The influence of learning motivation and procrastination on ChatGPT dependence

Influencia de la motivación hacia el aprendizaje y la procrastinación en la dependencia a ChatGPT

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ABSTRACT

In a short period of time, generative artificial intelligences such as ChatGPT have become a widely used support tool for students' learning processes, altering how many approach academic tasks. Their immediacy and accessibility make them attractive alternatives to traditional study resources, to the extent that some students may have even developed a certain degree of dependence on these tools. The present study investigates the impact of learning motivation and procrastination on ChatGPT dependence. A total of 467 university students from the field of education participated by completing a series of validated scales measuring different types of motivation defined in Self-Determination Theory (extrinsic motivation, intrinsic motivation, and amotivation), procrastination, and ChatGPT dependence. The indirect effects of the mediation analyses revealed that students with lower levels of intrinsic motivation (β = -.076; *LL* = -.121; *UL* = -.037) and higher levels of amotivation (β = .090; *LL* = .041; *UL* = .144) were more likely to procrastinate frequently, with procrastination emerging as a significant factor contributing to greater ChatGPT dependence. Similarly, results indicated that students with high extrinsic motivation (without procrastination serving as a mediator) were more prone to develop greater dependence on ChatGPT (β = .122; p = .022). These findings highlight the importance of implementing strategies that foster intrinsic motivation and self-regulation, helping students use generative AI-based tools appropriately while developing essential competencies that could be at risk from excessive use of these tools, such as critical thinking and problem-solving.

Keywords: motivation; dependence; ChatGPT; procrastination; artificial intelligence; higher education.

RESUMEN

En poco tiempo, las inteligencias artificiales generativas como ChatGPT se han convertido en herramientas de apoyo para el aprendizaje, transformando la forma en que muchos estudiantes afrontan las tareas académicas. Su inmediatez y accesibilidad las hacen especialmente atractivas frente a los recursos tradicionales, hasta el punto de que algunos estudiantes pueden desarrollar cierta dependencia a ellas. Este trabajo investiga el impacto de la motivación hacia el aprendizaje y la procrastinación en la dependencia a ChatGPT. 467 estudiantes universitarios del área de la Educación participaron completando una serie de escalas validadas para evaluar diferentes tipos de motivación definidas en la *Teoría de la Autodeterminación* (motivación extrínseca, intrínseca y amotivación), procrastinación y dependencia a ChatGPT. Los análisis de mediación mostraron que los estudiantes con menor motivación intrínseca (β = -.076; *LI* = -.121; *LS* = -.037) y mayor amotivación (β = .090; *LI* = .041; *LS* = .144) tendían a procrastinar con mayor frecuencia, siendo la procrastinación un factor clave que aumentaba la dependencia a *ChatGPT*. Además, el alumnado con alta motivación extrínseca (incluso sin la mediación de la procrastinación) resultó ser más propenso a desarrollar una mayor dependencia a *ChatGPT* (β = .122; p = .022). Estos hallazgos destacan la importancia de implementar estrategias que fomenten la motivación intrínseca y la autorregulación, ayudando a los estudiantes a utilizar adecuadamente las herramientas basadas en la IA generativa mientras desarrollan competencias esenciales que podrían estar en riesgo por el uso excesivo de estas herramientas, como el pensamiento crítico y la resolución de problemas.

Palabras clave: motivación; dependencia; ChatGPT; procrastinación; inteligencia artificial; educación superior.

How to cite: Galindo-Domínguez, H., Sainz-de-la-Maza, M., Campo, L., & Losada-Iglesias, D. (2026). The influence of learning motivation and procrastination on ChatGPT dependence [Influencia de la motivación hacia el aprendizaje y la procrastinación en la dependencia a ChatGPT]. *RIED-Revista Iberoamericana de Educación a Distancia, 29*(1), 217-240.
https://doi.org/10.5944/ried.45497

INTRODUCTION

In this study, the theoretical framework is designed to test a mediation model in which motivation serves as the independent variable, procrastination as the mediating variable, and dependence on ChatGPT as the dependent variable. To provide a clear roadmap for the reader, the literature review is structured logically. Firstly, it explores the foundational theories of motivation and procrastination, examining the established relationship between these two constructs. Secondly, dependence on artificial intelligence within the context of higher education is defined, focusing on an excessive reliance on these systems for academic tasks. Finally, the framework integrates these three concepts by linking motivation to dependence on ChatGPT and, subsequently, procrastination to this dependence, aligning the theoretical flow with the proposed model.

Motivation and procrastination in learning processes

Motivation constitutes a complex construct within human psychology and behavior, exerting an influence on the way people decide to allocate their time, the level of effort they put into a task, their thoughts and emotions about the activity, and their perseverance in completing it (Filgona et al., 2020).

Although numerous influential theories have been proposed to understand individual motivation, including *Attribution Theory*, *Expectancy-Value Theory*, the *ARCS model*, *Social Cognitive Theory*, and *Goal-Orientation Theory*, among others, the *Self-Determination Theory* (SDT henceforth) has recently gained increased prominence in explaining shifts in attitudes toward Artificial Intelligence (e.g., Chai et al., 2023; Chiu, 2024; Chiu & Chai, 2020; Xia et al., 2022). The taxonomy associated with this theory explains how different forms of motivation vary depending on the degree of self-determination, ranging from the absence of motivation, through motivations controlled by external factors, to more autonomous motivations linked to personal interests (Ryan & Deci, 2020). Indeed, amotivation refers to the absence of intention to act, often resulting from a perceived lack of competence or value in the activity. Extrinsic motivation, in contrast, is driven by external rewards or pressures, yet it varies in its level of autonomy depending on the degree of internalization. The highest form of autonomy in motivation is intrinsic, emerging from the inherent enjoyment and satisfaction derived from the activity itself, which promotes both engagement and persistence (Ryan & Deci, 2020).

Likewise, SDT posits that the different forms of motivation (intrinsic, extrinsic, and amotivation) are closely linked to the extent to which three basic psychological needs are fulfilled: Competence, Autonomy and Relatedness (Ryan & Deci, 2020).

Firstly, competence can be understood as the feeling of being effective and capable in one's interactions with the environment. It involves mastering tasks and achieving desired outcomes, fostering a sense of accomplishment and growth. Feeling competent strengthens intrinsic motivation as well as the more self-determined forms of extrinsic motivation, while a lack of competence may lead to amotivation. A variety of studies have shown how strong competence, often reflected in high performance in task execution, is a predictor of increased intrinsic motivation among students (e.g., Garon-Carrier et al., 2016; Van Bergen et al., 2022).

Secondly, autonomy can be defined as the sense of being in control of one's own actions and decisions. It allows individuals to act volitionally and pursue goals in a self-

endorsed way. Intrinsic motivation thrives when individuals perceive a sense of freedom and choice, whereas a lack of autonomy may contribute to amotivation or controlled forms of extrinsic motivation. In this regard, previous studies have revealed that students from autonomy-supportive teaching contexts have higher intrinsic motivation, greater classroom engagement and skill development, as well as a lower likelihood of dropout (e.g., Cheon et al., 2020; Ljubin-Golub et al., 2020; Reeve & Cheon, 2021).

Thirdly, the concept of relatedness concerns the fundamental need to establish connections with others, to experience belonging, and to develop meaningful interpersonal bonds. It encompasses the perception of being cared for, supported, and understood within social contexts. When this need is satisfied, individuals are more inclined to display autonomous forms of motivation, engaging more fully in activities that nurture their sense of connection. Previous evidence has shown that fostering relatedness in the classroom partially affects the increase in students' intrinsic motivation (e.g., Ganotice et al., 2024; Guay et al., 2019)

As previously observed, from the perspective of SDT, the main basic psychological needs have a significant impact on students' motivation. Furthermore, according to previous evidence, having this motivation is key to reducing certain constructs such as procrastination, a construct that is analyzed in more detail in this paper.

Procrastination is commonly described as an irrational tendency to delay essential tasks or responsibilities, despite the negative consequences this postponement may have for both individuals and organizations (Klingsieck, 2013). Procrastination represents a self-regulatory deficit associated with both personal dispositions and environmental factors (Hen & Goroshit, 2018). Specifically, studies indicate that task-related factors (such as unclear instructions, timing of rewards and punishments, and task aversiveness), personality traits (e.g., the five-factor model, motivation, and cognition), and environmental influences (e.g., temptation, incentives, and accountability) are key contributors to procrastination (Johnson & Bloom, 1995; Wypych et al., 2018). Procrastination may act as a barrier to achievement, exerting detrimental effects on emotional well-being and contributing to heightened levels of anxiety, depressive symptoms, and diminished self-esteem (Duru & Balkis, 2017). Moreover, chronic procrastinators frequently demonstrate reduced performance outcomes, such as lower academic results, postponed career advancements, and adverse health consequences (Legood et al., 2018; Bolden & Fillauer, 2020).

Focusing on the relationship between motivation and procrastination, this has been a widely explored topic in the scientific literature, showing that the relationship between motivation and procrastination is complex and appears to be primarily unidirectional, with motivation influencing procrastination rather than the other way around (e.g., Grund & Fries, 2018; Li et al., 2021; Wu & Fan, 2016). Specifically, previous evidence has revealed that lower levels of attainment value (Wypych et al., 2018; Wu & Fan, 2016), self-determination (Grund & Fries, 2018), perseverance (Wypych et al., 2018), and intrinsic motivation (Kok, 2016), as well as higher levels of cost (Wu & Fan, 2016), delay discounting (Wypych et al., 2018), amotivation and external motivation (Kok, 2016) lead to higher academic procrastination levels.

Dependence on artificial intelligence in higher education

Artificial Intelligence (AI) is defined as the ability of machines or computational systems to emulate and perform functions traditionally attributed to human intelligence, including reasoning, learning, and problem-solving (Morandín-Ahuerma, 2022). While the integration of AI into educational contexts remains a relatively recent phenomenon, existing research underscores several potential advantages, including support in drafting written assignments, the provision of automated feedback, and assistance with data and information analysis (Chen et al., 2020; Delgado et al., 2024; Wang et al., 2018). Nonetheless, studies also highlight notable limitations, such as reduced human interaction in the learning process, limited contextual understanding, and overdependence on AI, which may diminish essential skills like critical thinking and problem-solving (Ahmad et al., 2021; Jara & Ochoa, 2020; Korteling et al., 2021). This study centers on the latter concern: AI dependence.

In the clinical domain, dependence has historically been linked to the use of substances such as alcohol and drugs, typically identified through indicators like tolerance and withdrawal (American Psychiatric Association, 2013). Yet, with the advent of the artificial intelligence era, this understanding has expanded to encompass behavioral forms of addiction, including pathological gambling and internet addiction disorder, which exhibit comparable neurobiological and behavioral patterns. (e.g., Bucur et al., 2021; Siste et al., 2019). In an academic context, dependence on AI is defined as an excessive reliance on automated systems for tasks such as decision-making or task execution (Morales-García et al., 2024), a phenomenon that manifests as a lack of confidence in one's own academic abilities and a preference for using AI as the primary, if not sole, source of assistance (Del Cisne et al., 2024). In fact, recent evidence suggests that simply knowing that advice comes from an AI can lead students to overrely on it, even when it contradicts available information or their own judgment, potentially producing suboptimal outcomes for themselves and others (Klingbeil et al., 2024). One of the main reasons, as noted by Baird and Maruping (2021), is that AI systems and chatbots increasingly replicate human interactions in a more natural manner, leading students to place greater trust in these types of systems.

This phenomenon can be interpreted through the lens of the *Unified Theory of Acceptance and Use of Technology* (Venkatesh et al., 2003), which offers a framework for analyzing dependence on AI by identifying the primary factors affecting its adoption and use. The theory emphasizes that constructs such as “performance expectancy, effort expectancy, social influence, and facilitating conditions” are pivotal in shaping user behavior. Dependence on AI may emerge when users hold high performance expectancy, perceiving that AI substantially improves task efficiency or accuracy, and low effort expectancy, as AI simplifies otherwise complex processes. Furthermore, social influence, including peer pressure to adopt and use such tools, can amplify dependence on these systems. Lastly, facilitating conditions, such as accessible infrastructure and resources, create an environment conducive to frequent AI use, potentially leading to overdependence.

Currently, there are some studies that reveal how the prevalence of dependence on artificial intelligence tools such as ChatGPT is moderately low, ranging from 16% to 25% among university students (Hong & Chen, 2024; Huang et al., 2024; Stojanov, 2024). Some authors even suggest that this should not yet be a cause for excessive societal alarm (Huang et al., 2024). Although the rapid advancements of artificial intelligence in education, together with its wide range of functionalities, have created

new opportunities, the risk of excessive dependence calls for institutional regulation (Liu et al., 2023; Stojanov, 2024). In this regard, universities could play a crucial role by guiding students toward a balanced use of these tools, encouraging their integration in a critical manner while ensuring that learners continue to strengthen their own skills (Lee et al., 2024). This aligns with models of open and distance education, such as the *Community of Inquiry framework*, which emphasize the need for cognitive, social, and teaching presence to support self-regulated learning and prevent overreliance on technological tools (Carroll et al., 2025).

Impact of motivation and procrastination on ChatGPT dependence

ChatGPT (*Chat Generative Pre-Trained Transformer*), created by OpenAI, is a sophisticated AI-powered language model designed to handle complex linguistic tasks. Renowned for its ability to create human-like text, it facilitates a diversity of applications, including automated text generation, question answering, summarization, and image creation. By delivering responses that closely emulate human communication, ChatGPT has revolutionized interactions with chatbots and virtual assistants, achieving substantial global popularity and widespread use since its launch in November 2022 (Yu et al., 2024).

Although the existing literature analyzing the relationship between motivation, procrastination, and dependence on ChatGPT is extremely limited due to the novelty of the topic, certain studies provide some valuable insights.

First, regarding the relationship between motivation and dependence on ChatGPT, several studies have revealed that high levels of lazy thinking (which may reflect amotivation toward tasks), high levels of emotional stress (which may reflect exhaustion toward tasks), low levels of academic self-efficacy, and low levels of decision-making skills were associated with an increase in dependence on Generative AI (Ahmad et al., 2023; Estrada-Araoz et al., 2025; Naseer et al., 2025; Ye et al., 2024). Similarly, previous research highlights the effect of different types of motivation on dependence on AI. Specifically, low levels of achievement motivation (Hong & Chen, 2024) and Mastery Approach orientation (Stojanov, 2024), as well as high levels of escape motivation, social motivation (Huang et al., 2024), mastery avoidance orientation, and performance approach orientation (Stojanov, 2024), have been associated with increased levels of dependence on ChatGPT. As stated by Ye et al. (2024), individuals who have had a positive experience using ChatGPT may be more motivated to avoid learning tasks and rely on the responses provided by ChatGPT.

Secondly, regarding the relationship between procrastination and dependence on ChatGPT, previous studies, such as the one by Feng et al. (2023), hypothesize how procrastination may influence dependence on ChatGPT. This hypothesis has been partially tested. For example, Stojanov (2024) observed that procrastinating students, who represented nearly a quarter of the university student population, were highly dependent on ChatGPT for completing assigned tasks. Similarly, Swargiary (2024), through a pre-post design with a control group, conducted an intervention using ChatGPT for task completion with the intervention group. The results showed that the intervention group exhibited increased levels of procrastination and reduced academic performance compared to the comparison group. Finally, studies with qualitative approaches (e.g., Ayele, 2024; Paraso et al., 2024) revealed that university students reported that AI was extremely helpful, especially for those who tended to leave tasks until the last moment.

Based on these studies, procrastination might mediate the relationship between different types of motivation and AI dependence. This suggests that students who lack internal motivation or feel disengaged may increasingly postpone tasks, turning to AI tools as a compensatory strategy, a dynamic particularly relevant in certain environments, like open and distance education environments, where self-regulation is crucial.

The current study

The impact of Artificial Intelligence on education has garnered growing attention, prompting a proliferation of opinion articles. However, empirical research on this subject remains limited (Ye et al., 2024). One of the primary concerns for educators and researchers is the potential negative consequences of ChatGPT, particularly due to its problematic use (Ye et al., 2024). Despite this, as several studies point out, there is a severe lack of comprehensive analyses on inappropriate uses, such as AI dependence, which warrants further exploration (Yu et al., 2024). As a result, some scholars stress the importance of investigating the psychological factors that contribute to the development of this dependence (Ahmad et al., 2023; Ye et al., 2024), due to the fact that the intensive use of these tools might negatively impact students' self-regulation, critical thinking and problem-solving skills (Ali et al., 2024; Kamalov et al., 2023; Zhai et al., 2024).

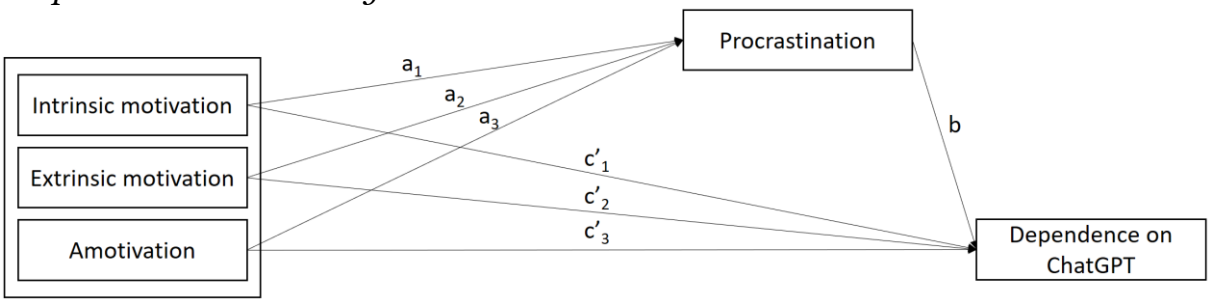
Similarly, as previously observed, there is some evidence linking motivation and procrastination-related factors with dependence on ChatGPT. However, to the authors' knowledge, the current evidence employing more complex analyses, such as structural equation modeling, mediation analysis, or moderation analysis, is extremely limited. This scarcity hinders a comprehensive understanding of the relationship between various constructs of interest, such as motivation or procrastination. Additionally, this is compounded by the lack of empirical studies on Artificial Intelligence dependence that are approached through robust frameworks, such as SDT, which is gaining significant traction in the field of AI (e.g., Chai et al., 2023; Chiu, 2024; Chiu & Chai, 2020; Xia et al., 2022). In addition, the past few years have witnessed a growth in scholarly articles examining procrastination in university students, clearly indicating growing scientific interest in the topic (Yan & Zhang, 2022).

Accordingly, this study seeks to address three distinct research questions:

- RQ_1: To what extent do different types of motivation (amotivation, intrinsic and extrinsic) impact dependence on ChatGPT?
- RQ_2: To what extent does procrastination impact dependence on ChatGPT?
- RQ_3: To what degree does procrastination mediate the relationship between various forms of motivation and dependence on ChatGPT?

Figure 1 presents the diagram of the model that is intended to be tested in the subsequent analyses.

Figure 1
Proposed mediation analysis



METHODOLOGY

Design and participants

The study employed a quantitative, cross-sectional, non-experimental design, following a descriptive–correlational approach. Mediation analyses were conducted to examine the indirect effects of learning motivation and procrastination on ChatGPT dependence.

In this design, 467 Spanish university students from the field of education at the University of the Basque Country participated (M = 20.44; SD = 2.83). Among them, 292 identified as male, 173 as female, and 2 as another gender. Regarding their academic programs, 40 students were enrolled in the Bachelor's Degree in Early Childhood Education, 379 in the Bachelor's Degree in Primary Education, and 48 in the master's degree in Secondary Education Teaching. In terms of academic progression, 274 participants were in their second year, 103 in their third year, 45 in their fourth year, and 45 in the Master's program (equivalent to a fifth year).

Participants were selected through non-probabilistic sampling based on proximity to the research team, as all students had been taught by one or more team members. Notably, previous studies suggest that non-probabilistic sampling methods often produce results similar to those obtained through randomized sampling techniques (Coppock et al., 2018). Likewise, an a priori power analysis was conducted using G*Power 3.1 for a linear multiple regression model with four predictors (three independent variables and one mediator). Assuming a medium effect size (f^2 = 0.15) and α = 0.05, the analysis indicated that a minimum sample of 55 participants was required to achieve a power of 0.80, a commonly used value in the context of correlational studies in education and psychology (Cohen, 1988). With the current sample of 467 participants, the study provides a robust level of statistical power to detect the anticipated effects.

Instruments

- **Learning motivation**

Intrinsic Motivation: The dimensions of Intrinsic Motivation to Know and Intrinsic Motivation toward Accomplishment were used from the short version of the Academic Motivation Scale (Kotera et al., 2023). These two dimensions comprise four 5-point Likert-type items each, capturing the respondent's internal intention to study

for the purpose of expanding knowledge (e.g., "I study because my studies allow me to continue to learn about many things that interest me") and improving as a student (e.g., "I study for the pleasure that I experience while I am surpassing myself in one of my personal accomplishments"). According to Kotera et al. (2023), these dimensions demonstrated reliability with α = .84 and .79, respectively. *Extrinsic Motivation:* To assess extrinsic motivation, the External Regulation dimension of the same scale was employed. This dimension consists of two 5-point Likert-type items that measure the respondent's intention to study for external rewards (e.g., "I study in order to obtain a more prestigious job later on"). The reliability of this dimension was reported as α = .82 (Kotera et al., 2023). *Amotivation:* Amotivation was measured using the Amotivation dimension of the same scale. This dimension includes two 5-point Likert-type items that capture the respondent's lack of interest in studying (e.g., "I can't see why I go to university and frankly, I couldn't care less"). According to Kotera et al. (2023), the reliability for this dimension was α = .79.

- **Procrastination**

To assess the level of procrastination, the Short Form of the Academic Procrastination Scale (Yockey, 2016) was utilized. This scale consists of five 5-point Likert-type items grouped into a single factor, designed to measure the extent to which students delay and postpone completing their tasks until the last moment (e.g., "When given an assignment, I usually put it away and forget about it until it is almost due"). According to Yockey (2016), the reliability of this scale is reported as α = .87.

- **Dependence on ChatGPT**

To evaluate the degree of dependence on ChatGPT, the ChatGPT Dependence Scale (Ye et al., 2024) was employed. This scale comprises a single dimension with five 5-point Likert-type items, measuring the extent to which individuals feel the need to use ChatGPT for academic tasks (e.g., "I would feel uncomfortable without ChatGPT"). According to Ye et al. (2024), the reliability of this scale is reported as α = .71.

Procedure

The procedure commenced with a review of various databases to identify appropriate scales for the study, which were then digitized using Google Forms. Subsequently, the sample was defined, including all students taught by the researchers involved in the study and enrolled in education-related programs. As noted earlier, although this was a non-probabilistic sample, prior research indicates that convenience samples often produce results comparable to those obtained from randomized samples (Coppock et al., 2018). Participants completed the Google Forms questionnaire during class hours using individual computers, after consenting to the study's participation conditions. These conditions complied with the principles outlined in the Declaration of Helsinki, ensuring anonymity and privacy of responses, the right to withdraw before or during participation, and appropriate data management and disposal during and after the research. Upon study completion, participants received a report summarizing the main findings and their implications.

Data analysis

First, to assess the validity of the data as much as possible, the goodness of fit of the model was examined through the X^2/df, CFI, RMSEA, and AIC indices using SPSS AMOS 25 software, expecting the indices to meet the following thresholds: $X^2/df < 5$; CFI > .90; RMSEA < .080; AIC = lowest possible value (Hooper et al., 2008). Subsequently, in SPSS Statistics 27, a descriptive analysis was conducted by studying the arithmetic mean and standard deviation.

This was followed by other analyses, such as the correlational analysis using Pearson's r between the main dimensions, as well as the reliability analysis using Cronbach's alpha. Finally, also in SPSS Statistics 27, the PROCESS macro was used to perform a mediation analysis, as shown in Figure 1. This analysis was carried out employing a total of 10,000 samples of bootstrapping. In this mediation analysis, particular attention was given to the direct and indirect effects obtained. Specifically, to answer RQ_1 and RQ_2, the direct effects were examined. For these effects, the R^2 values were observed to determine the effect size, indicating the proportion of the variance in the dependent variable explained by the independent variable. For RQ_3, the indirect effects were studied. To evaluate their effect size, the Proportion of Mediation (*PM*) was calculated. This metric indicates the proportion of the total effect of the independent variable on the dependent variable that is accounted for by the mediator. All parametric analyses were justified by the normal distribution of all measured variables, assessed through skewness and kurtosis, with all values falling within the skewness range of ±2 and the kurtosis range of ±7 (Hair et al., 2010). Multicollinearity was also tested, with all values falling within the acceptable range of VIF < 10 and Tolerance > .10 (Field, 2013). Independence of errors was assessed using the Durbin–Watson statistic, which yielded a value of 1.636; this falls within the 1.5–2.5 range, indicating a slight positive autocorrelation but generally considered acceptable (Field, 2013).

RESULTS

First, to determine whether any preliminary adjustments were necessary, the goodness of fit of the proposed model was assessed using the indices X^2/df, CFI, RMSEA, and AIC. The resulting model demonstrated good fit ($X^2/df = 2.328$; CFI = .955; RMSEA = .053; AIC = 382.995), as the values fell within the acceptable thresholds established for evaluating model fit in this study of $X^2/df < 5$; CFI > .90; RMSEA < .80; AIC = lowest value possible (Hooper et al., 2008).

Subsequently, descriptive statistics, correlations, and reliability indices for the main dimensions were analyzed. As shown in Table 1, participants generally exhibited high levels of intrinsic ($M = 3.48$; $SD = .843$) and extrinsic motivation ($M = 3.95$; $SD = .849$), alongside low levels of amotivation (M = 1.63; SD = .884). Additionally, moderate levels of procrastination ($M = 2.57$; $SD = .947$) and dependence on ChatGPT ($M = 2.37$; $SD = .996$) were observed. Likewise, correlation analyses indicated that intrinsic motivation was inversely related to procrastination ($r = -.287$, $p < .001$), while amotivation demonstrated a positive association with procrastination ($r = .403$, $p < .001$). Furthermore, the only type of motivation significantly associated with dependence on ChatGPT was amotivation ($r = .162$; $p < .001$), which also showed a positive correlation. Procrastination similarly demonstrated a positive correlation with ChatGPT dependence ($r = .231$; $p < .001$). Finally, all reliability indices exceeded the

threshold of α = .70 (Tavakol & Dennick, 2011), indicating good internal consistency for the dimensions used in the study.

Table 1

Descriptives, correlations and reliability indices of the main dimensions

	M	SD	1	2	3	4	5
IM	3.48	.843	(.865)	.176***	-.200***	-.287***	-.084
EM	3.95	.849		(.785)	-.046	-.091	.082
AM	1.63	.884			(.813)	.403***	.162***
PRC	2.57	.947				(.858)	.231***
GPT	2.37	.996					(.858)

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; IM, Intrinsic Motivation; EM, Extrinsic Motivation; AM, Amotivation; PRC, Procrastination; GPT, Dependence on ChatGPT. Cronbach's alpha reliability indices are presented on the main diagonal in parentheses.

To address the research questions posed in this study, a mediation analysis was conducted. Mediation analysis is employed to assess whether, and to what extent, the effect of an independent variable on a dependent variable operates indirectly through a mediator variable. In this model, the independent variables were the different types of motivation, the dependent variable was dependence on ChatGPT, and the mediating variable was procrastination.

The main results from the direct effects, presented in Table 2, indicate that both intrinsic motivation (R^2 = .082; β = –.322; $p < .001$) and amotivation (R^2 = .162; β = .432; $p < .001$) are significantly associated with procrastination. These R^2 values indicate that intrinsic motivation alone explains about 8% of the variance in procrastination, whereas amotivation accounts for 16%. Thus, lower intrinsic motivation and higher amotivation are associated with more pronounced procrastination, suggesting that the absence of self-determined reasons for engaging in academic tasks may be particularly detrimental. Additionally, and concerning RQ_1 and RQ_2, procrastination was found to be significantly associated with dependence on ChatGPT (R^2 = .053; β = .237; $p < .001$) indicating that procrastination explains around 5% of the variance in dependence on ChatGPT. Among the three types of motivation examined, the only one that was directly associated with dependence on ChatGPT was extrinsic motivation (R^2 = .026; β = .122; p = .022), indicating that although the effect was statistically significant, the proportion of variance explained was relatively low, suggesting that other factors likely contribute more substantially to dependence on ChatGPT.

Table 2

Results from the mediation analysis

	Path	R^2	PM	β	SE	LL	UL	p
Direct effects								
IM → PRC	a_1	.082	-	-.322	.050	-.420	-.224	< .001
EM → PRC	a_2	.008	-	-.101	.052	-.203	.000	.054
AM → PRC	a_3	.162	-	.432	.045	.342	.521	< .001

	Path	R^2	PM	β	SE	LL	UL	p
PRC → GPT	b	.053	-	.237	.050	.140	.334	< .001
IM → GPT	c'_1	.007	-	-.023	.056	-.133	.086	.677
EM → GPT	c'_2	.007	-	.122	.053	.018	.226	.022
AM → GPT	c'_3	.026	-	.093	.055	-.016	.202	.096
Indirect effects								
IM → PRC → GPT	$a_1 * b$	-	.764	-.076	.022	-.121	-.037	***
EM → PRC → GPT	$a_2 * b$	-	-.270	-.026	.015	-.058	.001	(ns)
AM → PRC → GPT	$a_3 * b$	-	.493	.090	.026	.041	.144	***

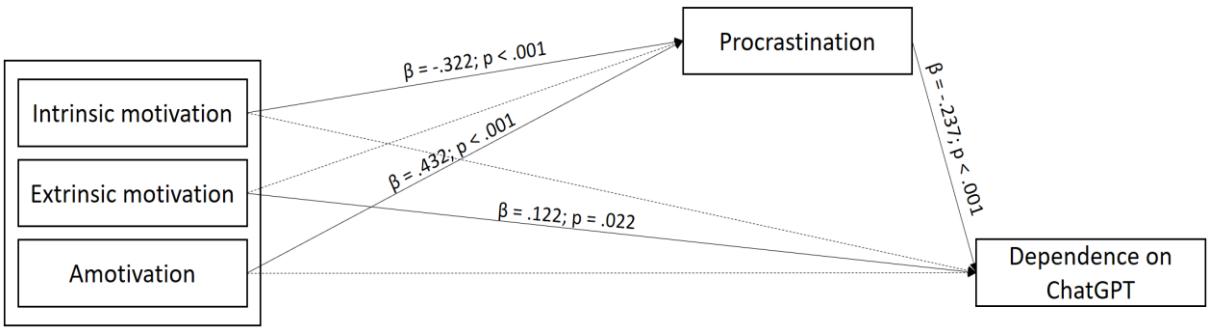
Note: IM, Intrinsic Motivation; EM, Extrinsic Motivation; AM, Amotivation; PRC, Procrastination; GPT, Dependence on ChatGPT.

Table 2 also displays the indirect effects, showing whether the independent variable influences the dependent variable via the mediator. Significance is established when the confidence interval excludes zero (MacKinnon et al., 2002). In this case, and answering RQ3, procrastination was found to mediate the relationships from intrinsic motivation (β = -.076; *LL* = -.121; *UL* = -.037) and amotivation (β = .090; *LL* = .041; *UL* = .144) to dependence on ChatGPT. In other words, high intrinsic motivation and minimal amotivation are associated with reduced procrastination, which subsequently serves to decrease dependence on ChatGPT. A representation of the main results can be observed in Figure 2.

Likewise, the proportion of mediation (*PM*) values were also calculated in Table 2 to determine the effect size of these indirect relationships. For the relationship from intrinsic motivation to dependence on ChatGPT mediated by procrastination, the *PM* was .764, indicating that a significant 76.4% of the total effect is mediated by procrastination. This suggests a nearly complete mediation, with a high relevance of procrastination. Similarly, for the path from amotivation to dependence on ChatGPT through procrastination, the PM was .493, showing that procrastination mediates almost half (49.3%) of the total effect. In both cases, procrastination was observed to be pivotal in understanding the relationship between intrinsic motivation, amotivation, and ChatGPT dependence.

Figure 2

Figure presenting the outcomes of the mediation analysis



DISCUSSION

The objective of the present study was threefold. First, it aimed to analyze the impact of motivation on dependence on ChatGPT. Second, it sought to examine the impact of procrastination on dependence on ChatGPT. Finally, it aimed to determine whether the association between different types of motivation and dependence on ChatGPT is mediated by levels of procrastination.

The results revealed that the only type of motivation analyzed that had a direct effect on dependence on ChatGPT was extrinsic motivation. However, the proportion of variance explained was relatively low, suggesting that other factors may have a stronger influence on ChatGPT dependence. Regarding intrinsic motivation and amotivation, it was observed that their relationship with dependence on ChatGPT is significantly mediated by students' procrastination. Specifically, high levels of intrinsic motivation and low levels of amotivation are associated with a reduction in students' procrastination levels, which in turn reduces dependence on ChatGPT.

Although these findings are novel, as to the authors' knowledge no previous mediation analyses have linked these variables, they are consistent with existing literature. First, evidence from multiple studies indicates that higher intrinsic motivation toward learning is associated with reduced dependence on ChatGPT. (e.g., Hong & Chen, 2024; Stojanov, 2024). Conversely, high levels of motivation driven by external factors (e.g., Huang et al., 2024; Stojanov, 2024), lack of motivation, or interest in learning (e.g., Ahmad et al., 2023; Ye et al., 2024) are associated with an increase in dependence on ChatGPT. Similarly, previous quantitative and qualitative studies indicate that students with a propensity to procrastinate are more likely to rely on ChatGPT for their academic tasks (e.g., Ayele, 2024; Feng et al., 2023; Paraso et al., 2024; Stojanov, 2024; Swargiary, 2024).This study integrates these findings through mediation analysis, revealing that strong intrinsic motivation and low amotivation are key to reducing students' procrastination, which, in turn, is a critical factor in decreasing dependence on ChatGPT. This can be explained by the SDT, which proposes a continuum of internalization (Ryan & Deci, 2020). Extrinsic motivation operates directly; students use ChatGPT as a quick fix to meet external demands with minimal effort. In contrast, intrinsic motivation and amotivation affect students' perceived cognitive cost of tasks, which triggers a coping mechanism: procrastination. Our findings suggest that this procrastination acts as the true mediator, facilitating the use of ChatGPT to avoid the aversive task. Thus, intrinsic motivation influences dependence indirectly through procrastination, while extrinsic motivation appears to lead to direct use.

Next, the present study has different implications that may be of interest to various stakeholders. First, these findings may be valuable for researchers as they contribute to a better understanding and consolidation of a theoretical framework as recent as the impact of emotional factors on dependence on generative AI, such as ChatGPT.

Likewise, these findings may assist university faculty by demonstrating that increasing intrinsic motivation and reducing amotivation and procrastination can significantly reduce university students' dependence on ChatGPT. As discussed in the theoretical framework of this paper, according to SDT, intrinsic motivation is influenced by the basic psychological needs of competence, autonomy, and relatedness (Ryan & Deci, 2020). Based on the results showing that procrastination mediates the relationships from both intrinsic motivation and amotivation to ChatGPT dependence,

there is a wide range of literature that contributes to improving each of these needs, with consequent effects on students' intrinsic motivation.

First, some strategies that teachers could apply to foster students' basic psychological needs of competence, autonomy and relatedness might include promoting positive and constructive feedback (García et al., 2019; Koike & Pearson, 2005), using scaffolding or gradual support techniques (e.g., Mulatsih, 2011; Neitzel & Stright, 2003), encouraging the use of executive functions such as short- and long-term goal planning (Benavides-Nieto et al., 2017; Ganesalingam et al., 2011; Roebers et al., 2012), fostering the use of metacognitive skills, such as self-reflection (Roebers et al., 2012; Jho & Chae, 2014) promoting the usage of cooperative learning techniques, like 1-2-4 or Jigsaw (Fernández-Río et al., 2017; Namaziandost et al., 2019), or using other learning strategies to organize information and link it with existing knowledge such as distributed learning, retrieval in any of its forms (practice testing), interleaved practice, summarizing, doing concept maps, or highlighting the relevant information (Donoghue & Hattie, 2021; Maldonado-Sánchez et al., 2019). These strategies would be particularly relevant for e-learning and distance education settings, as they can be easily adapted for online platforms. For instance, online learning systems can integrate features that provide automated and instant feedback; course modules can be designed with a scaffolded structure to promote autonomy; and virtual group projects can facilitate cooperative learning, which can help mitigate the isolation that can foster amotivation and dependence on external tools. In this context, through digital learning strategies and the promotion of self-regulation, educators would be able to guide students to perceive AI as a supportive aid rather than as a replacement for their own abilities (Darvishi et al., 2024).

Similarly, authors such as Kachgal et al. (2001) propose a series of effective strategies to reduce procrastination, including fostering self-awareness of how students manage their procrastination, encouraging reflection on the benefits they have gained from task avoidance, conducting formal assessments that allow students to understand their levels of procrastination (e.g., using the PASS scale), promoting self-regulation strategies that have a significant impact on time management (e.g., preparing calendars that allow students to track their progress), or teaching stress management strategies. These recommendations directly address the finding that procrastination is a key mediator in the relationship between amotivation and dependence on ChatGPT, suggesting that tackling procrastination might be essential for reducing this form of dependence. For e-learning, these strategies can be implemented through digital tools like time management apps, built-in quizzes for self-assessment, and integrated forums for peer-to-peer discussions on managing academic stress. These online resources might provide students with the structure and support needed to combat procrastination, thereby decreasing their dependence on generative AI.

Finally, this study has several limitations that should be considered when interpreting the results. First, the sample is entirely drawn from the social sciences field, with the majority of participants enrolled in the Primary Education program, while a smaller proportion are from the Early Childhood Education program or the Master's in Secondary Education Teaching. This imbalance, combined with the use of a convenience sampling method, may have partially biased the results and limits the generalizability of the findings. Future studies could conduct comparative analyses across different degree programs and universities, which would allow examining potential variations in educational AI use. Replicating these findings in students from

other disciplines, such as experimental or health sciences, would be valuable and could confirm the robustness of these results across different educational contexts. Additionally, the cross-sectional design restricts causal inferences, highlighting the need for longitudinal studies to strengthen the conclusions. Designs combining longitudinal and mixed-methods approaches could further explore the evolution of educational AI use over time. Data were also collected through self-report measures, which may introduce biases such as common method variance and social desirability, potentially affecting the observed relationships. Finally, while the current study tested a single theoretical mediation model, future research could provide more precise information about the conditions under which the proposed model operates most effectively by incorporating potential moderating variables. For instance, a lack of confidence in one's abilities may cause students with low academic self-efficacy to perceive AI as a resource that provides immediate answers, thereby reducing the need to confront challenges independently. This behavior, especially when students face academic pressure or stress, might reinforce their dependence on technology (Rodríguez et al., 2024). Consequently, variables like academic self-efficacy and workload could serve as control or moderating factors in future models, helping to explain the nuanced conditions under which students are more likely to develop dependence on AI. Despite these limitations, this work provides a foundation for future research exploring the impact of emotional variables on dependence on generative AI, exemplified by ChatGPT.

CONCLUSION

This study demonstrates that high intrinsic motivation and low amotivation reduce students' procrastination, which in turn decreases dependence on ChatGPT. These findings suggest that fostering students' basic psychological needs and implementing strategies to enhance motivation and self-regulation may help mitigate dependence on generative AI in educational contexts. Future research should replicate these results across different disciplines, employing longitudinal designs, replacing self-report measures, and exploring additional moderating or mediating factors influencing students' dependence on AI tools.

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Date of reception: 1 June 2025
Date of acceptance: 9 September 2025
Date of approval for layout: 2 October 2025
Date of publication in OnlineFirst: 17 October 2025
Date of publication: 1 January 2026