

Does intrinsic motivation mediate perceived artificial intelligence (AI) learning and computational thinking of students during the COVID-19 pandemic?

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ABSTRACT

The concept of Artificial Intelligence (AI), born as the possibility of simulating the human brain's learning capabilities, quickly evolves into one of the educational technology concepts that provide tools for students to better themselves in a plethora of areas. Unlike the previous educational technology iterations, which are limited to instrumental use for providing platforms to build learning applications, AI has proposed a unique education laboratory by enabling students to explore an instrument that functions as a dynamic system of computational concepts. However, the extent of the implications of AI adaptation in modern education is yet to be explored. Motivated to fill the literature gap and to consider the emerging significance of AI in education, this paper aims to analyze the possible intertwined relationship between students' intrinsic motivation for learning Artificial Intelligence during the COVID-19 pandemic; the relationship between students' computational thinking and understanding of AI concepts; and the underlying dynamic relation, if existing, between AI and computational thinking building efforts. To investigate the mentioned relationships, the present empirical study employs mediation analysis based upon collected 137 survey data from Universidad Politécnica de Madrid students in the Institute for Educational Science and the School of Naval Architecture and Marine Engineering during the first quarter of 2022. Findings show that intrinsic motivation mediates the relationship between perceived Artificial Intelligence learning and computational thinking. Also, the research indicates that intrinsic motivation has a significant relationship with computational thinking and perceived Artificial Intelligence learning.

1. Introduction

The concept of AI was born as the possibility of simulating the learning capabilities of the human brain. This means that when we think of AI, we refer to what makes it possible for us to interact and learn, and therefore there is a clear relationship with education (Ocaña-Fernández et al., 2019). The possibilities that AI offers us today are many. UNESCO suggests AI could tackle some of the biggest challenges facing education today, develop innovative teaching and learning practices, and accelerate progress toward achieving SDG 4 (McGuire, 2022). For some years now, it has been tried in the different activities carried out by teachers in

their classrooms, and students and teachers alike have benefited greatly. For instance, the use of AI-based gamification techniques, as well as chatbots, has allowed teachers to optimize some of their teaching tasks and enable students to pace up their learning (Ar & Abbas, 2021). Similarly, using educational AI-based systems has offered educators the capability of teaching in a more dynamic manner in such a way that adapting the curriculum and offering personalized content to students according to their needs becomes possible (Chen, Chen, & Lin, 2020). However, despite the great possibilities that AI presents in education, some studies show that it works superficially since there is a lack of studies that use the most advanced AI technologies and deeply engage

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with educational theories (Chen, Xie, et al., 2020).

Along the line, the COVID-19 pandemic has caused significant educational disruptions, among which the necessity to migrate to a virtual learning ecosystem became the chief concern (Abbas et al., 2022). Teachers have been forced to become a swift technological leap for which many were not trained or ready. These changes cause alterations in the teacher-student relationship. Once face-to-face and classroom-based interactions between students and teachers are moved to a new learning environment, namely online-teaching mediums. This has caused a wide variety of needs to be addressed the educational continuity of students (Martín-Núñez et al., 2022).

Students perceive transition between learning ecosystems during COVID-19 in a positive manner, and they generally refer the transaction efforts as useful given the global crisis conditions (Allo, 2020). Even though the student's perception in general has been positive, some studies show that students still believe there is a room for teachers to develop their online teaching skills to achieve better results in student engagement (Jiménez-Bucarey et al., 2021). AI in this regard during the COVID-19 has proven to be a significant support for the teacher. For instance, AI techniques have been employed to predict student performance during the pandemic and they are utilized to increase the engagement of the students (Ar & Abbas, 2021; Tarik et al., 2021).

However, the use of AI in educational environments, such as at the university level, is just in its infancy period. There is still a long way to go in the field of education. Optimization of lectures, building AI-based curriculum, institutionalization and international recognition of these programs, and maintenance of educational data and results are needed to be addressed. Some of the mentioned fields are still practically unexplored, such as the recognition of images, the automatic intervention in the validation of exams, or the optimal way to teach a subjects based on student performance. However, the transformation of the education system, even though slow, has already started (Martín-Núñez & Diaz Lantada, 2020).

Increasing significance and potential usage of AI makes it a priority field of study in higher education. Recent studies have pointed that there is an increasing interest in using AI for various education disciplines and purposes of the academic community with topics including intelligent tutoring systems for special education; natural language processing for language education; educational robots for AI education; educational data mining for performance prediction; discourse analysis in computer-supported collaborative learning; neural networks for teaching evaluation; affective computing for learner emotion detection; and recommender systems for personalized learning (Chen et al., 2022). However, most of these topics are focused on the application of AI in any aspect of education, not on the learning of AI from students. Some studies stand out, such as the one by Obando (2018), who analyzed in a pre-pandemic era the relationship between the brain and its learning, the use of Information and Communications Technology (ICT) in the classroom, as well as the socio-educational impact that emerges because of AI. Their results show the need for educators to develop new skills and abilities that impact students' learning and are consistent with their needs, interests, and talents (Obando, 2018). And on the part of students, learning AI will help them better face the emerging social, technological, and environmental challenges where factors such as self-efficacy in learning AI, AI readiness, or AI literacy, have shown a direct or indirect relationship with the intention of learning AI (Chai et al., 2021). Some studies assure a fruitful relationship between AI learning, computational thinking, and mathematics education (Gadanidis, 2017). Also in Science, Technology, Engineering, Arts, and Mathematics (STEAM) education, AI analytics are useful as educational scaffolds to develop students' AI thinking skills (How & Hung, 2019).

Strategies for the development of computational thinking, in general, are often closely related to increased motivation (Brennan & Resnick, 2012), and this, in turn, to improved academic performance. Computational thinking is an activity that involves problem-solving, system design, and understanding of human behavior based on the concepts of

computational sciences (Wing, 2006), which is closely related to the definition of AI (Ocaña-Fernández et al., 2019). Evaluation of the performance and experience of students learning with existing AI systems is one of the challenges of research on AI in education (Hwang et al., 2020). The present study analyzes the effect caused by the pandemic by moving AI students to a virtual learning ecosystem, in terms of their motivation, computation thinking, and Perceived AI learning. The concept of perceived AI learning corresponds to the general term of Perceived Learning and focuses on AI. With this paper, we intend to contribute to the literature on AI learning for university students by identifying AI trends in virtual learning ecosystems. This paper is organized as follows: Section 2, briefly describes Perceived AI learning, Intrinsic Motivation and computational thinking reported in the literature and the hypotheses development. Section 3, explains the material and methods used. Section 4, reports the results obtained and the discussions and conclusions are presented in Sections 5 and 6.

2. Relevant literature and hypotheses development

2.1. Perceived AI learning and computational thinking

The term computational thinking was coined by Seymour Papert in his book *Mindstorms* (Papert, 1980), although described in depth by Jeannette Wing in the article *computational Thinking* (Wing, 2006), and is understood as the ability to solve problems and communicate ideas taking advantage of the power offered by computers. Some studies analyze the potential of the relationship between computational thinking (by humans) and machine learning (by computers) and how they can enhance each other (Wong et al., 2020). Learning is a centralized aspect of both AI and computational thinking. The first is based on studying and understanding how machines learn and how they can perform human actions, and the second is concerned with how humans learn and how thought can be interpreted by a machine. With the growing relevance of both concepts, these two efforts have become more closely connected (Dohn et al., 2022, pp. 1–12). AI is a field of study that has become essential for most university studies. Students are immersed in a digital society in which AI is present in everyday activities, games, or functions integrated into mobile applications on their smartphones.

Even though they have been surrounded by AI and born into the more contemporary technologies, they may not have competencies to fully utilize and benefit out of artificial intelligence development. Their self-evaluations might be skewed and may not reflect their current skillset. This creates a false sense of perceived learning in terms of AI. Their perception on how fluent, competent, and able they are might not be realistic and skewed positively or negatively. If the perception of the students lenient towards higher proficiency than their current state, this might lead to lower level of motivation to further explore AI related concepts. On the contrary, if the students realize there is a major skill gap and they are not as efficient and proficient at AI system usages as they perceived, they are more likely than not to explore and study AI concepts (Rothman, 2020). Therefore, AI related in and out of class exercises and adapted problems should be broken down into small tasks of different levels to be tackled by a diverse group of students to establish a realistic perception of their abilities. This would enable them to create a more realistic perception and motivate them to further study the relevant concepts. In addition, it would help them link various structures that are directly or indirectly link to the AI applications in diverse environments.

One of the most prominent applications would be problem-solving with support of AI. It fully aligns with computational thinking skills using tools such as logical reasoning, critical and analytical thinking, and decision-making to solve them (Silapachote & Srisuphab, 2016). The learning of AI could be conditioned by the development of the student's computational thinking through exemplifying similarities and relations among concepts. Some studies show how students improve

their perception of AI after training on it by using Computation thinking tools with which to better understand its potential (Van Brummelen et al., 2021), but it could also be due to the fact that Computation thinking is also developed during the study of this AI dynamics. Thus, the following hypothesis is posited:

H1. Perceived AI learning has a significant relationship with computation thinking.

2.2. Perceived AI learning and intrinsic motivation

Intrinsic motivation originates within the individual and is driven by the needs for exploration, experimentation, curiosity, and manipulation, which are considered motivating behaviors by themselves. Intrinsic motivation has been studied over the years, and its relationship with learning shows that students with high intrinsic motivation often outperform students with low intrinsic motivation. Intrinsically motivated students are more persistent and likely to achieve set goals (Curry et al., 1990), with a much lower risk of dropping out of education (Hardre & Reeve, 2003). In addition, intrinsically motivated students are more curious and engage in deeper level learning regardless of their educational level or age (Turner et al., 1998). In relation to acceptance of technology and education, intrinsic motivation has shown that students with high intrinsic motivation do not do more, but tend to do different things (Firat et al., 2018). The greater the curiosity that students with high intrinsic motivation have, the more exploratory study behavior will develop and, therefore, would move them to discover options that may be unnoticed by other students. (Martens et al., 2004). In relation to AI, associated studies on students' perceptions of AI learning are largely limited to computer science and STEAM departments in higher education institutes (Zawacki-Richter et al., 2019). However, there is concern about awakening interest in AI from the earliest ages, and for the motivational learning models such as Keller's ARCS (1987), which have the potential to serve as a pedagogical framework to provide satisfactory learning experiences, maintaining students' motivation to learn AI is integral. Furthermore, this sustained motivation may lead some students to develop long-term career aspirations in the field of AI (Lin et al., 2021). In view of the above-stated arguments, the following hypothesis is proposed:

H2. Perceived AI learning has a significant relationship with intrinsic motivation.

2.3. Intrinsic motivation and computational thinking

Student motivation generally increases when students are actively involved and given full responsibility in the learning process (Keller, 1987). Some studies show that when STEAM students face a technological problem, a motivating factor is to offer them a learning process that involves designing a solution in which students can work in groups, share responsibilities and contribute experiences to solve a problem (Nikou & Economides, 2014). The use of technology in the development of Computation thinking is entirely appropriate to help students and motivate them to understand the elements of Computation thinking. The use of simulators and other technologies in the teaching and learning environment encourages students to be able to think critically, solve problems, be more skilled in the process of finding and organizing information, and be highly motivated (Sousa et al., 2021). However, not only can learning technology be motivating, but the use of technological means for learning in other fields can help improve student motivation (Liu et al., 2011). Similarly, the strategy of introducing Computation thinking in the teaching process as a learning strategy increases motivation, strengthens students' problem-solving skills, and improves learning performance (Parsazadeh et al., 2021). Based on the aforementioned arguments, the following hypothesis is proposed:

H3. Intrinsic motivation has a significant relationship with

computational thinking.

2.4. Intrinsic motivation mediates perceived AI learning and computational thinking

The previous section of paper postulates the possible relation between perceived AI Learning and intrinsic motivation (Hypothesis 3). However, if this relation exists, it is not clear what would be the role it plays in terms of learning is not clear. Even though the previous literature suggests that those students with high intrinsic motivation are more curious and explore relative similarities and structural constructs to apply one field to another (Huang & Qi, 2022; Cooper, 2001), there are still many steps that a student's needs to take in order to explore intellectual constructs and interchangeably use what it learns at one field to the other.

Similarly, a relationship can also be found between the development of computational thinking and perceived AI learning (Hypothesis 1). Students with a high development of computational thinking may have an affinity for learning AI because these fields complement each other in terms of functionality and instrumental usage (app building, platform structuring, task oriented autonomous robot development, etc.). This is due to the nature of these two constructs. While AI is focused on transferring and automating problem solving abilities and related task that of a human conduct to a machine and the other on postulates the problem-solving concepts to be supported by the computing and computer science through various mediums. Regardless, in order for a student to realize the similarities and successfully utilize the similarities between these two constructs, the student must overcome a steep learning curve. In addition, becoming proficient at these two concepts demand significant amount of time investment and mental resilience. While computational skills require technical background to understand it, AI proficiency require application and engineering of the gained skillset in the computational thinking. Thus, we speculate on a relationship between Perceived AI learning and Computation thinking mediated by intrinsic motivation. Accordingly, the following hypotheses can be postulated.

H4. Intrinsic motivation mediates between perceived AI learning and computational thinking.

3. Materials and methods

3.1. Participants and procedure

For this empirical research, we collected data from Bachelor's and Master's program students currently enrolled in two different schools of the Universidad Politécnica de Madrid in Spain. Participants in this empirical study took AI courses during the time of the COVID-19 pandemic and participated in some theoretical and practical course activities related to AI and computation thinking in education. In particular, two of the researchers collected data through convenient sampling techniques, and participants registered their responses through an online Google Form survey. Due to the COVID-19 pandemic, the survey was distributed in a hybrid classroom setting. The online survey link was distributed face to face among students (with QR Code) and through the university learning management platform—Moodle—during the first quarter of 2022.

The Google Form-based online survey contains two sections. The first section mainly covers "Confidentiality issues," including the privacy and security of the individual personal information collected. The description of the research is also presented in this first section. The second section contains questions related to (1) Perceived AI learning, (2) Intrinsic motivation, and (3) Computational thinking with a five-point Likert-type scale, where 1 represents "Strongly disagree" and 5 represents "Strongly agree". The research survey received 137 responses, of which 131 (95.62%) were complete responses and the remaining 6

(4.38%) responses were incomplete and thus excluded from the final data analysis.

3.2. Instruments

For this study, we designed an online survey with five-point Likert-type scale questions related to perceived AI learning, Intrinsic motivation, and computation thinking along with some basic questions related to demographic variables such as gender and scholarship. All survey questions and their scales were adapted from previously published work. The online Google Form survey was bilingual (Spanish and English language) because most of the surveyed programs are offered in English and Spanish. All items were based on a five-point Likert scale where 1 represents “Strongly disagree” and 5 represents “Strongly agree”.

We adapted five items from the work of Halic et al. (2010) to measure “Perceived AI learning” ($\alpha = 0.801$). We adapted four items from the work of Jaramillo et al. (2007) to measuring “Intrinsic motivation” ($\alpha = 0.707$). Lastly, we adapted ten items from the work of Korkmaz and Xuemei (2019) to measure “Computational thinking” ($\alpha = 0.671$). According to Cronbach (1951), the acceptable value of the Cronbach alpha (α) coefficient must be greater than 0.6 which confirms the reliability of the scale. Therefore, the data collected for our research study was reliable for further analysis.

3.3. Data analysis

For data collection, two professors of Universidad Politécnica de Madrid (UPM) distributed the survey to 137 students. The participants were currently enrolled in two different schools of the UPM that is, the Institute for Educational Science, and the School of Naval Architecture and Marine Engineering during the first quarter of 2022.

After completion of the data collection process, we downloaded the Excel based dataset file from Google Form and then converted it to .sav file form for further analysis in IBM SPSS and Jamovi software. In the next step of data analysis, we used statistics programs in MacOS, that is: IBM SPSS v26.0 and Jamovi v1.6. First, we used IBM SPSS software to statistically analyze the descriptive, correlation, and common method bias of the collected data. Second, for the analysis of the mediation model, we applied two different statistical tests (i.e., mediation by using “medmod” plugin of the Jamovi software). We used mediation to test mediating effects including total, indirect and direct effects and also path estimates.

4. Analyzed results

4.1. Common method bias

In academic research, self-reported data is commonly collected through a single source because there is a high chance of data bias. To avoid data bias, it is important to validate data bias prior to formal analysis. To test common method bias, we applied Harmon’s one-factor test (Harmon’s single-factor test) by using IBM SPSS. For the application of Harman’s one-factor (Harman’s single-factor) test, we combine 18 items of all three variables (Perceived AI learning, Intrinsic motivation, and Computational thinking) into one variable, and then checked extracted value through Harman’s one-factor test which confirms the percentage of the sum of the variable is 28.7%, which is in accordance with the set criteria of Fuller et al. (2016) that Harman’s one-factor test value is less than 50% sum of the variable confirms that there is no data bias (Fuller et al., 2016).

4.2. Descriptive statistics

The analyzed descriptive results of this empirical research showed—based on the 131 completed received responses—the demographic

information of the participants. With respect to gender, we found that 79 (60.3%) male students participated in the online survey and the remaining 52 (39.7%) were female students. Most of the participants—100 (76.3%)—were between the ages of 24 and 29 years of age, 16 (12.2%) between 18 and 23 years, and the remaining 15 (11.5%) were between the ages of 30 and above. A total of 112 (85.5%) respondents were studying in a Master’s program and the remaining 19 (14.5%) were Bachelor’s students. Of 89 (67.9%) enrolled students were part-time students and 42 (32.1%) were full-time students. Lastly, all 131 (100%) participants in the online survey studied in a hybrid educational setting due to the COVID-19 pandemic.

4.3. Correlation analysis

To explore the correlation between set variables i.e., Perceived AI learning, intrinsic motivation, and Computation thinking, we applied the Pearson correlation coefficient by using IBM SPSS software. The analyzed results (see Table 1) confirm that there exists a significant positive correlation between “Perceived AI learning” and “Computation thinking” ($r = 0.466$, $p < .01$), and also a positive correlation between “Intrinsic motivation” and Computation thinking ($r = 0.524$, $p < .01$).

4.4. Hypotheses testing

Before testing the mediating effects, we tested the total effects between the predictor or independent variable (i.e., “Perceived AI learning”), and the dependent variable (i.e., “Computation thinking”) (see Fig. 1). In Table 2 and Fig. 2, the analyzed results demonstrate that “total effects” and also “path estimate” affirm that the estimate values and level of significance (Estimate = 0.2738, $p < .001$, CI: 01848, 0363) support our first hypothesis i.e., “**H1**: Perceived AI learning has a significant relationship with computational thinking”.

After introducing the mediating variable i.e., “Intrinsic motivation” between the predictor/independent and the dependent variable, we found two more new relationships with “indirect” and “direct” effects. Indirect effects are based on two relationships (1) “Perceived AI learning → Intrinsic motivation”, and “Intrinsic motivation → Computation thinking”, where total effects-based relationship change to direct effects i.e., “Perceived AI learning → Computation thinking”.

In Table 3 and Fig. 3, the values of the path estimate i.e., “Perceived AI learning → Intrinsic motivation” (Estimate = 0.7928, $p < .001$, CI: 0.6937, 0.892) support our second and third hypotheses “**H2**: Perceived AI learning has a significant relationship with intrinsic motivation”, and “Intrinsic motivation → Computation thinking” (Estimate = 0.2544, $p < .001$, CI: 0.1070, 0.402) “**H3**: Intrinsic motivation has a significant relationship with computational thinking”. In Table 2, the value of indirect effects (Estimate = .2017, $p < .001$, CI: 0.0821, 0.321) and direct effects (Estimate = 0.0721, $p < .329$, CI: -0.0726, 0.217) confirms that full-mediation exists. Therefore, the analyzed results support our fourth hypothesis, “**H4**: Intrinsic motivation mediates between perceived AI learning and computational thinking”.

Table 1

Correlation of all variables (predictor/independent, mediator, dependent).

	Perceived AI learning	Intrinsic motivation	Computational thinking
Perceived AI learning	1 (.801)		
Intrinsic motivation	0.808**	1 (.707)	
Computational thinking	0.466**	0.524**	1 (.671)

Note. Level of significance: ** $p < .01$ (2-tailed).

Note. The Cronbach Alpha value (α) value is represented in bold and in parenthesis.

Table 2

Mediation estimates (Total, indirect, and direct effects).

Effect	Estimate	SE	95% CI		z	p
			Lower	Upper		
Total effect: Intrinsic motivation → Computation thinking	0.2738	0.0454	0.1848	0.363	6.032	<.001
Indirect effect: Perceived AI learning → Intrinsic motivation → Computation thinking	0.2017	0.0610	0.0821	0.321	3.683	<.001
Direct effect: Intrinsic motivation → Computation thinking	0.0721	0.0738	-0.0726	0.217	0.976	0.329

Note. CI = Confidence Interval.

Note. Level of significance: *p < .05, **p < .01, ***p < .001.

5. Discussion

Aiming to provide an in-depth understanding and emphasize significant findings, the discussion part of the paper is divided into two subsections. While the first subsection discusses the results and findings from a theoretical standpoint, the following section offers a more in-depth discussion that reveals the practical implications.

5.1. Theoretical contribution

There is limited research on how AI-based education systems can support learning practices, especially during times of crisis. This is especially the case for the relationship among AI, intrinsic motivation, and computational thinking. The evidence in this paper provides insight into the interaction among intrinsic learning motivation among students, computation thinking, and perceived AI learning outcomes. For instance, the relationship between learning AI and computational thinking is hypothesized in the H1. The path estimate affirms that the measured interaction is significant (Estimate = .2738, p < .001), and it supports our first hypothesis. It indicates that there is a significant and positive relationship between learning AI and computational thinking.

In other words, there is a positive movement between knowledge accumulation on AI and students' computational thinking abilities. This can be linked to the increase in understanding of how AI works can enable students to better conceptualize computational thinking notions since some of the constructs (conceptualizing a problem, breaking down into steps, establishing potential methods for a solution, etc.) are commonly occupied by both constructs.

The findings of the study also highlight that H2 is significant, "Perceived AI learning has a significant relationship with intrinsic motivation" (Estimate = 0.7928, p < .001). In previous studies, even though the direction of the relationship, as well as the significance, was captured, the authors call for more studies to explore this relationship (Agudo-Peregrina et al., 2014); Wang et al. (2021)). For instance, Fidan and Gencel (2022) introduce AI based chatbots to their students learning environment to measure the role of AI in students' intrinsic learning motivation. When students interact with the chatbots, their intrinsic motivation is measured significantly higher compared to students who did not have the opportunity to interact with AI. They report that there is a strong causation and correlation between these two constructs. The present manuscript provides further support to this line of thought and reveals that AI not only act as an information delivery platform but also as a learning opportunity for students if they study how AI works.

Furthermore, the authors are able to document the relationship between intrinsic motivation and computational thinking. It is hypothesized as, "H3: Intrinsic motivation has a significant relationship with

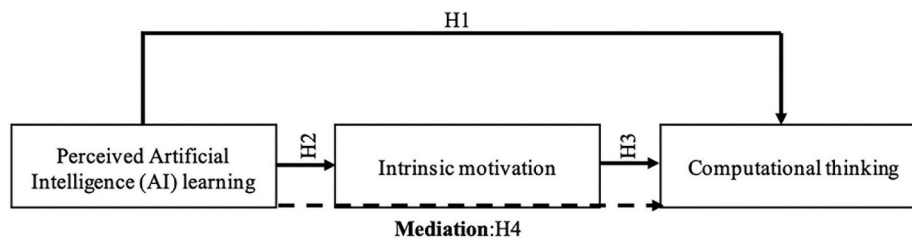
Table 3

Path estimates.

	Estimate	SE	95% CI		z	p
			Lower	Upper		
Perceived AI learning → Intrinsic motivation	0.7928	0.0506	0.6937	0.892	15.683	<.001
Intrinsic motivation → Computation thinking	0.2544	0.0752	0.1070	0.402	3.382	<.001
Perceived AI learning → Computation thinking	0.0721	0.0738	-0.0726	0.217	0.976	0.329

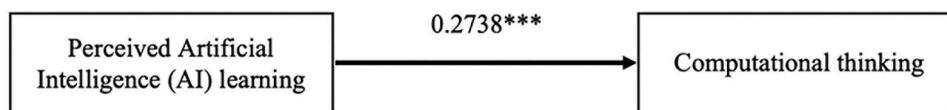
Note. CI = Confidence Interval.

Note. Level of significance: *p < .05, **p < .01, ***p < .001.



Note. 'H' represents hypotheses

Fig. 1. Proposed research model.



Note. Level of significance: *p<.05, **p<.01, ***p<.001

Fig. 2. Total effects.

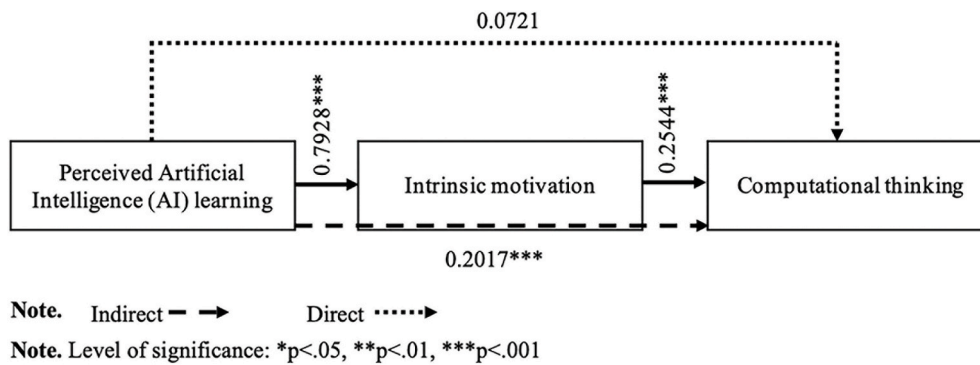


Fig. 3. Indirect and direct effects.

computational thinking” (Estimate = 0.2544, $p < .001$). Authors believe, in alignment with the relevant strand of the literature (Haslofça & Korkmaz, 2016; Gajewski, 2019), that this is due to when students become more able to use technology and tools to solve problems, the more they are willing to explore concepts and tap into their intrinsic motivation. As a result, they stay interested in learning for a prolonged time period and further explore computational thinking-related concepts.

Furthermore, this study provides a novel idea through hypothesizing mediation effect of intrinsic motivation. There are previously conducted correlation studies between intrinsic motivation and AI learning. On separate occasions, there are also an abundant number of studies that investigate computational thinking and AI. However, to the best of the authors’ knowledge, this study is one of the pioneering studies, if not the first one, that explore the following hypothesis “H4: Intrinsic motivation mediates between perceived AI learning and computational thinking.” The present study addresses this theoretical gap and provides a mediation model that reveals the nature of the mediation impact. The findings of the study indicate that there is a significant partial mediation (Estimate = 0.2738, $p < .001$) among intrinsic motivation, AI learning, and computational thinking. It means that the intrinsic motivation for AI learning can be further expanded into computational learning. This can be attributed, based on the previous path estimate results, to the student’s increasing motivation in learning AI can increase their interest on computational thinking since the more proficient they become in AI, they also start learning more about computational thinking and become more proficient due to transferable skills and concepts between the two constructs. As a result, they become more committed to learning and further explore computational thinking. However, it is necessary to show students what these transferable skills are and how to transfer one skill from one concept to another to sustain intrinsic motivation.

5.2. Implications

In conformity with the relevant literature (Montebello, 2017; Wang, 2022), this study shows that AI has become one of the focal points of education. It illustrates AI role in establishing a higher education eco-system where learning one subject can further motivate students to learn another. It is also important to mention that this study shows a significant relationship between perceived AI learning and intrinsic motivation. In the literature, this relationship is addressed in other way around and some studies proposed mixed results. For instance, Weiwei (2022) cites in his study that the “*experimental nature of AI implications*” could lower the learning motivation of students, who would become more prone to “distractions”. In a similar fashion, Grunhut et al. (2021) also touches upon AI predictive failures during the learning period and its disadvantageous nature in terms of limited interactive capabilities as well as misleading learning conceptualization. As a result, these studies highlight the possibility that AI conceptualization may lead to inferior learning results due to decreasing learning motivation and poor

applicability to other concepts. Nevertheless, the current study underscores that these shortcomings can be resolved, and AI could lead to a thriving learning environment by accommodating students’ intrinsic motivations by helping them bridge AI and computation thinking. Therefore, curriculum builders, lecturers, and practitioners should consider coupling AI learning and computational thinking-related subjects together to take advantage of students’ intrinsic motivation to learn.

6. Conclusion, limitations and suggestion for future work

The number of higher education institutions that recognize the usefulness of AI is increasing. The illustrated results further back that students’ intrinsic learning motivation can be supported by providing them with an AI reinforced learning subject by computation thinking. Albeit there are some concerns reflected in the previous scholarly work about intrinsic motivation and AI relationship, this study reveals that students with high intrinsic motivation can utilize AI imbued learning environments to further their computational skills. In addition, it provides evidence from the perspective of how learning AI and studying computation thinking in the same learning medium could lead to a better understanding of both concepts.

Furthermore, the study shows that all the proposed hypotheses are valid. In other words, intrinsic motivation mediates between perceived AI learning and Computation thinking, intrinsic motivation has a significant relationship with computation thinking, perceived AI learning has a significant relationship with intrinsic motivation and perceived AI learning has a significant relationship with computation thinking. Therefore, teaching AI and computation thinking together provides future positive opportunities for higher education institutions and students.

Another important conclusion that can be derived from this study is illustrating how relevant concepts can support students learning when provided together. Even though they may not be direct complementary subjects, their relationship in terms of how to conduct a process can help students conceptualize their ideas better. They can use certain aspects of, for instance, Computation thinking to understand AI or another way around. In this way, their ability to learn either concept can be boosted. Higher education institutions and curriculum designers may consider this complementary nature of topics to create more impactful learning designs and experiences.

AI may be fruitful not only for today’s education landscape but for future higher education practices as well. As all studies have, this study also suffers from some limitations. For instance, the data were collected from a single country setting. For future studies, this can be remedied by collaborating with multiple data resources. Another productive avenue for future studies is investigating how to build AI based programs and syllabuses while targeting computation thinking for computer science students. It will help students advance their understanding at a better pace. In addition, the data for this study were collected during the

COVID-19 pandemic. It would be an interesting study to collect data from an after COVID-19 scenario and conduct a comparison study.

Availability of data and material

The dataset is available from the first author on reasonable request.

Ethics

All procedures performed in this study were reconcilable with the ethical standards of the institution and the 1964 Helsinki declaration and its later amendments or comparable ethical standards. In line with this declaration, which was amended in 2008, study participants were informed about the study purpose and consented accordingly.

CRedit authorship contribution statement

J.L. Martín-Núñez: Conceptualization, literature review, data collection, data curation, validation, writing, project administration.

A.Y. Ar: Conceptualization, literature review, writing – review, revisions and editing.

R.P. Fernández: Data collection, writing – review and comments.

A. Abbas: Conceptualization, literature review, research design, survey design, data curation, formal data analysis, writing – final manuscript, review, revisions and editing, supervision.

D. Radovanović: Senior reviewer, writing – review, comments and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Survey questions

Perceived AI-learning (Halic et al., 2010)

1. The AI-learning helps me to share my knowledge and experience with my peers.
2. I believe that incorporating e-learning with teaching can enhance my AI-learning experience in general.
3. Other students' comments on my AI-learning are important.
4. The AI-learning discussions help me understand other point of view.
5. Overall e-learning has helped me learn AI during COVID-19 pandemic.

Intrinsic motivation (Jaramilio et al., 2007)

1. I do not need a reason to learn-AI; I am learning it because I want to.
2. Becoming successful in AI is something I want to do for myself.
3. I wish I did not have to graduate someday so I could always continue learning AI for the pleasure of it.
4. I am learning AI because I cherish the feeling of performing a useful skill.

Computational thinking (Keller, 1987)

1. I believe that I can solve the AI problem possible to occur when I encounter with a new situation.
2. I believe that I learn better the instructions made with the help of mathematical symbols and AI concepts.
3. I can digitalize a mathematical problem expressed verbally.
4. I am good at preparing regular plans regarding the solution of complex AI problems.
5. It is fun to try to solve complex AI problems.
6. I use a systematic method while comparing the options at hand and while reaching a decision.
7. I have problems with the issue of where and how I should use the variables such as X and Y in the solution of a problem.
8. I cannot apply the solutions I plan respectively and gradually.
9. I cannot produce so many options while thinking of the possible solutions regarding an AI problem.
10. I cannot develop my own computation thinking ideas in the environment of cooperative AI learning.

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