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Course Dropout Intention Scale: Development and Validation of a New Brief Measure in Academic College Context

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Abstract: University students may encounter situations where they perform poorly in a course and contemplate dropping out. This intention to drop out of a course manifests not only in thoughts or ideas but also in a cognitive self-evaluation of their performance and skills, enabling them to reflect on the possibility of dropping out. In this sense, there is a shortage of instruments that evaluate the intention to drop out of a course, so the aim was to develop and validate the Course Dropout Intention Scale (CDIS). Data from two samples (N1 = 198; N2 = 675) were used; the first was for the EFA, and the second was for the CFA, GRM, and SEM. The one-factor model was derived from the EFA and confirmed in the second sample, exhibiting appropriate goodness-of-fit indices. Similarly, the GRM obtained adequate fit indices; all items discriminated adequately, and the difficulty parameter had a monotonic increase. The SEM model of the effect of satisfaction with studies on the CDIS showed a negative and statistically significant effect. Thus, it was demonstrated that the CDIS is a robust instrument in its psychometric properties and empirical evidence with other variables.

Keywords: *Brief measure, college student, course dropout, dropout intention, dropout studies.*

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Introduction

Amidst the Covid-19 pandemic, difficulties in learning opportunities were observed owing to various factors such as lack of internet access, inability to adhere to a regular schedule, economic constraints, and generalized anxiety concerning Covid-19. These issues have placed 24 million students at risk of dropping out of school (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2020). Dropout rates can be influenced by many factors, including psychological factors such as self-regulation, anxiety, boredom, low satisfaction, undefined goals, and stress (Noman et al., 2021). Institutional factors such as the quality of student services and the freedom of expression are also crucial (Woodard et al., 2001). Dissatisfaction with infrastructure, pedagogical services, extracurricular activities, and the curriculum can also contribute to higher dropout rates (Bardach et al., 2020). Personal reasons like lack of interest, poor academic performance, distance from home to the university, and financial constraints can further exacerbate the issue (Tayebi et al., 2021). Thus, the multicausal nature of dropout has been extensively documented in the literature.

The act of college dropout is associated with adverse social outcomes such as limited career opportunities, decreased earnings, compromised health, elevated rates of criminal behavior, and reduced civic involvement (Rumberger, 2011). However, the trajectory leading to college dropout is intricate, with dropout intention emerging as a pivotal factor (Mashburn, 2000). Self-Determination Theory (Ryan & Deci, 2017) posits that students disengage from college due to deficiencies in autonomy, competence, or relatedness. Autonomy signifies the yearning for control over life choices; competence entails the need to feel proficient and capable in activities; and relatedness pertains to the desire for meaningful connections with others. Students perceiving unmet needs in these areas during their college tenure are more

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prone to contemplate dropping out. That is consistent with Hom et al. (1992), who propose that dropout intention stems from dissatisfaction, wherein students discontented with academic services and instructional methods are likely to harbor sentiments of disillusionment and frustration, ultimately influencing their decision to persist or discontinue their studies.

Hence, recurring sentiments of discontent contribute to the adoption of adverse attitudinal stances. The Theory of Reasoned Action (TRA) cogently elucidates that human conduct is intricately interwoven with underlying beliefs and attitudes (Ajzen, 2005). TRA posits that an individual's inclination to engage in a particular behavior is contingent upon their attitude and subjective norms. Attitude pertains to an individual's evaluation of the performance of a given behavior (Ajzen, 1985); succinctly put, it is the perception of the positive or negative outcomes associated with the behavior. Conversely, subjective norm refers to an individual's perception of societal pressures or the anticipations of others with respect to the enactment of a specific behavior. These norms may be influenced by friends, family, social groups, or any other external factor that the individual perceives as significant. According to TRA, the intention to perform a behavior is the most immediate predictor of the behavior itself (Fishbein & Ajzen, 2009). Consequently, students who negatively assess their academic circumstances and grapple with feelings of frustration, discontent, deficient efficacy beliefs, and limited self-regulation are more inclined to harbor an intention to withdraw from their academic pursuits (Díaz Mujica et al., 2019; Samuel & Burger, 2020).

Previous Measures

The multicausal nature of educational dropout permits an extensive examination of the problem; however, it can be a limiting factor in developing measurement instruments. That is, one could develop a general dropout intention instrument or create specific instruments targeting economic motives, motivational, institutional, and personal aspects. For this reason, several studies have utilized a general question (e.g., "Have you considered dropping out?") coupled with sociodemographic queries to measure dropout intention (e.g., "Have you thought about dropping out?"), usually integrated with sociodemographic questions (e.g. Alves et al., 2022; Marôco et al., 2020). Brief single-use instruments have also been developed for research purposes; nevertheless, they lack sound psychometric evidence (e.g. Duque et al., 2013; Litalien & Guay, 2015). Consequently, this highlights the need to explore dropout intention further as a complex construct.

Based on the above, the measurement of dropout intention has mainly focused on the general tendency to drop out of college while overlooking situations where a student may drop out of a specific course while continuing with other courses. Such a decision is influenced by the students' self-perception of their abilities, performance, and situation in that particular course. To address this issue, developing a measurement instrument focusing on specific course dropout intention would enable researchers to identify and measure the factors contributing to students' decision to drop a specific course. This measure could also be used to develop predictive models to identify students at risk of dropping a particular course (e.g., mathematics).

Psychometric Properties of a Measure

The developed instrument should undergo statistical processes to support its validity and reliability. For instance, exploratory factor analysis (EFA) can identify the underlying factors responsible for the observed correlations among variables. EFA is crucial for understanding the latent constructs being measured and for developing valid and reliable measures of these constructs. Theoretical models can be tested by evaluating how well the observed data fit the hypothesized factor structure (Gorsuch, 1997). Also, confirmatory factor analysis (CFA) can be utilized to examine whether a hypothesized factor structure fits the data. CFA is significant for evaluating the validity of theories and refining models as needed. In this way, evidence of construct validity is provided when the factor structure established in the EFA is confirmed (Kline, 2016; Schreiber et al., 2006). These analyses are situated within Classical Test Theory (CTT).

On the other hand, reporting evidence based on the Item Response Theory (IRT) of a psychological measure is essential for several reasons. First, IRT provides information about item difficulty and discrimination, which can improve the accuracy and precision of the measure (Embretson & Reise, 2000). Additionally, it improves the transparency and credibility of the measure by providing information about its psychometric properties and the underlying construct being measured. Cai and Monroe (2013) argue that IRT provides a framework for evaluating model fit and item properties. The authors also discuss the potential of IRT to improve the measurement of complex constructs that may be difficult to measure using traditional psychometric methods.

In addition, the instrument must exhibit additional empirical evidence demonstrating its association with identical or related variables. Therefore, validity evidence based on relationships with other variables refers to the extent to which a psychological measure is related to similar o different theoretical variables in a manner consistent with the literature (DeVellis & Thorpe, 2021). In other words, this validity evidence pertains to whether the measure functions as expected concerning other variables conceptually linked to the construct (Marsh et al., 2004; Meyer et al., 2001).

In general, reports on the psychometric properties of scales that have been developed or require validation should present evidence from different methods of analysis to enhance the robustness of the instrument's psychometric properties.

Present Study

Based on the need stated above, the present research had the objective of designing and validating an instrument on intention to drop out of a course focused on the higher level since these students have the power to decide about their studies and are not subject to a legal framework that requires their completion, unlike in primary education. In turn, different complementary objectives are used, such as: (a) to provide evidence of content-based validity; (b) to explore the internal structure of the measure; (c) to confirm the factorial structure of the instrument; (d) to analyze the instrument through the Item Response Theory; and, (e) to establish a predictive model of satisfaction with studies towards the intention to drop out of a course.

Methodology

Research Design

The study aims to develop and validate an instrument for measuring course dropout intention. The research design is instrumental (Ato et al., 2013) as it involves various statistical analyses, including exploratory factor analysis (EFA), confirmatory factor analysis (CFA), internal consistency reliability analysis, item response theory (IRT) analysis using the graded response model (GRM), and validity evidence based on the association with other variables using structural equation modeling (SEM).

Sample and Data Collection

Two samples were used. The first was obtained to perform an exploratory factor analysis (EFA). The guideline of having at least 20 participants per variable was adhered to, following the recommendation by Schumacker & Lomax (2015), thus necessitating a minimum of 80 participants for evaluation. Data were gathered from 198 university students through a non-probabilistic convenience sampling method. The participants were of both sexes, male (33.8%) and female (66.2%), with an average age of 23.48 years (*SD* = 5.28; range = 18-35 years), among single (88.9%), married (4.5%), cohabiting (5.6%), divorced (0.5%) and widowed (0.5%). In addition, 45.5% are engaged only in study, while 54.5% study and work.

The second sample was used for confirmatory factor analysis (CFA), item response theory (IRT), and structural equation modeling (SEM). The sample size was calculated through a Monte Carlo simulation (Beaujean, 2019), where a minimum sample of 600 respondents was obtained. Thus, information was collected from 675 university students with an average age of 21.72 years (*SD* = 4.53 years; range = 18-35 years), between males (41.2%) and females (58.8%). In terms of marital status, they were single (92.0%), cohabiting (4.1%), married (3.4%), and widowed (0.4%). Likewise, 55.0% were only studying, and 45.0% were studying and working.

Table 1. Sociodemographic Data of Samples

	Sample 1 (*n* = 198)	**Sample 2 (*n* = 675)**
Age (*M* ± *SD*)	23.48 ± 5.28	21.72 ± 4.53
Sex, *n* (%)		
Male	67 (33.8%)	278 (41.2%)
Female	131 (66.2%)	397 (58.8%)
Marital status, *n* (%)		
Single	176 (88.9%)	621 (92.0%)
Married	9 (4.5%)	23 (3.4%)
Divorced	1 (0.5%)	-
Widowed	1 (0.5%)	3 (0.4%)
Cohabitant	11 (5.6%)	28 (4.1%)
Work and Study, *n* (%)		
Study only	90 (45.5%)	371 (55.0%)
Study and work	108 (54.5%)	304 (45.0%)

Measurement Instruments and Materials

Brief Scale of Satisfaction with Studies (Escala Breve de Satisfacción con los Estudios [EBSE]) was developed by Merino-Soto et al. (2017). It evaluates the student's satisfaction with the way he/she studies. It comprises three items answered on a Likert-type scale with five response options (strongly disagree to strongly agree). Its fit was optimal (CFI = .92, GFI = .99). Likewise, its internal consistency was calculated through the alpha (α = .788) with confidence intervals (CI95%: .755 - .817).

Course Dropout Intention Scale (CDIS) was developed for the present study. The instrument assesses statements about the intention to drop out of an academic course based on their self-perception of skills, experience, and performance related to a course. It comprises four items with the same sense of wording (See Appendix). Each item is answered on a 5-point Likert-type scale from 1 (Strongly disagree) to 5 (Strongly agree).

The CDIS was developed in accordance with the Standards for Educational and Psychological Testing (American Educational Research Association [AERA] et al., 2014). A literature search was conducted to identify theoretical bases on intention, and a specifications table was developed that included the definition and indicators of the construct. From this table, four items were derived. These items were evaluated by expert judges who assessed their relevance, clarity, and coherence. Based on the judges' recommendations, some items were modified to better align with the theoretical construct. The final version was presented to a group of 10 university students who provided feedback on the items' comprehensibility and readability. Examples of feedback included statements such as "The statement is understandable", "Very understandable and precise", "I understand it", and "It is clear". The final version of the instrument, as modified based on expert feedback and student input, was used in this study.

Procedure

When the instrument was finalized, it was sent to five expert judges to provide their ratings and suggestions based on the items' clarity, relevance, and coherence. Thus, the final version of the CDIS was obtained by collecting comments. For data collection, a virtual form was created in Google Form that included the informed consent with the objectives and purposes of the study, a sociodemographic data sheet, the CDIS, and EBSE. All participants gave their informed consent to be part of the study. In this sense, the treatment of their data was specified, respecting anonymity. This process was conducted during November and December 2022.

Analyzing of Data

The analysis was performed in R Studio (v. 4.2.2). For content validity, Aiken's V coefficient and confidence intervals were used (Aiken, 1980). Subsequently, the descriptive data of the items were analyzed and assessed for univariate normality through skewness (±2) and kurtosis (±7) (Finney & DiStefano, 2013). The correlation matrix was obtained, where Cohen's (1988) criteria on the degree of relationship between variables were followed (weak: .10 to .29; moderate: .30 to .49; strong: > .50). An exploratory factor analysis was performed with the first sample using the packages *psych*, *GPArotation*, and *parameters*. The items were considered continuous variables because they had five response options (Rhemtulla et al., 2012). Sample adequacy was explored employing the KMO (> .80) and Bartlett's test of sphericity ($p <$ .05). An oblique rotation (oblimin) was used.

A confirmatory factor analysis (CFA), graduated response model (GRM; IRT), and structural equation model (SEM) were performed with the second sample. For the CFA, we used the *lavaan* and *semTools* packages and the robust version of the maximum likelihood estimator (MLR) because it is not affected by the non-normality of the data (Yuan & Bentler, 2000). In evaluating the model, fit indices such as the chi-square (χ^2), degrees of freedom (*df*), comparative fit index (CFI), Tucker Lewis index (TLI), root mean square error of approximation (RMSEA) with their confidence intervals, and standardized root mean square residual (SRMR) were analyzed. The evaluation criteria were: CFI and TLI > .90 and RMSEA and SRMR < .08 (Browne & Cudeck, 1992). Factor loadings were evaluated, which had to be greater than .50 to establish that they represent a latent construct (Dominguez-Lara, 2018). On the other hand, alpha and omega coefficients were used to calculate reliability (Choi et al., 2009), where coefficients above .80 are considered adequate (Raykov & Hancock, 2005). An SEM model was used to assess the association between study satisfaction and dropout intention. They followed the same model evaluation criteria as in the CFA. In addition, the R^2 was calculated to assess the common variance explained (Cohen, 1988).

Finally, as part of the analysis by Item Response Theory (IRT), the Graded Response Model (GRM) was used in its logistic model for 2-parameters in polytomous items (Hambleton et al., 2010). The *mirt* package was used to specify the GRM and goodness-of-fit indices such as *C2* for its usefulness for polytomous items ($p < .001$), RMSEA ≤ .08, SRMSR ≤ .05, CFI and TLI ≥ .95 (Cai et al., 2023; Maydeu-Olivares & Joe, 2014). Also, the discrimination (a) and difficulty (b) parameters were evaluated (Samejima, 1997). Parameter a allows differentiating between subjects with high and low levels in the construct, and parameter b indicates that the individual has a 50% probability of giving answers greater than those made (Edelen & Reeve, 2007).

Results

Content Validity

Aiken's V coefficient was obtained for each item with the evaluation of six expert judges. The results showed values above .80 when measuring clarity, coherence and relevance. Similarly, the confidence intervals illustrate the potential variation in these coefficients. Notably, the lowest interval was .55 for item 1 (Table 2). Furthermore, it has been ascertained that the four items exhibit syntactic, semantic, and logical coherence, along with an association with a theoretical construct.

Table 2. Content Validity

Items	Clarity				Coherence				Relevance			
	M	*SD*	*V*	CI95%	*M*	*SD*	*V*	CI95%	*M*	*SD*	*V*	CI95%
1	2.40	.89	.80	.55 - .93	2.40	.89	.80	.55 - .93	2.40	.89	.80	.55 - .93
2	3.00	.00	1.00	.80 - 1.0	3.00	.00	1.00	.80 - 1.0	3.00	.00	1.00	.80 - 1.0
3	2.60	.89	.87	.62 - .96	2.60	.89	.87	.62 - .96	2.60	.89	.87	.62 - .96
4	2.80	.45	.93	.61 - .99	2.60	.55	.87	.62 - .96	2.80	.45	.93	.61 - .99

M= mean; *SD*= standard deviation; *V*= Aiken's V; CI= Confidence Intervals

Exploratory Factor Analysis

Table 3 shows the preliminary analysis of the items for sample 1, where univariate normality was assured through skewness and kurtosis. Similarly, the correlation matrix shows strong associations between the items. This first evidence allowed assuring the viability of an EFA through the KMO= .78 and Bartlett's sphericity (p < .001). In this sense, we extracted a single factor that explains 60% of the total variance. Furthermore, the factor loadings of the items were optimal (Table 3). In turn, the reliability coefficients were adequate in alpha (.85) and omega (.86). This made it possible to establish its unidimensionality in sample 1.

Confirmatory Factor Analysis

Similarly, the initial analysis of the items for the CFA is shown in Table 3. Based on the descriptive data, we can determine that the skewness and kurtosis demonstrate univariate normality (±2 and ±7, respectively). The associations between items were found to be greater than .50, except for the correlation between items 4 and 1 of basic professional training. As anticipated, the remaining items display covariance with each other. When evaluating the fit indices of the second sample, adequate fit indices were obtained (χ^2 = 10.88, df = 2, p < .05; SRMR = .025; TLI = .940; CFI = .980; RMSEA = .080, CI90% = .054 - .110) confirming its unidimensional structure. The factor loadings were > .70, and the reliability coefficients were > .80 for the total sample.

Table 3. Descriptive Statistics, Item Correlation, Factor Loadings, Alpha, and Omega Coefficient.

Samples	Item	*M*	*SD*	g_1	g_2	Correlation				λ	α	ω
						1	2	3	4			
Sample 1 (n = 198)	1	1.70	.94	1.58	2.46	-				.66	.85	.86
	2	1.78	.95	1.30	1.26	.63	-			.85		
	3	1.75	.99	1.35	1.27	.51	.68	-		.82		
	4	1.85	1.06	1.25	.75	.41	.63	.68	-	.76		
Sample 2 (n = 675)	1	1.61	.92	1.61	2.12	-				.72	.87	.87
	2	1.64	.94	1.55	1.89	.65	-			.85		
	3	1.72	.99	1.37	1.23	.58	.66	-		.81		
	4	1.74	.97	1.26	.92	.51	.68	.68	-	.79		

M= mean; *SD*= standard deviation; g_1= skewness; g_2= kurtosis; λ= factor loadings; α= coefficient alpha; ω= coefficient omega.

Graduated Response Model

The IRT analysis reveals the discrimination (a) and difficulty (b) parameters (Table 4). The discrimination values were > 3, indicating accurate discrimination for all four items, particularly for item 2 ("I wish to stop attending class because I am doing poorly."). Additionally, the difficulty parameters demonstrate a monotonic increase. Likewise, the GRM fit was optimal ($C2$ = 23.2; df = 2; p < .001; RMSEA = .12; SRMRS = .068; TLI = .960; CFI = .987).

Table 4. Discrimination and Difficulty Parameters of CDIS

Items	a	b_1	b_2	b_3	b_4
1	3.21	.26	.89	1.42	1.98
2	3.89	.20	.61	1.04	1.59
3	3.72	.15	.79	1.53	2.01
4	3.45	.08	.82	1.64	2.27

a = discrimination; b = difficulty

Structural Equation Model

The effect of study satisfaction (EBSE) on educational dropout intention (CDIS) was evaluated, and a negative effect was found (β = -.43; p < .001), which represents 19% (R^2 = .19) variance explained by EBSE. Similarly, the structural model presented adequate goodness-of-fit indices (χ^2 = 27.84, df = 13, p < .001; SRMR = .022; TLI = .979; CFI = .987; RMSEA = .041). Thus, the assumption that satisfaction negatively influences the intention to drop out is proven.

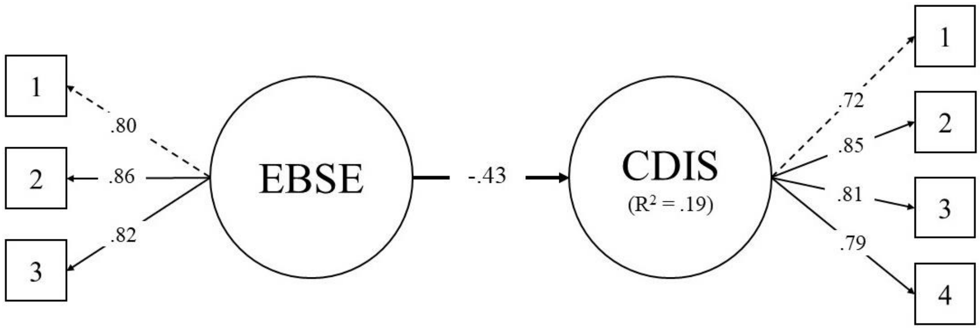

Figure 1. Regression Model of the Effect of EBSE on CDIS

Discussion

The literature has limited evidence on concise tools for evaluating dropout intention that has undergone rigorous psychometric evaluation. Therefore, this study aimed to develop and validate a new measure of the intention to drop out of a course in higher education. The development of the instrument followed the recommendations of the Standards for Educational and Psychological Testing (AERA et al., 2014). Initially, a comprehensive theoretical review was conducted to define a set of items for assessing dropout intention. Then, expert judges evaluated the items for clarity, coherence, and relevance. Aiken's V show that all items were important and representative (Aiken, 1980). Adjustments were made to some items based on the feedback received from the judges. The final version was tested with ten university students who provided feedback on the understandability and readability of the items.

The instrument's factor structure was explored with the first sample, and a stable latent factor model with satisfactory factor loadings was obtained. The unidimensional structure of the instrument was confirmed with the second sample, which allows for the calculation of total scores (McDonald, 1999; Samejima, 1997). The instrument demonstrated strong internal consistency, with coefficient alpha and omega greater than .80, indicating accurate measurement of the construct (McDonald, 1999). Factor loadings were consistent and higher than .50 (Dominguez-Lara, 2018), which suggests effective representation of the latent construct by the items. The CDIS provide a valid and reliable measurement of the intention to drop out of a course in university students.

On the other hand, the analysis employing the Graded Response Model (GRM) provided evidence on the discrimination and difficulty parameters. Particularly, item 2 ("I wish to stop attending class because I am doing poorly.") garnered the utmost discrimination parameter, signifying its capability to elicit responses spanning from strongly disagree to strongly agree. In simpler terms, item 2 effectively distinguishes individuals with varying levels of intention to drop a course (Tayebi et al., 2021). Furthermore, this demonstrates that item 2 offers deeper insights into the intention to drop out of a course, as it mirrors a cognitive pattern intertwined with self-perceptions of academic performance (Tayebi et al., 2021). Similarly, item 2 is more informative and confers greater robustness to the CDIS. Students harboring elevated intention to drop out find it easier to respond to item 2, unlike those with a low intention to drop out of the course. Its monotonic increase indicates that a more significant presence of the latent trait is necessary to respond to categories such as strongly agree.

The psychometric properties of the CDIS were examined using exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and graded response model (GRM) analysis. Structural equation modeling (SEM) was utilized to enhance the instrument's robustness and to examine its empirical performance in conjunction with other variables, such as the Educational Behavioral and Social Engagement (EBSE) scale. The effect of satisfaction with studies had an negative effect on the CDIS, aligning with the theoretical framework proposed by Hom et al. (1992). Specifically, students content with their academic experiences, including teaching quality and course relevance, are less prone to express dropout intention (Allen & Robbins, 2008). According to Tinto's (1994) student dropout model, individuals satisfied with both academic and social experiences are more inclined to persist in college and ultimately attain their degrees.

The current study has significant implications, as researchers can employ the CDIS to delve into course dropout intention as a latent factor underpinned by cognitive statements. This enables further investigation of the dropout intention construct. Moreover, educational institutions and educators can employ the CDIS to pinpoint students at risk of early course withdrawal, allowing for timely intervention and support. Finally, it aids researchers in gaining a more profound understanding of the complex nature of course dropout decisions and offers guidance for forthcoming research endeavors in this domain.

Conclusion

In conclusion, unlike other studies that assess the intention to drop out through a single, generic question (e.g. Alves et al., 2022; Marôco et al., 2020), the CDIS enables the examination of the intention to drop out as a complex construct with statements that assess the student's intention to discontinue a specific course or subject based on their previous self-assessment. Thus, employing the CDIS aligns with the theory that intention is predisposed by personal beliefs (Ajzen, 1985, 2005). Moreover, the CDIS, as a brief instrument, offers advantages over extensive scales, such as reducing application time, eliminating redundancy, reducing boredom of the evaluation, and improving the instrument's performance (Burisch, 1984). Additionally, the CDIS can be employed by researchers, educational institutions, and instructors to delve into the dropout intention construct. Furthermore, the CDIS allows for early identification of students at risk of course dropout, facilitating timely intervention and support. Finally, the CDIS aids researchers in gaining a deeper insight into the intricate nature of course withdrawal decisions and provides guidance for forthcoming research endeavors in this domain.

Recommendations

The study recommends that the scientific community replicate the study using samples with a larger number of participants to facilitate analysis of measurement invariance between groups, thereby ensuring the applicability of the CDIS across diverse groups. Similarly, employing larger samples enables the acquisition of normative data that could be utilized for diagnosing or categorizing levels of intention to drop out of a course.

In addition, it is recommended to utilize the CDIS in explanatory and predictive models due to its robustness within the university sample. This approach ensures a comprehensive assessment of the dropout intention construct, enabling the acquisition of empirical evidence and the development of theoretical models that contribute to the understanding of this phenomenon. Concurrently, the application of the CDIS facilitates the investigation of risk factors associated with dropping out of a course, providing valuable insights for educational institutions and educators.

Moreover, the study's scope could be expanded to include graduate populations, which often remain underserved. Further research should also delve into the intricate interplay between academic struggles, dropout intentions, and educational attrition. Exploring the perspectives and experiences of students contemplating dropping out could offer deeper insights into underlying factors, such as diminished motivation, inadequate social or financial support, and academic or personal obstacles. Lastly, conducting comparisons of the determinants of dropout intention among diverse student groups—varying in academic levels, fields of study, and cultural and social backgrounds—would yield valuable insights.

Limitations

However, some limitations were observed in the study. First, non-probabilistic sampling does not allow for population inferences. Moreover, although the sample size was adequate for the psychometric analyses conducted, a more extensive and diverse sample across all groups would have been desirable to explore the invariance of the CDIS. Therefore, we suggest that future studies may consider this as a new research direction.

Conflict of Interest

The authors declare no conflict of interest.

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Authorship Contribution Statement

Yupanqui-Lorenzo: Concept design, data acquisition, data analysis, drafting manuscript, final approval. Jara-Osorio: Concept design, data acquisition, writing, administration. Carbajal-León: Data acquisition, writing, reviewing, editing. Caycho-Rodríguez: Reviewing, editing, critical revision of manuscript. Cardoza Sernaqué: Data acquisition, reviewing, editing. Duran Quispe: Data acquisition, reviewing, editing.

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Appendix

Table A1. Course Dropout Intention Scale in Spanish and translated into English

No.	Ítems / Items	1	2	3	4	5
1	Pretendo abandonar el curso. / I intend to drop out of the course.					
2	Deseo dejar de asistir a clase porque me va mal. / I want to stop attending class because I am doing poorly.					
3	Realmente, siento que estoy perdiendo el tiempo en este curso. / Truly, I feel like I am wasting my time in this course.					
4	Considero que no tendré éxito en el curso, aunque me esfuerce. / I believe that I won't succeed in the course, even if I try.					