

Adaptation of the Allessphobia Scale in Education in a Sample of Spanish Adolescents

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ABSTRACT

The exponential growth of Artificial Intelligence (AI) in education has given rise to a new phenomenon: Allessphobia, the fear of lacking access to AI for educational tasks. To measure this emerging construct, a specific instrument is needed. Therefore, this study aimed to validate a Spanish version of an Allessphobia assessment scale for adolescents. The research involved 1,905 (49.2% boys) students aged 11-14 from 26 schools (mean age 12.60±0.82 years). Results revealed that 64.4% of participants had used AI applications or websites, primarily for academic purposes. The confirmatory factor analysis demonstrated adequate fit indices for a two-factor correlated model and sex invariance. The scale showed high item-total correlations, satisfactory factor loadings, and strong reliability indicators. A positive correlation was found between Allessphobia and nomophobia. No significant sex differences were observed across Secondary Education courses. Scores between 18-22 points per dimension or above 36 points total could indicate problematic levels. The study concludes by discussing practical implications and educational needs.

KEYWORDS

Artificial Intelligence, Education, Nomophobia, Phobia, Scale.

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I. INTRODUCTION

TECHNOLOGICAL advances, from smartphones to Artificial Intelligence (AI), have profoundly transformed social behavior patterns in recent decades, creating significant generational divides. What began as simple communication tools have become indispensable elements of daily life, deeply integrated into our social, professional, and educational spheres. This digital transformation has fulfilled McLuhan's concept of the global village, fundamentally reshaping human interactions, economic structures, and cultural practices. The result is an unprecedentedly interconnected ecosystem that poses unique challenges for education [1], [2].

By 2024, mobile device ownership reached exceptional levels, with over 90% of the global population possessing at least one device [3]. While these devices enable a wide range of activities—from instant messaging and web browsing to video recording and virtual meetings—their ubiquity has given rise to new psychological challenges. Some individuals experience severe distress when unable

to access the internet, manifesting in conditions such as netlessphobia [4] and nomophobia [5]. These technology-related phobias represent a dysregulation of behavioral patterns, leading to anxiety and dysfunctional behaviors [6], [7]. The most recent addition to these digital anxieties is Allessphobia—the irrational fear of losing access to Artificial Intelligence—which has emerged as a particular concern in university settings [8].

AI is defined as computer systems' ability to perform tasks that, under normal conditions, require human intelligence. Over the past few decades, AI has evolved from basic algorithms to advanced applications such as deep neural networks and generative models (GenAI) [9]. One of the main uses of GenAI in university education, which may have potential applications in other educational stages, has been to improve students' learning experience. Chatbots are one of the tools for this purpose, based on language models such as ChatGPT, which have stood out for their ability to generate coherent and contextual text in various languages and is widely used [10]. These systems employ advanced techniques such as deep learning to

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continuously improve their performance, standing out as key tools in the digital transformation of multiple sectors. University students have begun to use these chatbots in a generalized way for multiple learning, assistance, and tutoring tasks, and their performance seems to improve [11]. Another feature has been assistance for writing in other languages [12], allowing students to exchange ideas and get feedback on their writing through applications such as ChatGPT [13]. On the other hand, text-to-image AI generators, like DALL-E and Stable Diffusion, are valuable tools for teaching technical and artistic concepts in the arts and design [14]. GenAI tools are also considered useful as research aids, generating ideas, synthesizing information, and summarizing a large amount of textual data to help researchers analyze and draft their data [15].

Evidence demonstrates that generative AI tools like ChatGPT are reshaping education at all levels, including pre-university stages. These technologies enable personalized learning experiences, allowing students to engage with content tailored to their individual needs and learning styles. However, their integration presents significant challenges: ensuring equal access, preventing excessive dependence on AI for problem-solving, and assessing whether students' developmental stage supports appropriate adoption [16], [17].

Research increasingly warns that academic AI use may compromise students' development of core skills and competencies [18], [19]. While university students—typically in late adolescence (17-19 years) or emerging adulthood (20-24 years) [20]—may be better equipped to use AI appropriately due to their maturity and established skill base, its impact on younger students remains unclear. The emergence of Allessphobia among university students [8] raises concerns for secondary education, where students are still developing fundamental abilities. At this crucial stage, improper AI integration could foster technological dependence and hinder the development of essential academic skills.

Several premises of interest concur to meet this general gap in the literature. First, data indicate a high prevalence of AI use for academic purposes among young people. In the Spanish context, a study by Empantallados [21] indicates that 82% of pre-university students surveyed have used AI tools at some point. 58% use them to perform tasks, 56% to complement subject content, and 50% to study and prepare for exams. These findings on academic-focused use align with international trends. For example, in a study with university students in South Korea, 83% reported using ChatGPT for academic assistance (such as task tutoring, concept comprehension, and research guidance), and 49% used it for writing support (such as translation or proofreading) [22]. While these data suggest widespread adoption, it is important to note that in the Spanish case, the sample size was small ($n = 200$), and the first years of Secondary Education were not evaluated, highlighting a gap that this study addresses [21].

Second, the family context reveals both concern and an ongoing challenge for digital supervision. Although families are interested and concerned about their children's use of AI [21], this concern is often specific: loved ones argue that a dependency on AI is harmful because it undermines the user's skills and fosters excessive reliance [23]. This social disapproval can strain family dynamics, leading adolescents to hide their usage to avoid interpersonal conflict. This dynamic complicates the so-called Online Parental Mediation [24], [25], which is already a significant challenge. The difficulty is further amplified by the rapid evolution of AI, which often creates a knowledge gap between adolescents and their parents, leaving many caregivers feeling unequipped to provide effective guidance.

Third, there is a significant risk that unsupervised AI use could become a maladaptive coping mechanism for academic anxiety, hindering cognitive and emotional development. The concern that

students might use AI to “escape from anxiety about learning new content” is consistent with findings on the etiology of problematic technology use, often framed within the I-PACE Model [26]. Research suggests that for students, low academic self-efficacy can lead to increased academic stress, which in turn fosters a dependency on AI for immediate answers as a dysfunctional coping strategy [22]. This dependency is exacerbated by cognitive factors that limit self-regulation; users tend to prioritize immediate functional gains (e.g. efficiency) over potential long-term detriments (e.g. skill degradation) [23]. Paradoxically, a positive attitude towards AI can itself become a risk factor, as it may lead to over-confidence and foster patterns of excessive use [27], [28]. The reported negative consequences of this reliance are severe, including an increase in laziness, a decrease in creativity, and the restriction of critical and independent thought [22]. This could be particularly worrying in the compulsory stages of education, where these abilities are foundational.

Considering this background, the main objective of this study was to obtain indicators of the measurement properties of the adapted version of the Allessphobia Scale (Fear of not having Artificial Intelligence in the educational context) in the first years of Secondary Education (11-14 years) as developed by Gezgin and Kutça [8]. In addition, several secondary objectives will be carried out: 1) to analyze the frequencies of generative AI use; 2) to analyze possible differences as a function of sex and grade; 3) to analyze the convergent validity of Allessphobia with nomophobia. Regarding the hypotheses, we propose Hypothesis 1(H1): similar to the version for university students of the Allessphobia Scale [8], we expect to find adequate indicators of reliability and validity and that the two-factor structure proposed by the original authors will be reproduced: academic self-efficacy anxiety and lack of academic confidence without AI. H2 states that the prevalence of AI use in children aged 11-14 will be like that reported in previous studies [21], the main use of AI will be for academic purposes, and (H3) there will be no significant differences based on sex and grade.

II. METHODS

A. Desing and Participants

An instrumental, analytical, and cross-sectional study was conducted. The sample was obtained between October and December 2024. It comprised 1,905 students aged 11 to 14 years (938 males, 49.2%; 933 females, 49%; and 34 (1.8%) students who preferred not to answer any of the aforementioned options. Participants were recruited from 26 secondary schools across 10 Spanish regions (Andalusia, Aragon, Castilla la Mancha, Castilla-León, Community of Madrid, Valencian Community, Canary Islands, Galicia, La Rioja, and the Basque Country). The participants' mean age was 12.60 years ($SD = 0.82$), 58% ($n = 1105$) were enrolled in 1st grade of Compulsory Secondary Education (CSE) (Mage= 11.49, $SD = 0.58$), 26.9% ($n = 513$), were in 2nd grade of CSE, (Mage = 12.51, $SD = 0.61$) and the remaining 25.1% ($n = 287$) were in 3rd grade of CSE (Mage = 13.45, $SD = 0.52$). All the schools were located in urban areas. A non-probabilistic incidental sampling procedure was used in this study as the schools were selected based on formal collaboration agreements between the schools and the research team. Therefore no stratification procedures were employed so participants were included based on their voluntary participation and accessibility, not through a systematic selection process designed to ensure demographic representation.

B. Instruments

Firstly, participants reported sociodemographic variables (sex, age, grade, and school). Next, a series of questions were asked about the use of AI and then, two evaluation instruments were administered.

At the beginning of the questionnaire, the students were told the following: “Next, we’re going to ask you about how you use Artificial Intelligence (AI). In general, we refer to models such as ChatGPT, GPT-4, Copilot, Gemini, LLaMA, or LuzAI (among others). All of them are AI-based language models; that is, an Artificial Intelligence (AI) system allows computers and machines to imitate human skills, such as learning, reasoning, and solving problems. In other words, AI is a machine’s ability to “think” and act intelligently. We often use them to answer questions, generate ideas, translate languages, summarize text, and much more, all done by processing and generating text coherently and relevantly.” The first question after reading this was: Have you ever used any Artificial Intelligence applications or websites? (Yes/No). The next question was: How often do you use Artificial Intelligence, especially programs like ChatGPT, Copilot, Gemini, LLaMA, LuzAI, etc.? The response scale ranged from Never/Rarely/Quite Often/Very Often. In addition, participants were asked: For what purpose do you use Artificial Intelligence? Table I presents a 16 multiple-choice question exploring students’ use of AI across various academic and personal activities. These activities ranged from researching class assignments and correcting schoolwork to seeking health information, generating creative content, and manipulating images. The survey concluded with a screening question: “Have you ever used any website or Artificial Intelligence application to do homework or study?” Only participants who answered affirmatively proceeded to the subsequent questionnaire.

The adapted version to Spanish of the AllessphobiaScale (Fear of not having Artificial Intelligence) in the educational context in Secondary Education is an adaptation in Spanish of the questionnaire for Turkish university students of Gezgin and Kutça [8]. This has 18 items and two dimensions (Academic Self-efficacy Anxiety, which groups Items 1-10 and Lack of Academic Confidence without AI, which groups Items 11-18). Specifically, the scale that is validated assesses the fears and worries that an adolescent may experience when being disconnected or unable to use AI in the educational context (e.g., “If I can’t access an AI-based language model, I feel anxious about not being able to do my homework”), and the lack of confidence in the correct performance of academic tasks without using AI (e.g., “I get some AI-based language model to review my homework”). A translation-back translation process has been carried out with two bilingual professionals, performing a direct translation, a review of it by specialists, and a back translation. Five experts in the field of study participated in the process of validating the content, achieving high inter-judge reliability throughout the process ($k > .8$) in the different items of the questionnaire. Additionally, to assess the adequacy and comprehension of the items, three cognitive interviews were conducted with adolescents. The questionnaire was piloted with a sample of 83 participants, who did not participate in the final study afterwards. This process followed international standards for the design and adaptation of questionnaires [29], [30]. This guide has been particularly considered for the development phase (in terms of expert judgment and empirical analysis), confirmation (evaluation of psychometric properties, invariance, and norms), interpretation, and documentation (through the article itself). In general, almost all of the 29 criteria have been adequately addressed, either explicitly or implicitly. The Likert-type response options on this scale range from 0 (strongly disagree) to 4 (strongly agree). The range of scores varies between 0 – 72 for the total scale, between 0 – 40 for Academic Self-Efficacy Anxiety, and between 0 – 32 for Lack of Academic Confidence without AI.

The Nomophobia Questionnaire (NMP-SF [31]) is a 10-item scale that assesses intense fear and excessive worry about losing connection or being unable to communicate via mobile (e.g., “I would be nervous about being disconnected from my virtual identity”). The Likert-type

response options on this scale range from 0 (strongly disagree) to 6 (strongly agree). The scores range between 0 and 60. Cronbach’s alpha for this sample was .90.

C. Procedure

The questionnaires were administered online to the students during school hours, using the Survey Monkey© platform, supervised by the teachers of each classroom. The teaching staff had received prior training and instructions in a training session. The questionnaires took between 15 and 20 minutes to complete, depending on students’ age and reading comprehension. The study was approved by the participating schools and the University’s Research Ethics Committee of Universidad Internacional de La Rioja (PI: 099/2024).

All procedures were conducted in accordance with the ethical standards of the institutional research committee and with the Helsinki Declaration. Through official channels, the managers of each school gave the legal guardians a consent form that informed them about the study’s purpose, the research team’s contact details, and their right not to participate. Written informed consent was obtained from the parents or legal guardians of all participants prior to their inclusion in the study. Less than 2% of parents/guardians declined participation, and less than 0.5% of students opted out. No other exclusion criteria were applied other than refusals to participate by students or their legal guardians.

D. Statistical Analysis

The statistical analyses of the study were carried out with the statistical package for social sciences SPSS v. 23.0 and MPLUS 8.8. First, we analysed the reliability indicators of the questionnaires using Cronbach’s alpha. We then calculated descriptive analyses on the frequency and percentage of AI use, and purpose of use. Then, we calculated the arithmetic mean, standard deviation, item-total correlation, skewness, kurtosis, and frequency range of each item of the Allessphobia scale. These analyses showed that some items were not normally distributed (see Table II), so we used robust to non-normality statistics in the following analyses.

Confirmatory factor analysis used the Robust Weighted Least Squares Mean and Variance adjusted (WLSMV) method to analyse the factor structure. For this analysis, the criteria of Hu and Bentler [32] were considered to assess the goodness of fit of the indices: RMSEA values less than .06 indicate an excellent fit, between .06 and .08 is acceptable, and CFI and TLI values of .95 or higher reflect a good fit. Moreover, measurement invariance was tested according to sex (male vs female). For that purpose, models were calculated for each group. The configural invariance was tested to assess the invariance of the measurement model between sex and age. This model was compared with a more restrictive model (metric model), which assumes that the factor loadings are equivalent across groups, indicating that the items are similarly related to the latent construct for both sexes. In the final step, a scalar factorial invariance model was calculated, which further restricts the equivalence by assuming that both the factor loadings and the intercepts of the items are invariant across groups. The fit of each model was compared to the fit of the previous model. If the model fit did not worsen, the next model was selected. Although there are many different statistical methods to determine when model fit worsens, if the Δs is lower than .01, it is assumed that invariance exists [33].

Next, Allessphobia scores were compared using Spearman correlations with nomophobia to assess convergent validity. Finally, to analyse the differences according to sex and grade, Welch’s t-tests (Cohen’s d as effect size) and ANOVAs were calculated with Welch’s F test (eta squared as effect size) for each item, and the total score of the scale. Finally, the total scores of the scale questionnaire were compared according to the reported frequency of AI use (never/almost

never, rarely, quite often, or very often). Due to the large number of comparisons and to prevent Type 1 error, only values equal to or less than $p \leq .001$ were considered statistically significant.

III. RESULTS

A. Descriptive Analyses

Of the total sample, 1167 participants (64.4%) had used an application or website with AI at some point. Regarding the frequency of use, 21.8% indicated that they never or almost never used it ($n = 253$), 46.8% used it rarely ($n = 543$), 19.6% used it quite often ($n = 228$), and 11.8% used it very often ($n = 137$). Of the participants, 824 (70.4% of the sample that used AI and 43.3% of the total participants) had used an AI website or application to do homework or study. The purposes for using AI can be seen in Table I. It should be noted that school-type activities are the main purpose for which schoolchildren aged 11-14 years use AI, with the most frequent use (66.8%, $n = 780$) being “seeking information for class assignments.”

Table II shows the main descriptions of the items and dimensions of the adapted version of the Allessphobia Scale. The response to the questionnaire items suggests a marked positive asymmetry. All items had an adequate item-total correlation. It should be noted that the joint cumulative frequency of the value 3 (agree) and 4 (strongly agree) in the 18 items varies between 3.8% for Item 10 (If I cannot access the AI-based language model during classes, I become demotivated about what the teacher is saying) and 17.4% for Item 15 (I usually rely on an AI-based language model to learn the subject syllabus) and, in general, most of the clearly positive responses varied between 6-12%.

TABLE I. ANALYSIS OF THE RESPONSE FREQUENCY CONCERNING THE PURPOSES OF USING AI (N = 1167)

Purposes of using AI (multiple choice)	n (%)
1. Seeking information for classwork	780(66.8)
2. Seeking information on health topics (general)	420(36.0)
3. Correcting my own schoolwork	207(17.7)
4. Seeking information on sexual and reproductive health topics	323(27.7)
5. Knowing how to say something to another person	442(37.9)
6. Checking what someone else has said to me or I have seen on social networks	39(3.3)
7. Giving me ideas for doing some school activity	208(17.8)
8. Giving me ideas to create a post on social networks	99(8.5)
9. Making images (creating or modifying them)	477(40.9)
10. Making everyday activities easier for me	92(7.9)
11. Creating content	233(20.0)
12. Having fun	174(14.9)
13. Getting information on how to advance in video games or improve my gaming strategies	86(7.4)
14. Getting tips on how to improve my physique or appearance	412(35.3)
15. Summarizing texts or information	205(17.6)
16. Receiving personalized content recommendations (articles, videos, etc.)	114(9.8)
17. Solving academic doubts	379(32.5)

Note: n = number of participants; % = relative frequency doubts

B. Confirmatory Analysis and Model Invariance

Concerning reliability, the total score of the Allessphobia Scale obtained an $\alpha = .95$. Likewise, Factor 1 –F1– (Academic self-efficacy

anxiety) presented an $\alpha = .93$, and F2 (Lack of academic confidence without AI) an $\alpha = .89$. The correlation between F1 and F2 was $.77$ ($p < .001$)

Table III shows the results of the confirmatory analysis. The non-correlated two-factor model did not show good fit indices, but both the one-dimensional model and the two-factor correlated model had excellent indices, especially those of the latter. This two-factor correlated model, with factor loadings between $.76$ and $.93$ (see Table IV), was the final model for the invariance analyses. The standardized factor loadings of this model are shown in Table IV.

The invariance analyses, as seen in Table III, show that the model was invariant for sex both at the metric and scalar levels because the changes in the CFI and TLI were not greater than $.01$, nor were the changes in the RMSEA higher than $.01$.

C. Evidence of Validity

Regarding convergent validity with other variables, the correlation between total scores on the NMPQ-SF and the total score on the Allessphobia adapted scale was $.41$ ($p < .001$). In addition, Factors 1 and 2 also correlated positively and significantly with the NMPQ-SF ($r = .39$, $p < .001$, and $r = .37$, $p < .001$, respectively).

When comparing the total scores of the adapted version of the Allessphobia Scale according to the frequency of use (never/almost never, rarely, quite often, or very often), we found significant differences ($F = 35,264$, $p < .001$, $\eta^2 = .120$). The group of very often ($M = 20.06$, $SD = 19.75$) presented significant differences ($p < .001$) with the groups of rarely ($M = 8.68$, $SD = 9.92$) and never/almost never ($M = 5.20$; $SD = 8.09$).

D. Differences as a Function of Sex and Grade

Table IV shows the results for each item according to the participants' sex and grade. No significant differences were observed according to sex in any item, although Items 6, 12, and 14 showed a differential tendency ($p < .05$), with boys scoring higher, albeit with small size effects. Likewise, there were no differences depending on the grade in any of the items, although Items 14 and 17 also showed a differential tendency ($p < .05$), with 3rd-year students of CSE scoring higher than 1st-year students. Concerning the two factors of the questionnaire, there was only a differential tendency ($p = .044$) in Factor 2 for grade, revealing higher scores in 3rd-year students of CSE than in 1st-year students. There were no differences in the total score as a function of sex or grade.

Additionally, Table V shows the percentile scores of the adapted version of the Allessphobia Scale according to sex for the two dimensions. In general, there was no differential tendency between boys and girls consistent with what we explained above. It is important to note that scores above 18 – 20 for girls and between 20 – 22 for boys could indicate being at risk (being in the 95th percentile). The total score on the scale ranged from 37 for boys to 39 for girls. Among boys, 4.7% could be at risk, while among girls, 4.5% could be at risk.

Of the total sample, 1167 participants (64.4%) had used an application or website with AI at some point. Regarding the frequency of use, 21.8% indicated that they never or almost never used it ($n = 253$), 46.8% used it rarely ($n = 543$), 19.6% used it quite often ($n = 228$), and 11.8% used it very often ($n = 137$). Of the participants, 824 (70.4% of the sample that used AI and 43.3% of the total participants) had used an AI website or application to do homework or study. The purposes for using AI can be seen in Table I. It should be noted that school-type activities are the main purpose for which schoolchildren aged 11-14 years use AI, with the most frequent use (66.8%, $n = 780$) being “seeking information for class assignments.”

TABLE II. MEANS, STANDARD DEVIATION, TOTAL ITEM CORRELATION AND RESPONSE FREQUENCIES FOR THE SPANISH-ADAPTED VERSION OF THE ALLESSPHOBIA SCALE

Spanish version of the Allessphobia Scale (n = 796)	M[SD]	IT	Skew	Kurt	Response frequencies %				
					0	1	2	3	4
F1. Academic self-efficacy anxiety									
1. I feel anxious if I can't connect to an AI-based language model while doing homework.	0.54[0.94]	0.73	1.96	3.47	68.2	17.7	8.9	2.6	2.5
2. If I don't use an AI-based language model when doing homework, I feel like I'm at a disadvantage compared to my peers.	0.51[0.92]	0.75	1.95	3.43	69.4	16.5	9.4	2.6	2.0
3. If I can't access an AI-based language model, I feel anxious that I won't be able to do my homework.	0.51[0.95]	0.78	2.05	3.76	70.7	15.5	8.3	2.8	2.6
4. I'd rather have an AI-based language model do my homework than do it myself.	0.95[1.26]	0.63	1.17	0.22	53.2	19.7	13.1	6.7	7.3
5. I'm afraid I won't be able to do my homework without an AI-based language model.	0.52[0.96]	0.80	2.03	3.58	70.7	15.4	8.2	3.1	2.6
6. The first thing I do when faced with homework in class is to ask the teacher how to use an AI-based language model.	0.38[0.82]	0.68	2.46	5.99	77.1	12.9	6.4	2.1	1.4
7. I get bored when I can't search for information with an AI-based language model.	0.46[0.89]	0.76	2.24	4.79	73.1	14.8	7.7	2.0	2.3
8. I try not to do my homework with an AI-based language model, but I can't.	0.80[1.16]	0.66	1.35	0.79	58.7	17.9	12.5	6.3	4.7
9. Not being able to use an AI-based language model in classes bothers me.	0.51[0.99]	0.77	2.12	3.84	72.1	14.6	6.7	3.4	3.2
10. If I can't access the AI-based language model during classes, I become demotivated about what the teacher is saying.	0.39[0.83]	0.78	2.49	6.24	75.9	14.4	5.8	2.0	1.8
F2. Lack of academic confidence without AI									
11. I get some AI-based language model to review my homework.	0.84[1.20]	0.65	1.23	0.30	59.0	15.5	12.1	8.9	4.5
12. I send emails/messages to teachers with the help of some AI-based language model.	0.41[0.90]	0.68	2.50	5.80	77.5	12.0	5.2	2.8	2.5
13. I use some AI-based language model when I do online activities/exams.	0.63[1.06]	0.69	1.60	1.51	67.1	13.8	10.1	6.6	2.4
14. I use some AI-based language model in practical activities or to relate concepts.	0.71[1.09]	0.68	1.43	0.98	63.1	15.4	11.8	7.0	2.7
15. I usually rely on an AI-based language model to learn the syllabus of the subjects.	1.03[1.28]	0.60	0.90	-0.50	52.5	14.8	15.3	12.0	5.4
16. I feel like I perform better in studies when I use some AI-based language model.	0.74[1.10]	0.73	1.39	1.03	60.6	16.8	13.9	5.3	3.4
17. When I am given homework, I am relieved to know that I can use some AI-based language model.	0.82[1.13]	0.72	1.27	0.60	56.7	19.4	12.9	7.3	3.7
18. I think it is necessary to use some AI-based language model in the school or institute.	0.81[1.12]	0.71	1.23	0.50	7.2	17.8	14.7	7.0	3.3

TABLE III. FIT AND MEASUREMENT INVARIANCE FOR THE SPANISH-ADAPTED VERSION OF THE ALLESSPHOBIA SCALE

Model	χ^2 (df)	p	Comp. models	$\Delta \chi^2$	Δ df	$\Delta (\chi^2/df)$ p-value	CFI	Δ CFI	TLI	Δ TLI	RMSEA	CI	Δ RMSEA	SRMR	Δ SRMR
Allessphobia Scale															
Model 1 (M1) Unidimensional	987.809 (135)	.000	--	--	--	--	.962	--	.957	--	.089	[.084-.094]	--	.041	--
M2. Two uncorrelated factors	13789.80 (135)	.000	--	--	--	--	.388	--	.307	--	.357	[.352, .362]	--	.369	--
M3. Two correlated factors	744.121 (134)	.000	--	--	--	--	.973	--	.969	--	.076	[.070, .081]	--	.035	--
Gender Measurement invariance for M3															
Boys	425.586 (136)	.000	--	--	--	--	.974	--	.971	--	.076	[.068, .084]	--	.033	--
Girls	405.98 (136)	.000	--	--	--	--	.976	--	.973	--	.071	[.063, .079]	--	.045	--
Configural	821.884 (268)	.000	--	--	--	--	.975	--	.972	--	.073	[.067, .079]	--	.040	--
Metric	863.28 (284)	.000	3-4	51.93	16	.000	.974	.001	.972	.000	.072	[.067, .078]	.001	.040	.000
Scalar	878.23 (336)	.000	4-5	145.129	68	.000	.976	.002	.978	.002	.064	[.059, .070]	.008	.041	.001

Note: Note: χ^2 = chi-squared test; df = Degrees of freedom; p = significance value; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; $\Delta \chi^2$ = Chi-square difference, Δ df = difference in degrees of freedom, Δ RMSEA = difference in root mean square error of approximation; Δ CFI = difference in comparative fit index, Δ TLI = TLI difference; Δ SRMR = SRMR difference.

TABLE IV. DIFFERENCES IN ITEMS AND TOTAL SCORE BASED ON GENDER AND GRADE

Items	Gender-related differences				Grade-related differences					CFA Loadings		
	Boys (n=378)	Girls (n=401)	Welch's t (p)	d	1st grade CSE a (n = 388)	2nd grade CSE b (n = 241)	3rd Grade CSE c (n = 159)	Welch's F (p)	η^2	Post-hoc differences (G-H)	Factor LO 1	Factor LO 2
	M(SD)	M(SD)			M(SD)	M(SD)	M(SD)					
Item 1	0.53(0.96)	0.54(0.92)	0.58(.565)	--	0.47(0.84)	0.57(0.99)	0.60(1.04)	1.58(.207)	---	---	.85	
Item 2	0.53(0.94)	0.50(0.90)	0.13(.882)	--	0.45(0.83)	0.56(0.99)	0.56(0.94)	1.46(.232)	---	---	.87	
Item 3	0.55(1.00)	0.48(0.91)	0.61(.546)	--	0.49(0.94)	0.50(0.94)	0.55(0.96)	0.21(.913)	---	---	.91	
Item 4	0.99(1.29)	0.92(1.24)	0.51(.603)	--	0.92(1.24)	0.94(1.30)	0.99(1.19)	0.21(.913)	---	---	.75	
Item 5	0.57(1.00)	0.48(0.92)	0.86(.432)	--	0.47(0.91)	0.54(1.01)	0.57(0.96)	0.69(.504)	---	---	.92	
Item 6	0.47(0.93)	0.29(0.68)	4.64(.015)	0.22	0.40(0.83)	0.35(0.80)	0.39(0.81)	0.25(.781)	---	---	.85	
Item 7	0.53(1.00)	0.39(0.79)	2.48(.095)	--	0.42(0.82)	0.44(0.90)	0.56(1.03)	1.51(.221)	---	---	.90	
Item 8	0.76(1.17)	0.84(1.15)	0.42(.660)	--	0.78(1.17)	0.75(1.13)	0.92(1.13)	1.12(.326)	---	---	.77	
Item 9	0.55(1.03)	0.48(0.94)	0.51(.606)	--	0.47(0.93)	0.55(1.02)	0.52(0.99)	0.55(.576)	---	---	.89	
Item 10	0.46(0.91)	0.32(0.74)	2.74(.076)	--	0.37(0.80)	0.44(0.92)	0.35(0.75)	0.65(.524)	---	---	.93	
Item 11	0.79(1.18)	0.89(1.22)	0.69(.507)	--	0.80(1.17)	0.78(1.16)	1.01(1.29)	2.13(.119)	---	---		.76
Item 12	0.51(1.02)	0.31(0.75)	5.66(.007)	0.22	0.43(0.94)	0.40(0.90)	0.38(0.79)	0.17(.846)	---	---		.86
Item 13	0.70(1.11)	0.58(1.01)	1.37(.266)	--	0.57(1.00)	0.65(1.10)	0.76(1.11)	1.90(.150)	---	---		.81
Item 14	0.79(1.15)	0.64(1.04)	3.46(.040)	0.14	0.64(1.04)	0.67(1.08)	0.88(1.15)	3.03(.049)	.008	a < c		.81
Item 15	0.96(1.25)	1.10(1.31)	1.23(.302)	--	0.98(1.26)	1.04(1.27)	1.15(1.35)	1.06(.348)	---	---		.74
Item 16	0.74(1.07)	0.75(1.12)	0.43(.651)	--	0.67(1.05)	0.73(1.10)	0.90(1.15)	2.70(.068)	---	---		.84
Item 17	0.84(1.14)	0.59(1.00)	0.50(.611)	--	0.70(1.05)	0.83(1.14)	1.04(1.26)	5.00(.007)	.013	a < c		.84
Item 18	0.82(1.12)	0.81(1.13)	0.10(.909)	--	0.74(1.08)	0.78(1.09)	0.99(1.21)	2.85(.058)	---	---		.82
Factor 1	5.87(8.18)	5.19(7.10)	0.77(.468)	--	5.19(7.29)	5.61(8.10)	5.92(7.48)	0.60(.550)	---	---	--	.92 ψ
Factor 2	6.06(7.07)	5.85(6.29)	0.17(.848)	--	5.47(6.34)	5.83(6.84)	7.03(6.96)	3.14(.044)	.008	a < c	.92 ψ	--
Total	11.90 (14.55)	11.02 (12.68)	0.42 (.657)	--	10.62 (12.91)	11.41 (14.32)	12.91 (13.59)	1.62(.198)	---	---		

Note: M = Mean; SD = Standard deviation; p = significance; CSE = Compulsory Second Education; the letters a, b, c in superscript indicates the letter for the post-hoc comparisons; G-H = Games Howell; Factor LO 1= factor 1 loadings; Factor LO 2= factor 2 loadings, ψ Covariance among F1 and F2

TABLE V. SCORES FOR THE PERCENTILES OF THE SPANISH-ADAPTED VERSION OF THE ALLESSPHOBIA SCALE BY GENDER

Percentiles	F1.		F2.		Total	
	Boys (n = 380)	Girls (n = 402)	Boys (n = 378)	Girls (n = 402)	Boys (n = 380)	Girls (n = 403)
1	0	0	0	0	0	0
5	0	0	0	0	0	0
10	0	0	0	0	0	0
15	0	0	0	0	0	0
20	0	0	0	0	0	0
25	0	0	0	0	0	1
30	0	0	0	1	1	2
35	0	1	0	2	2	3
40	1	1	1	2	3	4
45	2	2	2	3	4	5
50	3	2	4	4	7	6
55	3	3	5	5	9	9
60	4	4	6	6	11	11
65	6	4	8	8	14	12
70	7	6	8	8	16	14
75	9	8	10	9	18	18
80	10	10	12	11	21	20
85	14	12	14	13	27	23
90	18	15	16	15	34	29
95	22	21	20	18	37	39
99	40	31	32	24	72	59

Note: F1 Academic self-efficacy anxiety (Range 0 – 40); F2 Lack of academic confidence without AI (Range 0 – 32); Total: Allessphobia Scale (Range 0-72)

IV. DISCUSSION

The rapid integration of generative AI technologies has fundamentally altered how adolescents communicate, build their identities, and approach learning [34]. During adolescence—a period marked by intense neurobiological, cognitive, and socio-emotional changes—individuals are particularly susceptible to digital influences. This vulnerability can heighten risks associated with AI technologies, including dependency on instant feedback and exposure to harmful content [35]. AI-enhanced online experiences significantly impact young people’s psychological well-being and mental health, highlighting the need to understand both the benefits and potential risks of these tools [36]. While the internet offers valuable learning opportunities for youth, new challenges like Allessphobia have emerged. The growing presence of AI in education presents a complex challenge: how to harness its benefits while preventing the erosion of students’ fundamental skills and competencies [37], [38].

Regarding the main objective, the confirmatory factor analysis of the adapted version of the Allessphobia Scale for students aged 11-14 years shows adequate fit indices for the correlated two-factor model. However, the single-factor model also presents acceptable indicators but is slightly worse than the former model. This model could allow researchers to use each of the dimensions separately or the total score of the questionnaire. In addition, the data suggest high item-total correlations and satisfactory factor loadings in all the items. Hence, the new version confirms the measurement model for students in non-university compulsory stages, like its original version for university students [8]. Thus, we also confirmed the first hypothesis (H1). Moreover, the reliability analyses indicated a high internal consistency of the scale, and the analysis of invariance for sex was another contribution to the assessment tool, which aligns with the original study of Gezgin and Kutça [8]. Also noteworthy are the contributions to the convergent validity of the scale by relating it positively and significantly to another similar construct: nomophobia. Although we are not aware of previous studies, the relationship between these two problems could be due to the psychological distress caused by not

using the device or not having access to it. The version of the Adapted Allessphobia Scale also captures differences depending on the reported use of AI, as the higher the usage frequency, the higher the total score in the questionnaire. Aligned with this, this new assessment tool represents a step forward in research, as it can be used in contexts of non-university compulsory education, unlike the previous version, which is adapted only to the university context [8].

However, while establishing tools to measure new technology-related phenomena is important, it is crucial to proceed with caution to avoid the over-pathologization of everyday behaviors. Several authors have warned against the tendency to frame every new technological challenge as a “behavioral addiction” [39], [40]. In this context, we deliberately conceptualize this phenomenon as a ‘phobia’ rather than an ‘addiction’. We believe this framework better captures the core experience, which is a specific, situational anxiety about being unable to access AI for educational tasks, rather than a generalized loss of control or the experience of abstinence-like symptoms characteristic of addiction models. In fact, the concept of “AI addiction” itself has been questioned, urging researchers to expand diagnostic boundaries with caution and to deconstruct the components of potentially problematic use rather than creating new labels [41], [42], [43]. Thus, Allessphobia is proposed not as a formal clinical diagnosis but as a tool to measure a specific form of distress and dependency that aligns more closely with an anxiety-based (phobia) model than with the component-model of addiction. Therefore, while Allessphobia captures a specific form of anxiety within an educational context, it should be interpreted as a measure of distress and dependency rather than a formal clinical diagnosis, a perspective that is consistent with recent research on problematic internet use in Spanish adolescents [44].

Concerning the first specific objective, it is difficult to establish real comparisons on the prevalence of AI usage in the current context. Most studies have been carried out in university samples, generally adults, showing high prevalences such as 56.5% in German university students [45] and 75% in Swedish adolescents and young adults aged 15 to 24 years who use generative AI for educational purposes [46]. Other studies with smaller samples reported prevalences of 52.6% in young people aged 15-19, and 14.8% in children aged 12-16 years [47]. In Spain, only the study by Empatallados [21] found a prevalence of 82% in pre-university students (n = 200, 14-17 years). In our study, almost 65% of the 11-14-year-old sample uses AI, mainly for academic purposes (seeking information for homework, correcting schoolwork, and solving doubts). This suggests that AI is being used increasingly more, and that its inclusion in the educational field is particularly fast, which may lead to its widespread use in a short time. After all the above, H2 could not be confirmed because, although both prevalences (82%, in Empatallados study vs. 65% in ours) are very high, there are differences between the two.

The data on scores in boys and girls hardly show significant differences, except for some items with a differential tendency, in line with the study of Klarin et al [47]. This could be due to the increasing integration of technological tools such as AI into the daily lives of young people, regardless of sex. Regarding the differences according to grade, minimal significant differences are also found, which partially contrasts with von Garrel and Mayer [45], who indicate that the use of AI increases with age and in higher educational stages. This could be due to older adolescents facing more complex tasks that require the use of GenAI tools and increased use of technology. Perhaps our sample presents a more homogeneous profile in the first years of Secondary Education.

The present study has several limitations. First, the Spanish-adapted Allessphobia scale is self-reported, which can introduce biases and social desirability, so future research should include additional measures or hetero-reports [7]. Second, although the

instrument's psychometric properties are adequate, it would be useful to perform additional analyses, such as predictive validity and test-retest reliability, and relate Allessphobia with other problems and variables of academic performance [6]. Third, the items show positive asymmetry and low standard deviations, reflecting the nature of a rare phobia in the sample. Fourth, age invariance could not be calculated due to the lack of some response categories in certain groups. Fifth, this study met most of the test adaptation criteria suggested by the International Test Commission [30] and Hernández et al. [29]. However, two specific guidelines were not fulfilled. First, we could not obtain explicit permission from the original authors to adapt the scale. Second, creating and providing a standard administration manual did not seem necessary for this specific instrument. Finally, the sampling was neither random nor representative of the Spanish population, so the results should be interpreted cautiously.

Despite the limitations, the study has significant practical implications. High ownership of smartphones at an early age requires effective online parental mediation to maximize opportunities and minimize risks [24]. In addition, the use of AI and GenAI should be addressed both in school and family settings. The manuscript highlights the problem of using AI in compulsory education due to its high prevalence and psychosocial consequences for students. It is essential to consider Allessphobia as an Internet risk that should be prevented in psychoeducational programs [48], [49] and to develop training strategies for families, teachers, and students that reduce the negative impact while enhancing the positive aspects of technology [25]. Finally, exploring the potential clinical relevance of this measure in child and adolescent mental health settings represents a promising line of near-future research. In this way, its predictive capacity could be further analyzed.

V. CONCLUSION

In conclusion, this manuscript presents an instrument validated in Spanish that allows for the assessment of Allessphobia (Academic Self-Efficacy Anxiety and Lack of Academic Confidence without AI) in a sample of adolescents aged 11-14 years, showing no significant differences between boys and girls or across. In addition, the high prevalence of AI usage at these ages, its main use for academic activities, and its relationship with nomophobia have been confirmed.

CREDiT AUTHORSHIP CONTRIBUTION STATEMENT

Conceptualization: JMM, JGC; Data curation: JMM, JGC, APF; Data extraction: JGC, ADL; Funding acquisition: JGC; Investigation: JGC, ADL; Methodology: JMM, JGC; Project administration: JGC; Resources: JGC, APF, VCM, JOB; Supervision: JMM, JGC; Visualization: APF, VCM, JOB, ADL, JGC; Writing – original draft: JGC, JMM; Writing – review & editing: APF, VCM, JOB, ADL, JMM, JGC.

DATA STATEMENT

The data that support the findings of this study are available on request from the corresponding author.

DECLARATION OF CONFLICTS OF INTEREST

The authors have no conflict of interest to declare.

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REFERENCES

- [1] M. McLuhan, "La aldea global: transformaciones en la vida y los medios de comunicación mundiales en el siglo XX: The global village: transformations in world life and media in the 20th century". Editorial Gedisa, 2015.
- [2] J. E. Mendoza, S. J. J. Sánchez, and L. F. J. Cañarte, "Implicaciones éticas en el uso de inteligencia artificial en estudiantes universitarios [Ethical implications in the use of artificial intelligence in university students]," *Polo del Conocimiento*, vol. 9, no. 3, pp. 877–904, 2024, <https://doi.org/10.23857/pc.v9i3.6691>
- [3] Statista, "Consumo mundial de smartphones." 2025. [Online]. Available: <https://es.statista.com/temas/10145/industria-y-consumo-mundial-de-smartphones/>
- [4] U. C. Öztürk, "Netlessfobia" Stay in Connection or Not That is The All Fear: Fear of Being Without Internet and Organizational Reflections," *Journal of International Social Research*, vol. 8, no. 37, pp. 629–629, Apr. 2015, <https://doi.org/10.17719/jisr.20153710629>
- [5] C. Yildirim and A.-P. Correia, "Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire," *Computers in Human Behavior*, vol. 49, pp. 130–137, Aug. 2015, <https://doi.org/10.1016/j.chb.2015.02.059>
- [6] A. C. León-Mejía, M. Gutiérrez-Ortega, I. Serrano-Pintado, and J. González-Cabrera, "A systematic review on nomophobia prevalence: Surfacing results and standard guidelines for future research," *PLOS ONE*, vol. 16, no. 5, p. e0250509, May 2021, <https://doi.org/10.1371/journal.pone.0250509>
- [7] J. González-Cabrera and J. M. Machimbarrena, "Quality of Life and Its Relationship with Bullying and Cyberbullying," in *Handbook of Anger, Aggression, and Violence*, C. Martin, V. R. Preedy, and V. B. Patel, Eds., Cham: Springer International Publishing, 2023, pp. 1–18. https://doi.org/10.1007/978-3-030-98711-4_171-1
- [8] D. M. Gezgin and T. T. Kurtça, "Developing the Allessphobia in education scale and examining its psychometric characteristics," *Education and Information Technologies*, vol. 30, no. 4, pp. 4471–4491, Mar. 2025, <https://doi.org/10.1007/s10639-024-12984-6>
- [9] L. Floridi, *Ética de la Inteligencia Artificial: Ethics of Artificial Intelligence*. Herder Editorial, 2024.
- [10] N. Saif, S. U. Khan, I. Shaheen, F. A. ALotaibi, M. M. Alnfai, and M. Arif, "Chat-GPT; validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism," *Computers in Human Behavior*, vol. 154, p. 108097, May 2024, <https://doi.org/10.1016/j.chb.2023.108097>
- [11] R. Wu and Z. Yu, "Do AI chatbots improve students learning outcomes? Evidence from a meta-analysis," *British Journal of Educational Technology*, vol. 55, no. 1, pp. 10–33, Jan. 2024, <https://doi.org/10.1111/bjet.13334>
- [12] C. K. Y. Chan and K. K. W. Lee, "The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers?," *Smart Learning Environments*, vol. 10, no. 1, p. 60, Nov. 2023, <https://doi.org/10.1186/s40561-023-00269-3>
- [13] S. Atlas, "ChatGPT for Higher Education and Professional Development: A Guide to Conversational AI." 2023. [Online]. Available: https://digitalcommons.uri.edu/cba_facpubs/548
- [14] N. Dehouche and K. Dehouche, "What's in a text-to-image prompt? The potential of stable diffusion in visual arts education," *Heliyon*, vol. 9, no. 6, p. e16757, Jun. 2023, <https://doi.org/10.1016/j.heliyon.2023.e16757>
- [15] J. P. Andersen et al., "Generative Artificial Intelligence (GenAI) in the research process – A survey of researchers' practices and perceptions," *Technology in Society*, vol. 81, p. 102813, Jun. 2025, <https://doi.org/10.1016/j.techsoc.2025.102813>
- [16] J. S. Jauhainen and A. Garagorry Guerra, "Generative AI and education: dynamic personalization of pupils' school learning material with ChatGPT," *Frontiers in Education*, vol. 9, p. 1288723, Nov. 2024, <https://doi.org/10.3389/educ.2024.1288723>
- [17] T. K. F. Chiu, Q. Xia, X. Zhou, C. S. Chai, and M. Cheng, "Systematic literature review on opportunities, challenges, and future research

- recommendations of artificial intelligence in education,” *Computers and Education: Artificial Intelligence*, vol. 4, p. 100118, 2023, <https://doi.org/10.1016/j.caeai.2022.100118>
- [18] M. Loján, J. Romero, D. Aguilera, and A. Romero, “Consecuencias de la Dependencia de la Inteligencia Artificial en Habilidades Críticas y Aprendizaje Autónomo en los Estudiantes [Consequences of Artificial Intelligence Dependence on Critical Skills and Autonomous Learning in Students],” *Ciencia Latina Revista Científica Multidisciplinar*, vol. 8, no. 2, pp. 2368–2382, 2024.
- [19] S. S. Shah and M. M. Asad, “Impact of critical thinking approach on learners’ dependence on innovative transformation through artificial intelligence,” in *The Evolution of Artificial Intelligence in Higher Education: Challenges, Risks, and Ethical Considerations*, Emerald Publishing Limited, 2024, pp. 161–182.
- [20] K. Salmela-Aro, “Stages of Adolescence,” in *Encyclopedia of Adolescence*, Elsevier, 2011, pp. 360–368. <https://doi.org/10.1016/B978-0-12-373951-3.00043-0>
- [21] Empantallados, “El impacto de la AI en la educación en España [The impact of AI on education in Spain].” 2024. [Online]. Available: <https://empantallados.com/ia/>
- [22] X. Zhang, M. Yin, M. Zhang, Z. Li, and H. Li, “The Development and Validation of an Artificial Intelligence Chatbot Dependence Scale,” *Cyberpsychology, Behavior, and Social Networking*, vol. 28, no. 2, pp. 126–131, Feb. 2025, doi: 10.1089/cyber.2024.0240
- [23] Z. Deng and Z. Deng, “Becoming a cognitive miser? Antecedents and consequences of addictive ChatGPT use,” *Social Science & Medicine*, vol. 383, p. 118467, Oct. 2025, <https://doi.org/10.1016/j.socscimed.2025.118467>
- [24] S. Livingstone, K. Ólafsson, E. J. Helsper, F. Lupiáñez-Villanueva, G. A. Veltri, and F. Folkvord, “Maximizing Opportunities and Minimizing Risks for Children Online: The Role of Digital Skills in Emerging Strategies of Parental Mediation: Maximizing Opportunities and Minimizing Risks,” *Journal of Communication*, vol. 67, no. 1, pp. 82–105, Feb. 2017, <https://doi.org/10.1111/jcom.12277>
- [25] D. Sevilla-Fernández, A. Díaz-López, V. Caba-Machado, J. M. Machimbarrena, J. Ortega-Barón, and J. González-Cabrera, “Parental mediation and the use of social networks: A systematic review,” *PLoS ONE*, vol. 20, no. 2, p. e0312011, Feb. 2025, <https://doi.org/10.1371/journal.pone.0312011>
- [26] M. Brand et al., “The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors,” *Neuroscience & Biobehavioral Reviews*, vol. 104, pp. 1–10, Sep. 2019, <https://doi.org/10.1016/j.neubiorev.2019.06.032>
- [27] A. Klingbeil, C. Grützner, and P. Schreck, “Trust and reliance on AI – An experimental study on the extent and costs of overreliance on AI,” *Computers in Human Behavior*, vol. 160, p. 108352, Nov. 2024, <https://doi.org/10.1016/j.chb.2024.108352>
- [28] C. Montag and J. D. Elhai, “The darker side of positive AI attitudes: Investigating associations with (problematic) social media use,” *Addictive Behaviors Reports*, vol. 22, p. 100613, Dec. 2025, <https://doi.org/10.1016/j.abrep.2025.100613>
- [29] A. Hernández, M. Hidalgo, R. Hambleton, and J. Gómez-Benito, “International Test Commission guidelines for test adaptation: A criterion checklist,” *Psicothema*, vol. 3, no. 32, pp. 390–398, Aug. 2020, <https://doi.org/10.7334/psicothema2019.306>
- [30] “TTC Guidelines for Translating and Adapting Tests (Second Edition),” *International Journal of Testing*, vol. 18, no. 2, pp. 101–134, Apr. 2018, <https://doi.org/10.1080/15305058.2017.1398166>
- [31] V. Caba-Machado, J. M. Machimbarrena, A. Díaz-López, D. Sevilla-Fernández, C. Pérez-Sancho, and J. González-Cabrera, “Nomophobia Questionnaire Short-Form: Psychometric Properties and Longitudinal Association with Anxiety, Stress, and Depression in Adolescents,” *International Journal of Human-Computer Interaction*, vol. 40, no. 17, pp. 4585–4595, Sep. 2024, <https://doi.org/10.1080/10447318.2023.2215626>
- [32] L. Hu and P. M. Bentler, “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 6, no. 1, pp. 1–55, Jan. 1999, <https://doi.org/10.1080/10705519909540118>
- [33] G. W. Cheung and R. B. Rensvold, “Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 9, no. 2, pp. 233–255, Apr. 2002, https://doi.org/10.1207/S15328007SEM0902_5
- [34] E. Ortega-Ochoa, J.-M. Sabaté, M. Arguedas, J. Conesa, T. Daradoumis, and S. Caballé, “Exploring the utilization and deficiencies of Generative Artificial Intelligence in students’ cognitive and emotional needs: a systematic mini-review,” *Frontiers in Artificial Intelligence*, vol. 7, Nov. 2024, <https://doi.org/10.3389/frai.2024.1493566>
- [35] S. Carcelén-García, M. J. Narros-González, and M. Galmes-Cerezo, “Digital vulnerability in young people: gender, age and online participation patterns,” *International Journal of Adolescence and Youth*, vol. 28, no. 1, p. 2287115, Dec. 2023, <https://doi.org/10.1080/02673843.2023.2287115>
- [36] K. V. C. Cabrera-Loayza, “Transformando la Educación Básica: Retos y Perspectivas de la Inteligencia Artificial,” *Revista Científica de Salud y Desarrollo Humano*, vol. 5, no. 2, Art. no. 2, Apr. 2024, <https://doi.org/10.61368/r.s.d.h.v5i2.113>
- [37] S. S. Shah and M. M. Asad, “Impact of Critical Thinking Approach on Learners’ Dependence on Innovative Transformation Through Artificial Intelligence,” in *The Evolution of Artificial Intelligence in Higher Education*, M. D. Lytras, A. Alkhaldi, S. Malik, A. C. Serban, and T. Aldosemani, Eds., Emerald Publishing Limited, 2024, pp. 161–182. <https://doi.org/10.1108/978-1-83549-486-820241010>
- [38] M. Del Cisne Loján, J. Antonio Romero, D. Sancho Aguilera, and A. Yajaira Romero, “Consecuencias de la Dependencia de la Inteligencia Artificial en Habilidades Críticas y Aprendizaje Autónomo en los Estudiantes,” *Ciencia Latina*, vol. 8, no. 2, pp. 2368–2382, Apr. 2024, <https://doi.org/10.1108/978-1-83549-486-820241010>
- [39] J. Billieux, A. Schimmenti, Y. Khazaal, P. Maurage, and A. Heeren, “Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research,” *Journal of Behavioral Addictions*, vol. 4, no. 3, pp. 119–123, Sep. 2015, <https://doi.org/10.1556/2006.4.2015.009>
- [40] D. Kardefelt-Winther et al., “How can we conceptualize behavioural addiction without pathologizing common behaviours?: How to conceptualize behavioral addiction,” *Addiction*, vol. 112, no. 10, pp. 1709–1715, Oct. 2017, <https://doi.org/10.1111/add.13763>
- [41] J. Billieux, M. Flayelle, and D. L. King, “Addiction: expand diagnostic borders with care,” *Nature*, vol. 611, no. 7937, pp. 665–665, Nov. 2022, <https://doi.org/10.1038/d41586-022-03760-y>
- [42] V. Ciudad-Fernández, C. Von Hammerstein, and J. Billieux, “People are not becoming ‘AIholic’: Questioning the ‘ChatGPT addiction’ construct,” *Addictive Behaviors*, vol. 166, p. 108325, Jul. 2025, <https://doi.org/10.1016/j.addbeh.2025.108325>
- [43] L. Fournier et al., “Deconstructing the components model of addiction: an illustration through ‘addictive’ use of social media,” *Addictive Behaviors*, vol. 143, p. 107694, Aug. 2023, <https://doi.org/10.1016/j.addbeh.2023.107694>
- [44] A. Nogueira-López, A. Rial-Boubeta, I. Guadix-García, V. J. Villanueva-Blasco, and J. Billieux, “Prevalence of problematic Internet use and problematic gaming in Spanish adolescents,” *Psychiatry Research*, vol. 326, p. 115317, Aug. 2023, <https://doi.org/10.1016/j.psychres.2023.115317>
- [45] J. Von Garrel and J. Mayer, “Artificial Intelligence in studies—use of ChatGPT and AI-based tools among students in Germany,” *Humanities and Social Sciences Communications*, vol. 10, no. 1, p. 799, Nov. 2023, <https://doi.org/10.1057/s41599-023-02304-7>
- [46] The Nordic Youth Barometer, “Back2School.” 2023. [Online]. Available: <https://info.ungdomsbarometern.se/publika-rapporter/back2school-2023>
- [47] J. Klarin, E. Hoff, A. Larsson, and D. Daukantaitė, “Adolescents’ use and perceived usefulness of generative AI for schoolwork: exploring their relationships with executive functioning and academic achievement,” *Frontiers in Artificial Intelligence*, vol. 7, p. 1415782, Aug. 2024, <https://doi.org/10.3389/frai.2024.1415782>
- [48] J. Ortega-Barón, J. González-Cabrera, J. M. Machimbarrena, and I. Montiel, “Safety.Net: A Pilot Study on a Multi-Risk Internet Prevention Program,” *International Journal of Environmental Research and Public Health*, vol. 18, no. 8, p. 4249, Apr. 2021, <https://doi.org/10.3390/ijerph18084249>
- [49] J. Ortega-Barón, J. M. Machimbarrena, A. Díaz-López, V. Caba-Machado, B. Tejero, and J. González-Cabrera, “Eficacia de un programa de prevención multirriesgo en internet: Safety.net,” *Revista de Psicodidáctica*, vol. 29, no. 2, pp. 97–106, Jul. 2024, <https://doi.org/10.1016/j.psicod.2024.01.004>



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