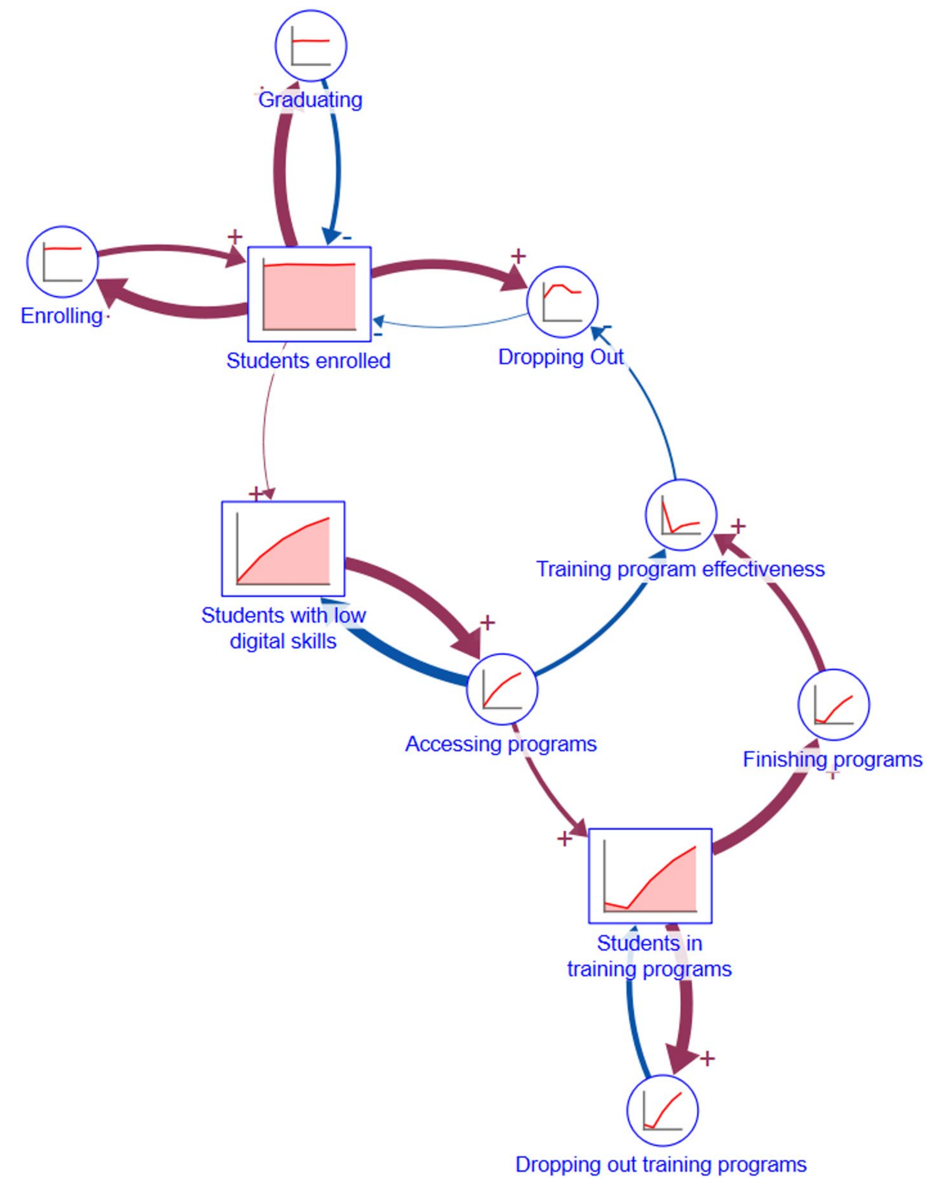

Fig. 4 Dominance loop diagram

Sensitivity analysis and reference model

In order to assess the robustness of the model against variations in key parameters, a sensitivity analysis was conducted involving modifications to seven system variables. The results are presented for two stocks and one count-based variable: enrolled students (Fig. 6a), students who drop out (Fig. 6b), and students who drop out due to the digital divide (Fig. 6c).

Based on calculations using a 95% confidence interval (CI), it is estimated that the number of students enrolled at time t = 20 will range between 45 and 3,460 students (Fig. 6a). This behavior reflects a sustained decreasing trend, with early convergence toward equilibrium. The narrow range between percentiles indicates high model stability with respect to this stock, suggesting that student enrollment is relatively insensitive to parameter uncertainty within the conditions tested. In contrast, the number of students who drop out (Fig. 6b) is expected to range from 2,240 to 5,666 by the end of the

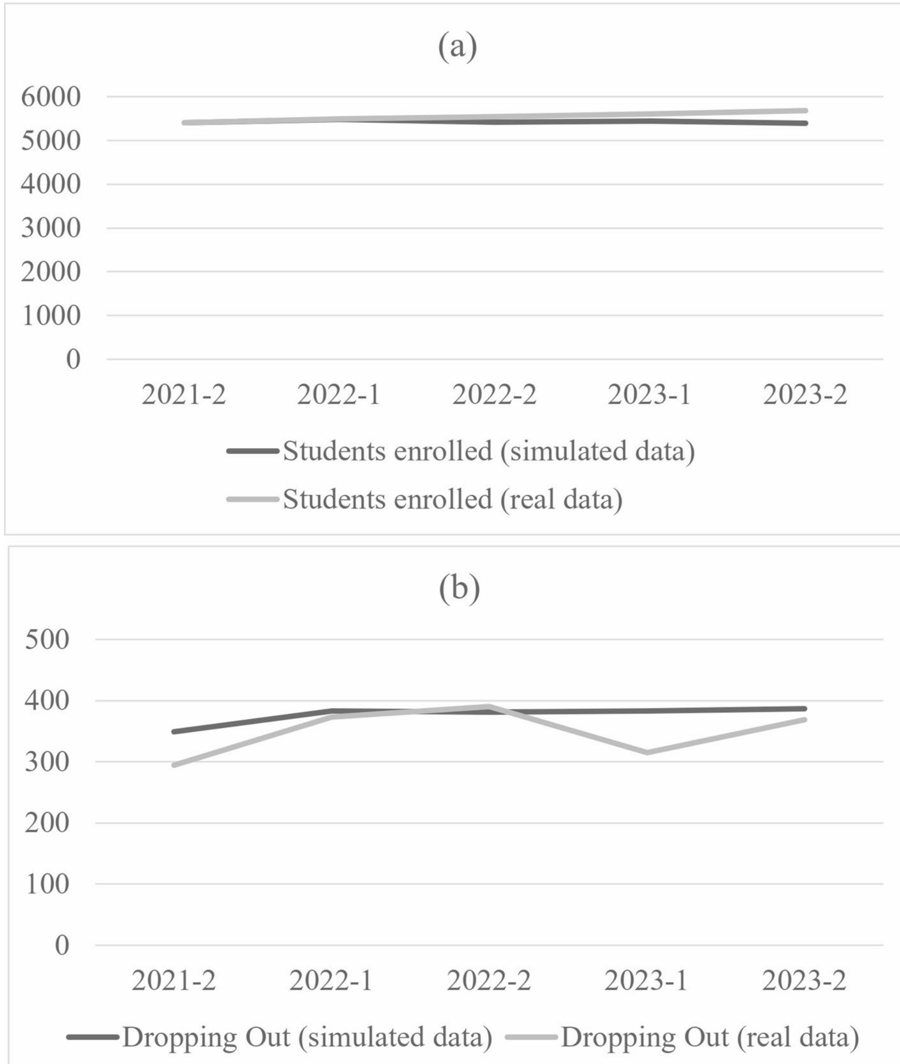

Fig. 5 comparison between simulated data and SPADIES records for enrolled and dropout students (2021-2 to 2023-2)

simulation period 20. This variable shows an early phase of rapid increase followed by stabilization. The broader confidence bands suggest that dropout rates are more sensitive to changes in model parameters.

Regarding student dropout due to the digital divide (Fig. 6c), the projected range at t = 20 spans from 33 to 140 students within the 95% CI. This stock follows a slower, steady growth trajectory, and the widening of the percentile bands over time reveals that this variable is highly sensitive to changes in the variables of the model.

Figure 7 presents the dynamic behavior of the main endogenous variables in the reference model, simulated over 20 semesters. This configuration allows for the observation of the joint evolution of enrollment processes, dropout, dropout associated with the digital divide, and digital skills training. As shown in Fig. 7a, the cumulative number of enrolled students exhibits progressive growth throughout the simulation period, reaching a value of 6.89 students by the end of semester 20. However, this growth proves insufficient when compared to the parallel dynamic of dropout accumulation, which displays a steeper growth pattern, totaling 8,546 dropout cases over the same period.

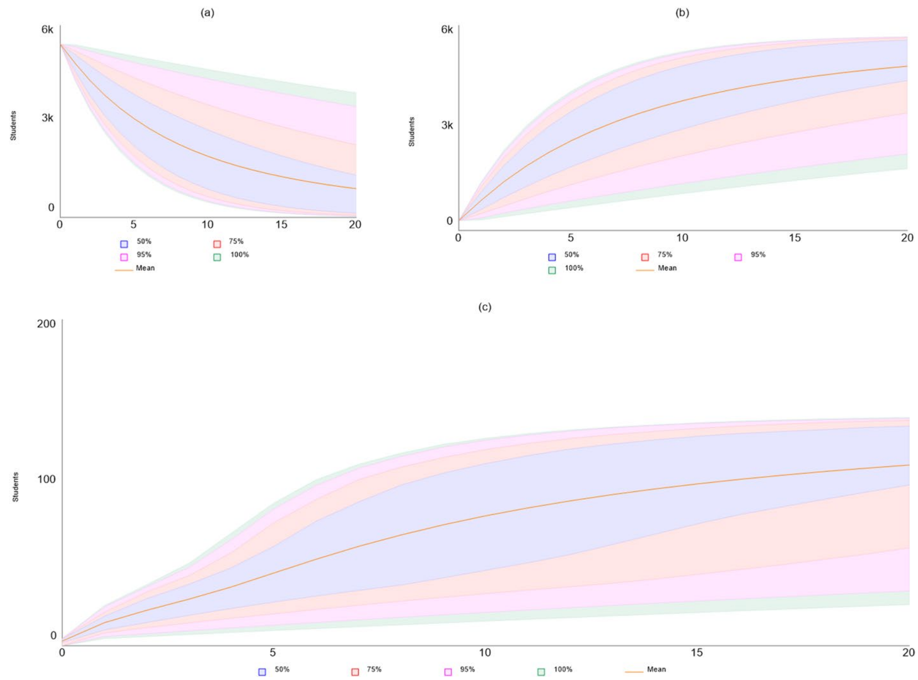

Fig. 6 Sensitivity Analysis and Reference Model. (**a**) enrolled students, (**b**) students who drop out, and (**c**) students who drop out due to the digital divide

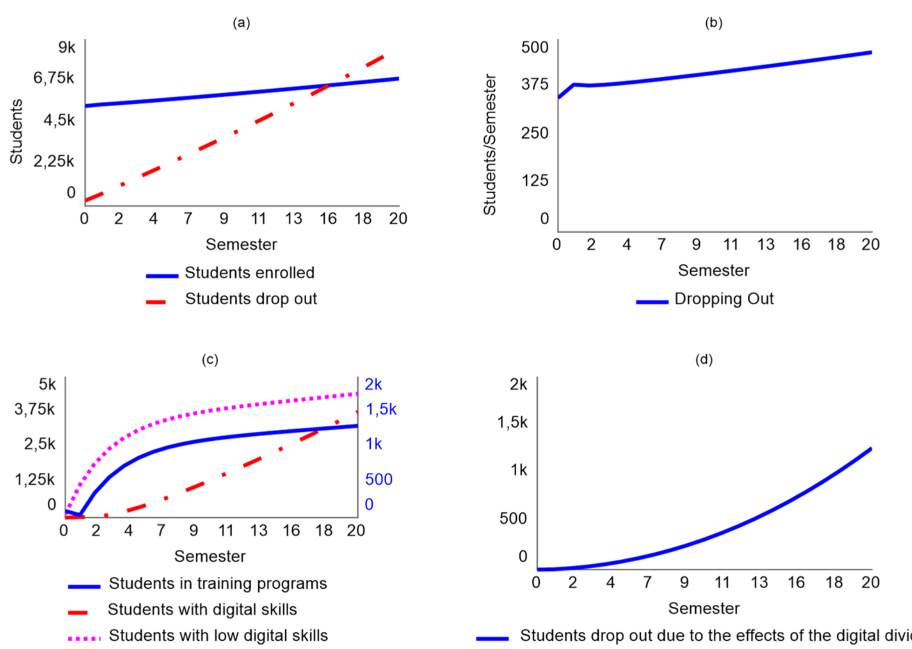

Fig. 7 Reference Model Results. (**a**) Evolution of enrolled and cumulative dropout students. (**b**) General dropout flow. (**c**) Students in digital training programs, with and without digital skills. (**d**) Dropout attributable to the digital divide

Simulations: household equipment

The reference scenario (see Fig. 8), corresponding to an average household income of USD 420 per month, assumes an internet connection speed of 42 Mbps and a device provision rate of 8.4%. In this case, cumulative dropout attributable to the digital divide

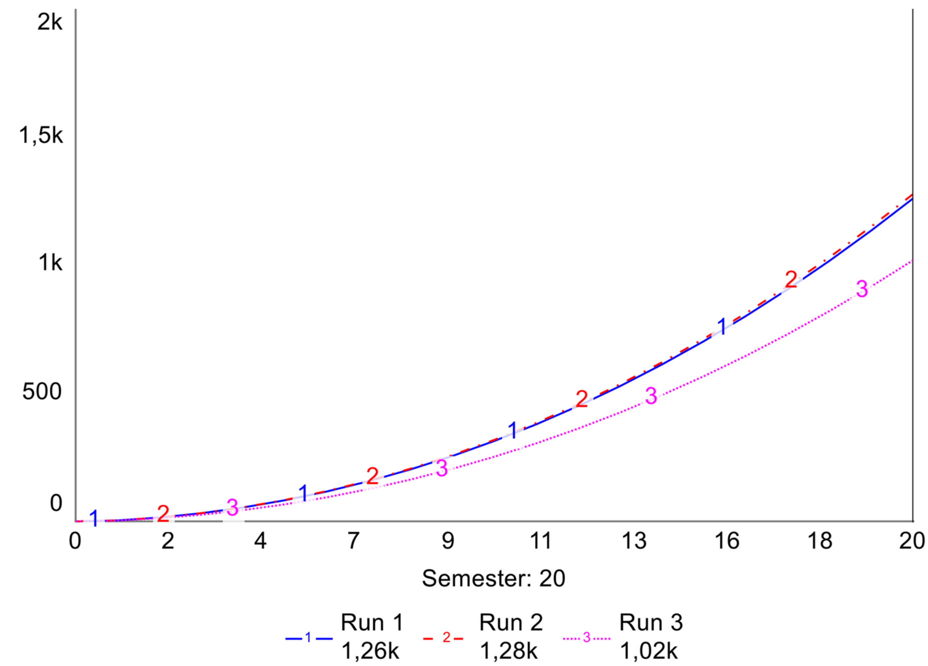

Fig. 8 Effect of household income on student dropout attributable to the digital divide under different connectivity and equipment scenarios. Note: Run 1 corresponds to the reference scenario, with an average household income of USD 420. Run 2 represents an unfavorable scenario, with an income of USD 350. Run 3 simulates a favorable scenario, with an income of USD 1,000

reaches 1,260 students by the end of semester 20. This behavior reflects a moderately restrictive structural condition, in which technological limitations increasingly hinder educational continuity. The model displays a quasi-exponential growth curve, indicating a progressively reinforcing negative feedback loop associated with digital exclusion. When household income is reduced to USD 350, with an average internet speed of 35.36 Mbps and device access at 7%, the model predicts an even higher dropout rate, reaching 1,280 students. In the most favorable scenario, with an average household income of USD 1,000, internet speed increases to 200 Mbps and device provision reaches 20%. This environment enables greater technological adoption and significantly more equitable conditions for digital learning. In this context, dropout attributable to the digital divide decreases notably, ending semester 20 with only 1,020 students having dropped out.

Simulations: training programs

This set of simulations examined variations in the Program Linkage Rate and the Dropout Training Programs Rate, but not simultaneously. Figure 9 illustrates the cumulative number of students who drop out due to the digital divide across 20 semesters, under three different scenarios defined by varying levels of the Program Linkage Rate. The scenarios correspond to rates of 0.3 (Run 1), 0.5 (Run 2), and 0.8 (Run 3). Despite the expected variation, the three curves exhibit a equal quasi-exponential trajectory, suggesting that increasing the program linkage rate alone does not produce a substantial reduction in dropout rates.

Regarding the dropout rate of the training program, Fig. 10 depicts the cumulative number of students dropping out due to the digital divide under three scenarios characterized by different dropout rates from digital skills training programs: 0.3 (Run 1),

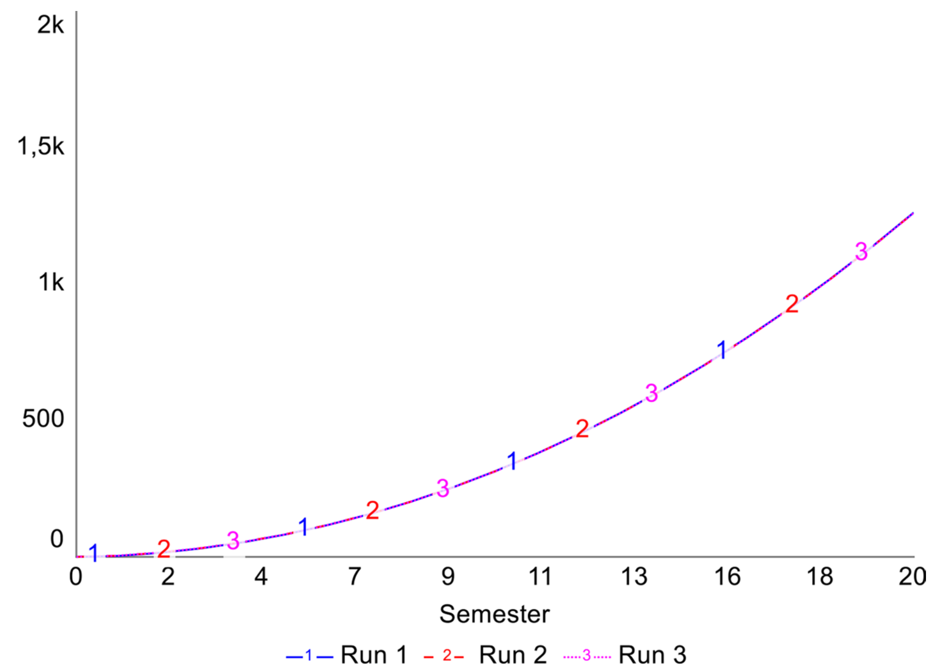

Fig. 9 Cumulative Student Dropout Due to the Digital Divide Under Different Program Linkage Rate Scenarios. Note: Run 1 = 30% program linkage (reference), Run 2 = 50%, Run 3 = 80%

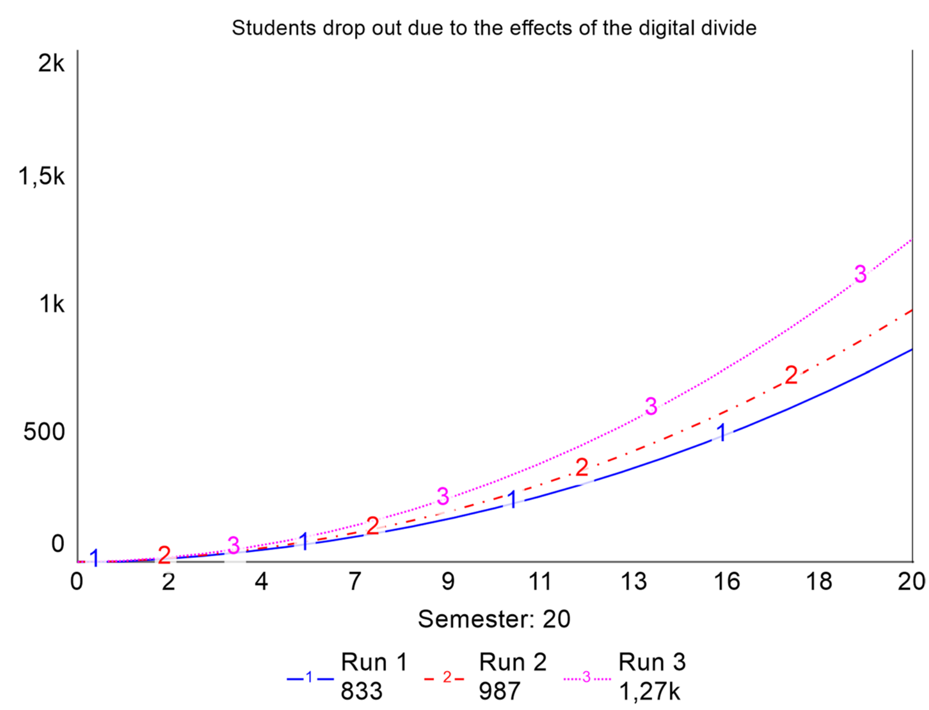

Fig. 10 Cumulative Student Dropout Due to the Digital Divide Under Different Digital Training Program Dropout Rates. Note: Run 1 = 30% dropout rate, Run 2 = 50%, Run 3 = 80% (reference scenario). Lower dropout from training programs significantly mitigates digital exclusion effects on student retention

0.5 (Run 2), and 0.8 (Run 3, reference scenario). The results indicate a strong inverse relationship between training program retention and dropout due to the digital divide. Run 1, with the lowest dropout rate (30%), results in the fewest students leaving the system—833 by semester 20. Run 2, with a moderate dropout rate (50%), shows an intermediate trajectory, ending at 987 students. In contrast, Run 3, where the dropout rate is highest (80%), shows a steep and accelerating curve, culminating in 1,270 students dropping out.

These findings highlight that training program effectiveness is a critical leverage point in reducing dropout due to digital divide. While access to training is essential, the actual retention and completion of such programs significantly conditions their long-term impact.

Simulations: student access

From an institutional perspective, a rising enrollment rate is generally a positive indicator. However, higher Enrollment Rates can also lead to an increase in students with limited digital skills, which in turn contributes to higher dropout rates associated with the digital divide. This concern prompted a closer examination of these dynamics through a series of simulations, presented in Table 3. In Run 2, the scenario with the lowest enrollment rate (10%), the system collapses progressively. The sharp increase in dropout attributable to the digital divide—reaching 819 students by semester 20—suggests an unstable system unable to retain its student base.

Figure 11 provides additional insight into system stability. Under Run 2, the number of students enrolled (blue line) declines exponentially, while the number of dropout students (red dashed line) increases and plateaus, overtaking enrollments around semester 7, as shown in Fig. 11a. This crossover point signifies a collapse threshold, beyond which the system is no longer viable.

Furthermore, the decrease in enrollment deteriorates the financial and operational capacity of the higher education institution (HEI), progressively undermining its infrastructure. This is particularly critical for students who lack access to ICTs at home and rely on institutional resources—such as computer labs, campus Wi-Fi, or loaned equipment—to participate in academic life. The resulting infrastructure degradation exacerbates the digital divide and intensifies educational inequality, further increasing dropout.

Discussion

To gain a better understanding of how the digital divide impacts student dropout rates in higher education undergraduate programs, it is essential to recognize that this phenomenon extends beyond disparities in access, use, and technological skills. The digital divide also has significant implications for equity, diversity, and inclusion in higher education (Silva et al., 2023). Over time, the concept has evolved beyond the mere lack of technological devices to encompass a broader range of socioeconomic, cultural, and social capital factors (Gil de Zúñiga et al., 2022; Cañón et al., 2024; Heeks, 2022).

Table 3 Simulations for dropout rates involving enrollment rates

Enrollment Rate	Students drop out due to the effects of the digital divide
0.31 (reference mode)	1,260
0.10	819
0,60	12,500

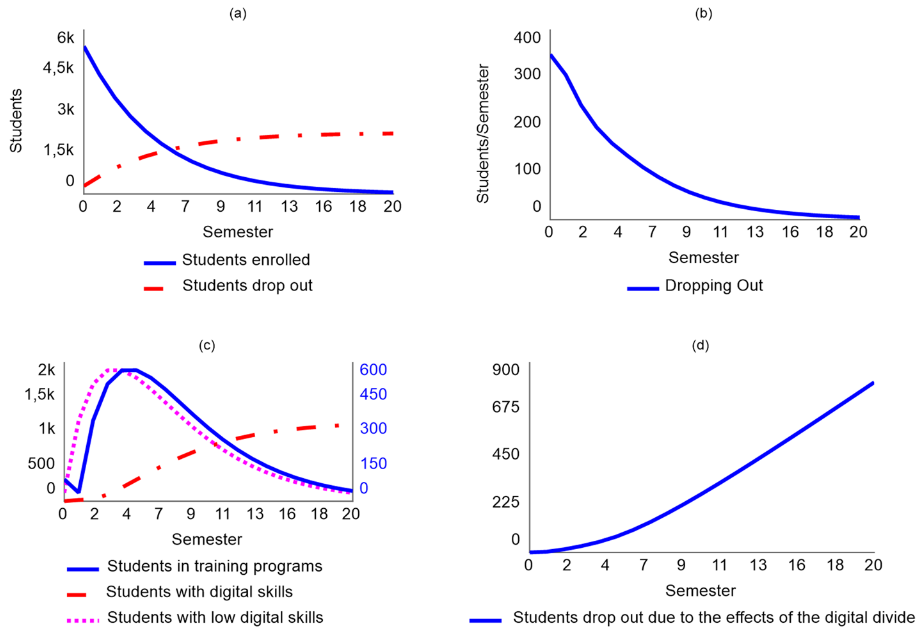

Fig. 11 Dynamic Behavior of Key Endogenous Variables in the run 2. (**a**) Students enrolled and general dropout. (**b**) Dropout flow over time. (**c**) Evolution of digital skills training: students in training programs with digital skills, and with low digital skills. (**d**) Dropout attributable to the digital divide

The digital divide is evident in three key aspects: (1) Access to technology and connectivity (Cañón et al., 2024; Elrayah & Alshiha, 2024); (2) digital skills and technological training (Elrayah & Alshiha, 2024; Guzmán et al., 2023; Selwyn, 2004); and (3) effective use of technology in learning (Ventrella & Cotnam-Kappel, 2024; Greaves, 2024; Bracco et al., 2022).

The theoretical framework developed for study identified the most relevant variables related to the digital divide that have a significant impact on student dropout rates. These include limited access to devices and connectivity, absence of digital skills, unfavorable socioeconomic conditions, insufficient institutional support, and low quality of online learning (Elrayah & Alshiha, 2024; García et al., 2023; Sun et al., 2022; Caprara & Caprara, 2022).

Consequently, the digital divide has emerged as a significant barrier to student retention, directly influencing dropout rates. Levano-Francia et al. (2019) emphasize the urgency of closing this gap by promoting, recognizing, and incentivizing the development of digital skills, as these competences contribute to more inclusive and socially cohesive communities. Similarly, Nkansah and Oldac (2024) highlight the need for HEIs, governments, and communities to collaborate in addressing the digital divide and enhancing student retention through comprehensive digital literacy initiatives across all educational levels. Additionally, improving internet access and ensuring that institutions are equipped with adequate technological resources are essential steps toward fostering students' academic and professional success.

This challenge aligns closely with the global agenda outlined in Sustainable Development Goal 4 (SDG 4), which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. In particular, the study's findings are relevant to targets 4.3 and 4.4, which emphasize equal access to quality tertiary education and the development of relevant digital skills among youth and adults. As Nedungadi et al. (2024) argue, generative artificial intelligence (GAI) holds transformative potential for advancing these targets by personalizing learning, reducing accessibility barriers, and fostering digital inclusion. However, they also caution that the ethical and algorithmic risks associated with GAI must be addressed through strategic, equity-oriented policy design. In this context, simulation models such as the one proposed in this study offer valuable insights to support institutional and policy-level decisions aimed at closing digital gaps and advancing educational equity.

This study identified key strategies to mitigate student dropouts caused by the digital divide. These strategies include increased investments by HEIs' in digital infrastructure, expanding their digital training programs, enhanced institutional support and academic guidance, as well as the implementation of simulation models to better understand this phenomenon and inform decision-making (Nkansah & Oldac, 2024; Barragán & González, 2024; García, 2021; Guzmán et al., 2021; Cosenz, 2022; Ramoni & Orlandoni, 2022).

In other words, HEIs must improve their digital skills training programs and strengthen the support mechanisms that facilitate student success. Additionally, they must ensure that students complete these programs, as their successful completion positively impacts retention rates. Since student dropout is a multifaceted issue, it is essential for HEIs to continuously diagnose, monitor, and address dropout causes beyond the digital divide (Fig. 1). These factors have a more substantial impact on overall student retention and require targeted interventions.

Conclusions

The implementation of the SD methodology, as outlined in this article, successfully achieved the study's objective: simulating the effect of the digital divide on student dropout in higher education undergraduate programs.

SD enabled us to simulate the impact of the digital divide on student dropout rates in undergraduate programs. This methodology offers deeper insight into the inherent complexity of the education system, serving as a powerful tool for modeling scenarios, evaluating social interventions, and designing improvement strategies in this dynamic context.

The findings highlight the digital divide as a key factor influencing student dropout and retention in undergraduate higher education programs, as it directly impacts the access, learning, and participation in digital environments. Mitigating this issue requires strengthening technological infrastructure, enhancing digital skills training, and implementing institutional policies that address inequalities in technology access.

It is essential for HEIs to develop comprehensive, evidence-based strategies (such as those generated in this study through SD simulation models) to foster inclusive and equitable education in the digital age. This aligns directly with Sustainable Development Goal 4 (SDG 4), which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. By doing so, HEIs can advance equity and social justice, ensuring that all students have the necessary resources and support to succeed in an increasingly digital learning environment.

Limitations of this study

While the model provides valuable insights into simulating the effect of the digital divide on student dropout, it currently assumes that access to and development of digital skills rely almost entirely on institutional support. This assumption may overlook the broader interplay of factors in an evolving technological landscape. Additionally, the study subtly does not address other potential limitations, such as parameter uncertainty, and the inherent assumptions underpinning the model.

Research opportunities

Future research should focus on extending the model to capture emerging scenarios including post-COVID hybrid learning environments, new forms of digital exclusion (e.g., algorithmic bias), and behavioral factors leading to dropout. With the advent of technologies like large language models (LLMs), AI-powered tutors, and virtual labs, it becomes imperative to incorporate variables that could substantially reduce digital exclusion. For instance, factors such as autonomous technology use, AI-mediated learning, and platform-independent digital competency development could be integrated into the model (Jyothy et al., 2024; Moore et al., 2023).

Abbreviations

HEI	Higher education institution
ICT	Information and communication technologies
COVID-19	Respiratory disease caused by the SARS-CoV-2 virus

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The authors declare that they made substantial contributions to this article by participating in the modelling and analysis, drafting and revision process. They also provide final approval of the version to be published and agreed to be accountable for all aspects of the work. To enhance the manuscript's clarity and readability, Artificial Intelligence tools were exclusively used for proofreading, grammar and style improvements, as well as for verifying the accuracy and consistency of bibliographic references.

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Declarations

Competing interests
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