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Extended CAITIZEN: A PLS-SEM Study of Sustainable AI-Assisted Citizenship Innovation

CAITIZEN extendido: estudio PLS-SEM de la innovación en ciudadanía sostenible asistida por IA

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ABSTRACT

Context. Artificial intelligence is transforming higher education by reshaping learning, creativity, decision-making, and civic participation. This study examines **CAITIZEN—Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked Formation**—as an extended model for validating **AI**-assisted sustainable citizenship as an innovation for sustainable development, aligned with **SDG4** and **SDG9**.

Problem. Although the original **CAITIZEN** model was qualitatively grounded as an ethical–cognitive–social framework, its explanatory and predictive capacity had not been empirically tested. AI education still prioritizes efficiency, automation, and technical adoption, with limited evidence on how critical **AI** literacy, ethics, data justice, human–**AI** collaboration, and metacognitive prompting contribute to sustainable AI-assisted citizenship.

Purpose. This study validates the extended **CAITIZEN** model through **PLS-SEM** by examining how **Critical Artificial Intelligence Literacy (CAIL)** enables **Ethical Awareness and Responsibility (EAR)**, **Awareness of Fairness and Data Justice (AFDJ)**, **Human–AI Creative Collaboration (HAIC)**, and **Metacognitive Transparency in Prompting Practices (MTPP)**, and how these capacities predict **CAITIZEN**.

Methodology. This research builds on a previous qualitative phase conducted in Guadalajara, Jalisco, Mexico, during July–December 2025, and complements it with an explanatory-predictive quantitative design using **SmartPLS 4.1.1.8** to assess reflective constructs and predictive relevance through **PLSpredict.**

Theoretical and Practical Findings. Results show that **CAIL** significantly predicts **EAR**, **AFDJ**, **HAIC**, and **MTPP**, confirming its role as foundational antecedent. **AFDJ**, **HAIC**, and **MTPP** significantly predict **CAITIZEN**, whereas **EAR** does not show a direct effect. Predictive relevance is confirmed because all **Q^2_predict** values for **CAITIZEN** indicators are positive and all **PLS-LM RMSE** differences favor **PLS-SEM.**

Originality. The study transforms the qualitative **CAITIZEN** model into an empirically validated explanatory-predictive structure.

Conclusions and Limitations. The extended **CAITIZEN** model provides a measurable framework for responsible AI education and sustainable innovation. Limitations include non-probabilistic sampling, cross-sectional design, and student sample.

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RESUMEN

Contexto. La inteligencia artificial transforma la educación superior al reconfigurar el aprendizaje, la creatividad, la toma de decisiones y la participación cívica. Este estudio examina **CAITIZEN —Ciudadanía Asistida por Inteligencia Artificial para una Formación Sostenible, Ética y en Red—** como modelo extendido para validar la ciudadanía sostenible asistida por **IA** como innovación para el desarrollo sostenible, alineada con el **ODS4** y el **ODS9**.

Problema. Aunque el modelo **CAITIZEN** original fue fundamentado cualitativamente como marco ético–cognitivo–social, su capacidad explicativa y predictiva no había sido probada empíricamente. La educación en **IA** aún prioriza eficiencia, automatización y adopción técnica, con evidencia limitada sobre cómo alfabetización crítica en **IA**, ética, justicia de datos, colaboración humano–**IA** y metacognición en prompts contribuyen a dicha ciudadanía.

Propósito. Este estudio valida el modelo **CAITIZEN** extendido mediante **PLS-SEM**, examinando cómo **CAIL** habilita **EAR**, **AFDJ**, **HAIC** y **MTPP**, y cómo estas capacidades predicen **CAITIZEN**.

Metodología. Este estudio parte de una investigación cualitativa previa realizada en Guadalajara, Jalisco, México, durante julio–diciembre de 2025, y lo complementa con un diseño cuantitativo explicativo-predictivo mediante **SmartPLS 4.1.1.8** para evaluar constructos reflectivos y relevancia predictiva mediante **PLSpredict.**

Hallazgos teóricos y prácticos. Los resultados muestran que **CAIL** predice significativamente **EAR**, **AFDJ**, **HAIC** y **MTPP**, confirmando su papel como antecedente fundacional. **AFDJ**, **HAIC** y **MTPP** predicen significativamente **CAITIZEN**, mientras **EAR** no muestra efecto directo. La relevancia predictiva se confirma porque todos los valores **Q^2_predict** son positivos y las diferencias **PLS-LM RMSE** favorecen a **PLS-SEM**.

Originalidad. El estudio transforma el modelo cualitativo **CAITIZEN** en una estructura explicativa-predictiva validada empíricamente.

Conclusiones y limitaciones. El modelo **CAITIZEN** extendido ofrece un marco medible para educación responsable en **IA** e innovación sostenible. Sus limitaciones incluyen muestreo no probabilístico, diseño transversal y muestra estudiantil.

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1.INTRODUCTION

Artificial intelligence (**AI**) transforms higher education by reshaping learning, creativity, decision-making, civic participation, and institutional innovation. This article analyzes AI-assisted sustainable citizenship as a formative condition of university students who interact with intelligent systems and require critical, ethical, creative, and responsible competencies for sustainable development (Córdova-Esparza, 2025; Mejía-Trejo, 2025b).

In this study, **CAITIZEN** is retained as the name of the original model proposed by Mejía-Trejo (2025[a]), and its meaning is specified as Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked formation. This formulation preserves the focus on AI-assisted sustainable citizenship while making explicit its formative, ethical, and relational scope. The model includes five dimensions: Critical Artificial Intelligence Literacy (**CAIL**), Ethical Awareness and Responsibility (**EAR**), Awareness of Fairness and Data Justice (**AFDJ**), Human–AI Creative Collaboration (**HAIC**), and Metacognitive Transparency in Prompting Practices (**MTPP**), which frame citizenship in higher education (Mejía-Trejo, 2025[a]).

The problem is that AI education privileges efficiency, automation, and technical adoption, while limited evidence explains how these dimensions predict AI-assisted sustainable citizenship. This gap matters because universities require models connecting AI literacy, ethics, fairness, creativity, and metacognition with transformation, civic agency, learning, and responsibility (Southworth et al., 2023).

The solution is **CAITIZEN**, a structural model that analyzes how **CAIL, EAR, AFDJ, HAIC**, and **MTPP** predict AI-assisted sustainable citizenship. Its originality lies in transforming a qualitative ethical–cognitive–social framework into an empirically testable model. According to the Oslo Manual, it is posed as social and conceptual innovation for sustainable development, aligned with **SDG 4** and **SDG 9,** because it strengthens quality education and innovation-oriented transformation (OECD & Eurostat, 2005, 2018; United Nations, 2015).

The study integrates education, AI, ethics, data justice, creativity, metacognition, innovation, and sustainability. Research question: To what extent do **CAIL**, **EAR, AFDJ, HAIC,** and **MTPP** predict AI-assisted sustainable citizenship among higher education students? (Hair et al., 2022).

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2. CONTEXT

This section contextualizes the environment in which AI-assisted sustainable citizenship develops and relates it to the empirical validation of **CAITIZEN**. The discussion is organized at three levels: global, international, and national-local. These levels show how artificial intelligence in higher education is no longer only a technological issue, but also an educational, ethical, civic, and innovation-for-sustainable-development challenge.

2.1. Global level

At the global level, artificial intelligence has reshaped education, work, innovation, and civic participation. UNESCO established that teachers and learners require AI competencies grounded in human-centered values, ethical principles, and responsible pedagogical use, which connects directly with SDG 4 on quality education (Miao & Cukurova, 2024). The World Economic Forum also observes that AI literacy is becoming a core future-work competence, because institutions and individuals face accelerated changes in skills, productivity, and innovation ecosystems (World Economic Forum, 2025). Likewise, the OECD reports a persistent AI skills gap, where technological adoption grows faster than training, governance, and critical understanding (OECD, 2025). In this environment, the subject of study—AI-assisted sustainable citizenship among higher education students—emerges as a formative condition required for responsible participation in AI-mediated societies.

2.2. International level

At the international level, the state of the art shows that AI literacy, ethical awareness, fairness, data justice, human–AI collaboration, and metacognitive prompting are increasingly treated as interdependent competencies. AI literacy is understood as the capacity to understand, evaluate, and use AI systems critically, beyond operational skills (Ng et al., 2021). Ethical awareness is observed as necessary for responsible decision-making and accountability when students use AI tools (Kong & Zhu, 2025). Fairness and data justice are established as core concerns because algorithmic systems can reproduce bias, discrimination, and unequal access to opportunities (Demirchyan, 2025). Human–AI creative collaboration is analyzed as an emerging innovation process in which AI supports ideation, design, writing, and knowledge production (Rafner et al., 2025).

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Metacognitive prompting is also faced as a new learning challenge because students must formulate, monitor, and evaluate their interaction with generative AI systems (Haidar et al., 2025). Therefore, the object of study—**CAITIZEN**—is justified as an empirical model that connects these dimensions and evaluates their predictive relationship with AI-assisted sustainable citizenship.

2.3. México

In México, digital adoption has expanded, but gaps remain in critical, ethical, and responsible **AI** use. INEGI reported that internet use is widespread among the population, yet digital access does not necessarily imply algorithmic understanding, data governance awareness, or responsible use of **AI** in educational contexts (INEGI, 2023). At the institutional level, UNESCO and CANIETI promoted a model for ethical and responsible artificial intelligence in Mexican organizations, showing that the country faces the need to move from technological adoption toward trustworthy **AI** ecosystems (UNESCO & CANIETI, 2025). Within higher education, this challenge becomes more specific because university students are citizens in formation who increasingly use AI for learning, creativity, decision-making, and academic production.

The previous **CAITIZEN** qualitative study established a contextual precedent by analyzing **511** undergraduate and graduate students and identifying five dimensions: **CAIL**, **EAR, AFDJ, HAIC**, **and MTPP**. That study positioned **CAITIZEN** as a conceptual and social innovation aligned with sustainable development (Mejía-Trejo, 2025[a]). However, the explanatory and predictive capacity of the model remains quantitatively untested. Therefore, **CAITIZEN** is proposed as a necessary empirical extension to validate whether those dimensions predict AI-assisted sustainable citizenship in higher education, contributing mainly to **SDG4** and complementarily to **SDG9** through educational innovation and institutional transformation. This contextualization supports the methodological transition from qualitative interpretation to structural validation, consistent with multidisciplinary innovation for sustainable development in universities.

3. LITERATURE REVIEW

The extended **CAITIZEN** model is grounded in the need to explain AI-assisted sustainable citizenship as a multidimensional process in which critical literacy enables ethical, fairness-oriented, collaborative, and metacognitive capacities. The qualitative **CAITIZEN** study previously

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conceptualized **AI**-assisted sustainable citizenship as an ethical–cognitive–social system composed of Critical Artificial Intelligence Literacy (**CAIL**), Ethical Awareness and Responsibility (**EAR**), Awareness of Fairness and Data Justice (**AFDJ**), Human–**AI** Creative Collaboration (HAIC), and Metacognitive Transparency in Prompting Practices (**MTPP**) (Mejía-Trejo, 2025[a]). However, the qualitative model was not designed to test causal relationships among these dimensions. Therefore, the present study re-specifies the original framework into an extended structural model for quantitative validation. In this re-specification, **CAIL** is positioned as a foundational antecedent, while **EAR, AFDJ, HAIC, and MTPP** are specified as proximal capacities that directly contribute to **CAITIZEN**. **CAIL** represents the cognitive and critical foundation of the model. **AI** literacy has been defined as the capacity to understand, use, evaluate, and critically engage with artificial intelligence systems. Long and Magerko (2020) established **AI** literacy as a competence that extends beyond technical operation and includes conceptual understanding of **AI** systems. Ng et al. (2021) conceptualized **AI** literacy as a multidimensional construct involving knowledge, application, evaluation, and ethical awareness. Southworth et al. (2023) further argued that AI literacy should be embedded across higher education curricula, while Wang and Wang (2025) showed that critical **AI** literacy supports reflective evaluation of **AI**-assisted writing. Therefore, **CAIL** is not treated only as a direct predictor of **AI**-assisted citizenship, but as a foundational condition that enables students to recognize ethical implications, fairness concerns, collaborative possibilities, and metacognitive demands in **AI**-mediated environments.

The first relationship proposed in the model links **CAIL** to **EAR**. Ethical awareness in **AI** use requires more than general moral sensitivity; it requires understanding how AI systems operate, how outputs are produced, and how algorithmic decisions may affect users, institutions, and society. Responsible **AI** literature emphasizes accountability, transparency, human oversight, and moral responsibility as central principles of **AI** governance. Gunasekara et al. (2025) synthesized responsible **AI** principles and practices, while Papagiannidis et al. (2025) framed responsible **AI** governance as a mechanism for aligning AI systems with ethical and organizational responsibility. Kong and Zhu (2025) validated an **AI** ethical awareness scale for students, showing that ethical awareness can be developed through AI-based problem-solving. Thus, students with higher **CAIL** are expected to show stronger **EAR.** Hence, we have:

H1a. CAIL positively and significantly predicts EAR.

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The second relationship links **CAIL** to **AFDJ.** Awareness of fairness and data justice requires understanding that **AI** systems may reproduce bias, discrimination, unequal visibility, and unfair decision-making when data, algorithms, and institutional uses lack transparency or accountability. Decker et al. (2025) emphasized procedural fairness and public engagement in algorithmic decision-making. Demirchyan (2025) highlighted the regulatory challenges of algorithmic fairness, while González-Argote et al. (2025) identified algorithmic bias and data justice as ethical challenges in **AI** systems. In educational contexts, Pham et al. (2025) showed that fairness is a relevant concern in machine learning software. Since recognizing unfairness requires critical understanding of **AI** systems, **CAIL** is expected to strengthen **AFDJ**. Hence, we have:

H1b. CAIL positively and significantly predicts AFDJ.

The third relationship proposes that **CAIL** enables **HAIC**. Human–**AI** creative collaboration requires users to understand **AI** as a co-creative tool whose outputs must be guided, evaluated, and redirected by human agency. Georgieva and Georgiev (2025) examined the role of generative AI in design creativity, while Rafner et al. (2025) analyzed agency in human–**AI** collaboration for image generation and creative writing. Salma et al. (2025) identified paradoxes in co-creative systems, emphasizing the need to preserve human intentionality. Wang et al. (2025) showed that human–AI co-creation varies according to design experience. These studies suggest that critical AI literacy allows users to collaborate with AI more intentionally, creatively, and responsibly. Hence, we have: **H1c. CAIL positively and significantly predicts HAIC.**

The fourth relationship links **CAIL** to **MTPP**. Prompting practices are not merely technical instructions; they involve metacognitive awareness, goal clarification, evaluation of **AI** responses, and iterative refinement. Haidar et al. (2025) found that metacognitive prompts improve writing skills and metacognitive awareness in **AI**-supported learning. Tsakeni et al. (2025) mapped the role of **AI** tools in scaffolding metacognition and learning, while Waaler et al. (2025) demonstrated the importance of prompt engineering for improving compliance with intended instructional goals. Since students need critical understanding of **AI** systems to formulate, adjust, and evaluate prompts responsibly, **CAIL** is expected to strengthen **MTPP**. Therefore, we propose:

H1d. CAIL positively and significantly predicts MTPP.

The second stage of the model specifies **EAR, AFDJ, HAIC, and MTPP** as direct predictors of **CAITIZEN**. **EAR** is expected to contribute to **AI-**assisted sustainable citizenship because

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ethical responsibility guides the use of **AI** toward accountability, academic integrity, social responsibility, and the common good. Responsible **AI** governance emphasizes that ethical principles are essential for trustworthy, legitimate, and socially aligned AI adoption (Gunasekara et al., 2025; Papagiannidis et al., 2025; UNESCO & CANIETI, 2025). Hence, we have:

H2. EAR positively and significantly predicts CAITIZEN.

AFDJ is expected to predict **CAITIZEN** because sustainable citizenship in AI-mediated societies requires awareness of bias, fairness, inclusion, and data justice. Algorithmic systems increasingly shape access, opportunity, visibility, and decision-making. Therefore, recognizing and questioning unfair AI outcomes becomes a civic competence linked to equity, trust, and responsible participation in digital environments (Decker et al., 2025; Demirchyan, 2025; González-Argote et al., 2025; Pham et al., 2025). Therefore, we have:

H3. AFDJ positively and significantly predicts CAITIZEN.

HAIC is expected to predict **CAITIZEN** because **AI-**assisted citizenship is not limited to ethical caution; it also involves creative agency, collaborative problem-solving, innovation-oriented participation, and the capacity to use **AI** as a partner for knowledge production. Human–**AI** collaboration can enhance creativity when users maintain agency, intentionality, critical control, and reflective judgment over the process (Georgieva & Georgiev, 2025; Rafner et al., 2025; Salma et al., 2025; Wang et al., 2025). Therefore, we have

H4. HAIC positively and significantly predicts CAITIZEN.

MTPP is expected to predict **CAITIZEN** because responsible A**I** use requires self-regulation, transparency, and conscious interaction with generative systems. Students who reflect on how they formulate prompts, evaluate outputs, adjust instructions, and recognize the limits of AI are better positioned to use AI autonomously, ethically, and sustainably. Metacognitive prompting therefore supports reflective AI engagement and responsible digital participation (Haidar et al., 2025; Tsakeni et al., 2025; Waaler et al., 2025). Hence, we propose:

H5. MTPP positively and significantly predicts CAITIZEN.

Finally, the model assumes that **CAIL** has indirect effects on **CAITIZEN** through the proximal capacities of **EAR, AFDJ, HAIC, and MTPP**. This assumption is consistent with **AI** literacy research, which frames literacy not merely as knowledge, but as a capacity that enables ethical judgment, critical evaluation, creative collaboration, and reflective regulation. In this sense, **CAIL**

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functions as the foundational literacy layer of the model, while the other dimensions represent applied mechanisms through which **AI**-assisted sustainable citizenship is enacted.

Together, these arguments support the extended **CAITIZEN** model as a quantitative re-specification of the qualitative framework proposed by Mejía-Trejo (2025[a]). The original model identified the key dimensions of AI-assisted sustainable citizenship, whereas the present model specifies their internal structural logic by positioning **CAIL** as the foundational antecedent **of EAR, AFDJ, HAIC, and MTPP**. These proximal capacities, in turn, are expected to shape **AI-assisted sustainable citizenship**. Thus, the model advances from qualitative conceptualization to quantitative explanation, while framing **CAITIZEN** as a social and conceptual innovation in higher education, aligned mainly with **SDG 4** and complementarily with **SDG 9** (OECD & Eurostat, 2018; United Nations, 2015).

3.1. Measurement Instrument Design

The measurement instrument was designed as a quantitative continuation and structural refinement of the qualitative **CAITIZEN** framework. The questionnaire operationalized six reflective constructs: **CAIL**, **EAR**, **AFDJ**, **HAIC**, **MTPP**, and **AI-assisted sustainable citizenship (CAITIZEN)**. The items were derived from the conceptual definitions of the original qualitative model and from the reviewed literature on AI literacy, responsible AI, algorithmic fairness, human–AI collaboration, metacognitive prompting, and sustainable citizenship.

A Likert-type scale was selected to measure students' agreement with statements related to critical AI literacy, ethical responsibility, fairness and data justice, creative collaboration, metacognitive prompting, and AI-assisted sustainable citizenship. The instrument was structured to support **PLS-SEM** analysis by representing each construct through observable reflective indicators. This design enabled the evaluation of reliability, convergent validity, discriminant validity, collinearity, path coefficients, effect sizes, explanatory power, and complementary indirect effects.

In line with the extended structural model, the instrument allowed **CAIL** to be examined as a foundational antecedent of **EAR**, **AFDJ**, **HAIC**, and **MTPP**, while these four dimensions were specified as proximal predictors of **CAITIZEN**. Thus, the questionnaire translated the qualitative

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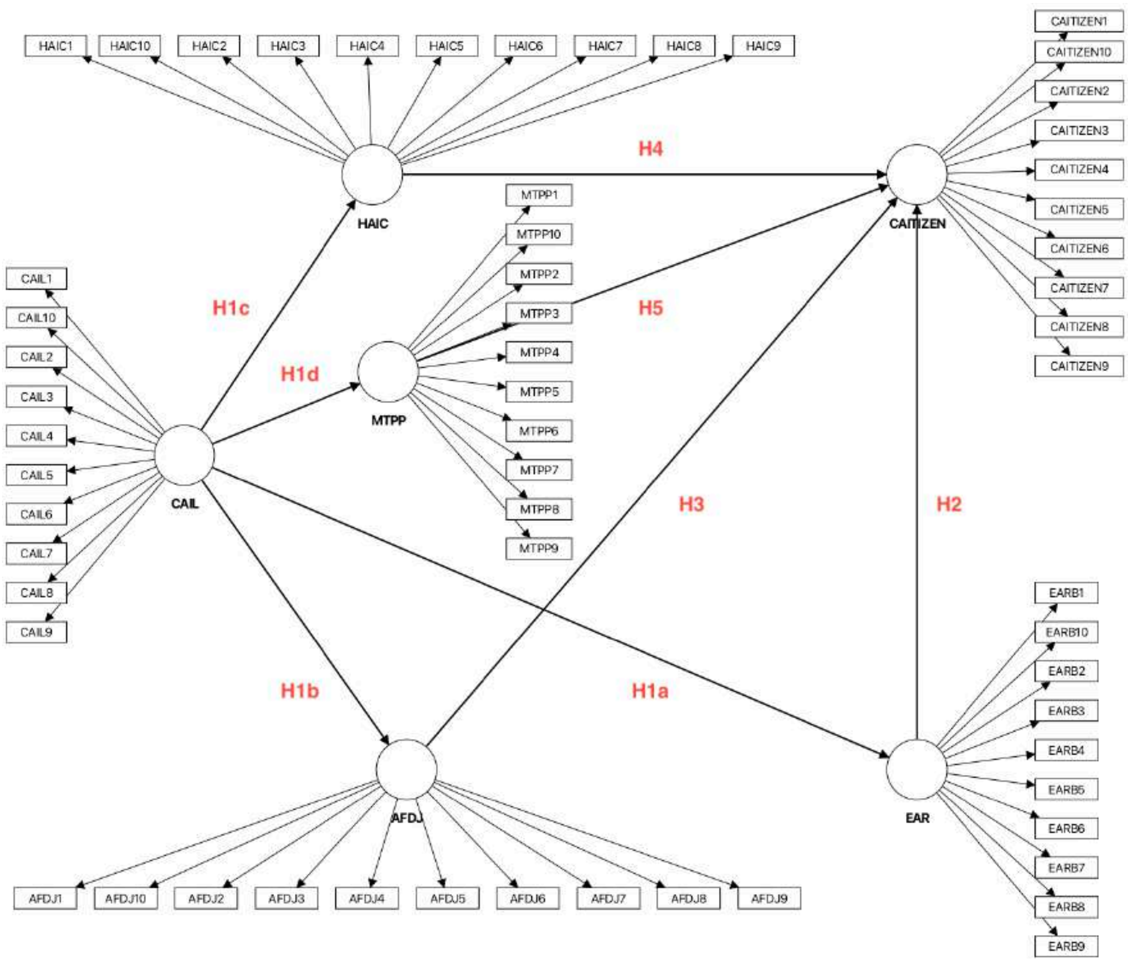
dimensions of the **CAITIZEN** framework into measurable indicators, allowing the study to move from conceptual interpretation to empirical validation and structural explanation.

3.2. Conceptual Model

The **CAITIZEN** conceptual model is proposed **ex ante** as an extended structural model. It positions **CAIL** as the foundational antecedent of **EAR**, **AFDJ**, **HAIC**, and **MTPP**, which in turn directly predict **AI-assisted sustainable citizenship (CAITIZEN)** among higher education students. Thus, the model does not replace the original qualitative **CAITIZEN** framework; it refines its explanatory structure and tests its predictive capacity through **PLS-SEM**. See **Figure 1**

Figure 1. The extended CAITIZEN ex ante model



Note: In this study, **CAITIZEN** is conceptually specified as *Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked formation.*
Source: Author's own elaboration based on the qualitative **CAITIZEN** model proposed by Mejía-Trejo (2025[a]).

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This structure is justified because **CAIL** is specified as the foundational literacy condition, while **EAR**, **AFDJ**, **HAIC**, and **MTPP** represent proximal ethical, fairness-oriented, creative, and metacognitive capacities. **PLS-SEM** is appropriate because the study aims to test an explanatory and predictive model through reflective constructs, path coefficients, explained variance, effect sizes, and predictive relevance. Thus, the extended **CAITIZEN** model enables empirical validation of **AI-assisted sustainable citizenship** as a social and conceptual innovation in higher education.

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4. METHODOLOGY

This study adopted a quantitative, explanatory-predictive research design aimed at empirically validating the extended **CAITIZEN** model. The model specifies Critical Artificial Intelligence Literacy (**CAIL**) as a foundational antecedent of Ethical Awareness and Responsibility (**EAR**), Awareness of Fairness and Data Justice (**AFDJ**), Human–**AI** Creative Collaboration (**HAIC**), and Metacognitive Transparency in Prompting Practices (**MTPP**), which in turn predict **AI**-assisted Sustainable Citizenship (**CAITIZEN**). Given the growing role of artificial intelligence in higher education, the study examines how students' critical AI literacy enables ethical, fairness-oriented, creative, and metacognitive capacities related to sustainable citizenship. As a quantitative continuation of the qualitative **CAITIZEN** framework, the methodological procedure translated its dimensions into measurable reflective constructs suitable for **PLS-SEM** analysis.

Stage 1. Model Proposition. The extended **CAITIZEN** model was proposed **ex ante** as a structural model in which **Critical Artificial Intelligence Literacy (CAIL)** functions as a foundational antecedent of four proximal capacities: **Ethical Awareness and Responsibility (EAR)**, **Awareness of Fairness and Data Justice (AFDJ)**, **Human–AI Creative Collaboration (HAIC)**, and **Metacognitive Transparency in Prompting Practices (MTPP)**. These four constructs, in turn, were specified as direct predictors of **AI-assisted Sustainable Citizenship (CAITIZEN)**. All constructs were operationalized as reflective constructs. The model assumes that AI-assisted sustainable citizenship among higher education students is shaped by ethical responsibility, fairness awareness, creative human–AI collaboration, and metacognitive prompting practices, while these capacities are enabled by critical AI literacy. Accordingly, eight direct hypotheses were proposed: four testing the effect of **CAIL** on **EAR**, **AFDJ**, **HAIC**, and **MTPP**, and four testing the effect of these proximal capacities on **CAITIZEN**.

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Stage 2. Data Analysis Technique. Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected because the objective was explanatory and predictive. **PLS-SEM** allowed the simultaneous assessment of the measurement model and the structural model. The measurement model was evaluated through indicator loadings, **Cronbach's alpha**, **composite reliability**, **rho_A**, **average variance extracted (AVE)**, the **Fornell–Larcker criterion**, **HTMT**, and collinearity diagnostics. The structural model was assessed through **path coefficients**, **bootstrapping**, **coefficient of determination (R^2)**, **effect sizes (f^2)**, predictive relevance, and **PLSpredict**. This procedure made it possible to examine reliability, validity, explanatory power, effect magnitude, and predictive relevance. Data were analyzed using spreadsheet software for descriptive statistics and **SmartPLS** for **PLS-SEM** estimation.

Stage 3. Study Subject and Sampling. The subject of study consisted of undergraduate and graduate students who had interacted with artificial intelligence tools in academic, learning, creative, or decision-making activities. A non-probabilistic purposive sampling procedure was used because participants had to meet two inclusion criteria: being enrolled in higher education and having previous experience using AI tools. The study was not designed as a population census; it analyzed the complete and valid responses obtained from participants who met the inclusion criteria. Sample size adequacy was assessed according to **PLS-SEM** requirements, considering the five direct predictors of **CAITIZEN**, expected effect size, significance level, and desired statistical power.

Stage 4. Data Collection. Data were collected through an online questionnaire administered via Google Forms between July and December 2025. The questionnaire was distributed among undergraduate and graduate students of the University of Guadalajara, Jalisco, Mexico, through academic networks, institutional mailing lists, classroom groups, and online learning communities. This local-institutional scope is consistent with the study's purposive sampling strategy and supports the empirical validation of the **CAITIZEN** model within a higher education context. Participation was voluntary, anonymous, and without compensation. Before answering, participants were informed about the academic purpose of the study, the voluntary nature of participation, and the confidential treatment of responses. From approximately 800 invited participants, **600** accessed the questionnaire, and **511** complete and valid responses were retained after screening.

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Stage 5. Demographic Data. Demographic data were analyzed to characterize the profile of the higher education students participating in the study. The variables considered included age, gender, marital status, educational level, type of higher education institution, and previous experience using artificial intelligence tools. These variables were not included as structural predictors in the **CAITIZEN** model; rather, they were used to contextualize the subject of study and describe the composition of the sample. Frequency and percentage distributions were calculated and organized in **Table 1.**

Table 1. Demographic profile of the research sample

Measure	Items	Frequency	Percentage	
Age	18-29	492	96.3%	100%
	30-39	10	2.0%	
	40-49	4	0.8%	
	50-59	5	1.0%	
Gender	Male	235	45.9%	100%
	Female	276	54.1%	
Marital Status	Single	500	97.8%	100%
	Married	11	2.2%	
Education Level	Undergraduate	499	97.6%	100%
	Master Degree	8	1.6%	
	Doctor Degree	4	0.8%	
Type Educational Institute or University	Public	461	90.2%	100%
	Private	50	9.8%	

Source: Own elaboration.

Stage 6. Questionnaire Design and Data Preparation. The questionnaire included six reflective constructs: **CAI**L, **EAR, AFDJ, HAIC, MTPP**, and **CAITIZEN**. Each construct was measured through ten Likert-type statements, resulting in **60** observable indicators. The items were formulated in first person and measured agreement with behaviors, perceptions, and competencies related to AI literacy, ethical responsibility, algorithmic fairness, creative collaboration, metacognitive prompting, and sustainable citizenship. A seven-point Likert scale was used, from 1 = Strongly disagree to 7 = Strongly agree. After data collection, the database was exported, coded, and cleaned. Missing values, duplicated entries, incomplete questionnaires, and inconsistent response patterns were reviewed. Only complete and valid responses were retained for descriptive and inferential analysis. The quantitative database corresponded to the closed-ended Likert-type section of the broader **CAITIZEN** data collection process. While the previous qualitative phase

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analyzed open-ended responses, the present study focused on the closed-ended indicators suitable for **PLS-SEM** analysis.

5. RESULTS

This section presents the findings obtained from **Partial Least Squares Structural Equation Modeling (PLS-SEM)** using **SmartPLS 4.1.1.8.** The results are organized into three components: measurement model evaluation, structural model assessment, and empirical validation of the extended **CAITIZEN** model. The analysis first examines the reliability and validity of the reflective constructs. It then evaluates the structural relationships in which **CAIL** acts as a foundational antecedent of **EAR**, **AFDJ**, **HAIC**, and **MTPP**, while these proximal capacities predict **AI-assisted Sustainable Citizenship (CAITIZEN)**. Finally, the empirical results are used to assess the explanatory and predictive capacity of the proposed model.

5.1. Measurement Model Evaluation

The reflective measurement model was assessed using established **PLS-SEM** criteria. The evaluation included internal consistency reliability, indicator reliability, convergent validity, discriminant validity, and collinearity diagnostics before proceeding to the structural model assessment.

5.1.1. Reliability, Indicator Reliability, and Convergent Validity

Internal consistency reliability was evaluated through **Cronbach's alpha**, **rho_A**, and **composite reliability**. The constructs **CAIL**, **EAR**, **AFDJ**, **HAIC**, **MTPP**, and **CAITIZEN** met the recommended reliability threshold of **0.70**, supporting adequate internal consistency.
Convergent validity was assessed through the **average variance extracted (AVE)**. The retained constructs achieved acceptable **AVE** values, indicating that each construct explained a sufficient proportion of the variance of its indicators. Indicator reliability was evaluated using **outer loadings**, and the retained indicators showed acceptable loadings and statistical significance after **Bootstrapping** with **[5,000]** subsamples.

Item purification was applied when indicators showed weak outer loadings, cross-loading concerns, or a negative effect on reliability, **AVE**, or discriminant validity. Indicators were

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removed only when their exclusion improved the empirical quality of the construct without compromising its conceptual meaning. In total, **one indicator, CAIL2, was removed**, and the final measurement model retained **59 valid indicators**.

These results confirmed that the **CAITIZEN** measurement model achieved acceptable reliability and convergent validity. See **Table 2**.

Table 2. Assessment of internal consistency, outer loadings, and convergent validity for the CAITIZEN measurement model

Factor 1	Code	**CAIL**. Critical Artificial Intelligence Literacy. Students' capacity to understand, evaluate, verify, and responsibly use AI systems in academic, professional, and civic contexts Cronbach's Alpha (≥ 0.70) = 0.884; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.889; rho_c (Composite Reliability ≥ 0.70) = 0.907; AVE (≥ 0.50) = 0.521.	Outer loading (*t-value*)	*p* - Value	Associated references
Critical Artificial Intelligence Literacy	**CAI L1**	I understand how artificial intelligence systems transform data into patterns or predictions.	0.660 (19.115)	0.000	Long & Magerko (2020)
Critical Artificial Intelligence Literacy	**CAI L2**	I distinguish among the main types of artificial intelligence, such as predictive, generative, and autonomous AI, and their applications.	Indicator removed to improve the construct's AVE		Ng et al. (2021)
Critical Artificial Intelligence Literacy	**CAI L3**	I understand how the clarity and precision of a prompt influence AI-generated responses.	0.586 (15.182)	0.000	Waaler et al. (2025)
Critical Artificial Intelligence Literacy	**CAI L4**	I identify the technical limitations and margins of error of the AI models I use.	0.757 (31.206)	0.000	Southworth et al. (2023)
Critical Artificial Intelligence Literacy	**CAI L5**	I detect when an AI-generated output contains bias or unsupported inferences.	0.754 (29.560)	0.000	Wang & Wang (2025)
Critical Artificial Intelligence Literacy	**CAI L6**	I verify AI-generated information by comparing it with reliable academic or human sources.	0.715 (23.848)	0.000	Córdova-Esparza (2025)
Critical Artificial Intelligence Literacy	**CAI L7**	I recognize when a decision should be made by a person rather than by an algorithm.	0.744 (25.217)	0.000	Gunasekara et al. (2025)
Critical Artificial Intelligence Literacy	**CAI L8**	I analyze the ethical implications of using AI in teaching, research, and institutional management.	0.804 (42.441)	0.000	Miao & Cukurova (2024)

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Critical Artificial Intelligence Literacy	**CAI L9**	I identify when an AI application may violate privacy, equity, or digital rights.	0.744 (29.890)	0.000	González-Argote et al. (2025)
Critical Artificial Intelligence Literacy	**CAI L10**	I promote the responsible, transparent, and traceable use of AI in my professional or academic environment.	0.710 (24.931)	0.000	Gunasekara et al. (2025)
Factor 2	Code	EAR. Ethical Awareness and Responsibility. Students' capacity to recognize ethical risks, assume responsibility, preserve academic integrity, protect privacy, and promote transparent and socially responsible AI use. Cronbach's Alpha (≥ 0.70) = 0.911; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.915; rho_c (Composite Reliability ≥ 0.70) = 0.926 AVE (≥ 0.50) = 0.555.	Outer loading ***(t-value)***	*p* - Value	Associated references
Ethical Awareness and Responsibility	EAR 1	I explicitly declare when and how I use artificial intelligence in my academic work to maintain transparency and personal responsibility.	0.642 (19.683)	0.000	Kong & Zhu (2025)
Ethical Awareness and Responsibility	EAR 2	Before using AI, I analyze possible ethical risks, such as bias, privacy, authorship, or misinformation, and how to prevent them.	0.718 (29.455)	0.000	Gunasekara et al. (2025)
Ethical Awareness and Responsibility	EAR 3	I respect privacy and data protection when using AI tools by avoiding the disclosure of sensitive information.	0.730 (26.453)	0.000	González-Argote et al. (2025)
Ethical Awareness and Responsibility	EAR 4	I avoid applying AI in ways that may cause harm, exclusion, or misinformation in my academic environment.	0.765 (31.081)	0.000	Córdova-Esparza (2025)
Ethical Awareness and Responsibility	EAR 5	I encourage my peers to use AI ethically, transparently, and responsibly as a practice of academic integrity.	0.758 (33.419)	0.000	Kong & Zhu (2025)
Ethical Awareness and Responsibility	EAR 6	I take responsibility for AI-generated outputs in my academic activities and correct errors derived from their use.	0.772 (32.162)	0.000	Papagiannidis et al. (2025)
Ethical Awareness and Responsibility	EAR 7	I evaluate the social effects of the AI I use, considering equity, inclusion, and sustainability.	0.768 (33.737)	0.000	Córdova-Esparza (2025)
Ethical Awareness and Responsibility	EAR 8	I recognize that academic products must preserve human authorship, using AI only as technical or creative support.	0.751 (29.612)	0.000	Wang & Wang (2025)
Ethical Awareness and Responsibility	EAR 9	I reject using AI to plagiarize, falsify, or impersonate my own or others' academic work.	0.748 (26.849)	0.000	Kong & Zhu (2025)
Ethical Awareness and Responsibility	EAR 10	I promote transparency and the common good in the use of AI, ensuring that its benefits are shared equitably.	0.789 (40.308)	0.000	Papagiannidis et al. (2025)
Factor 3	Code	AFDJ. Awareness of Fairness and Data Justice. Students' capacity to identify algorithmic bias, recognize data-related inequalities, value transparency, and support fairness, accountability, and justice in AI systems. Cronbach's Alpha (≥ 0.70) = 0.919; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.921;	Outer loading ***(t-value)***	*p* - Value	Associated references

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		rho_c(Composite Reliability ≥ 0.70) = 0.933; AVE (≥ 0.50) = 0.581.			
Awareness of Fairness and Data Justice	AFDJ 1	I recognize that limited or homogeneous datasets may generate unfair algorithmic decisions.	0.684 (23.114)	0.000	González-Argote et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 2	I consider external auditing of algorithms necessary to detect and correct bias.	0.752 (28.681)	0.000	Decker et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 3	I value AI systems making public the criteria they use to make decisions.	0.773 (34.180)	0.000	Demirchyan (2025)
Awareness of Fairness and Data Justice	AFDJ 4	I believe that including cultural and gender diversity in development teams improves algorithmic fairness.	0.718 (26.522)	0.000	Pham et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 5	I identify the importance of continuously supervising AI models to prevent discrimination.	0.745 (31.297)	0.000	Demirchyan (2025)
Awareness of Fairness and Data Justice	AFDJ 6	I consider it essential for educational institutions to establish policies to evaluate algorithmic justice.	0.781 (31.711)	0.000	Decker et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 7	I observe that imbalance in data representation can affect a system’s accuracy and impartiality.	0.812 (42.996)	0.000	Pham et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 8	I defend people’s right to know the variables that influence an algorithm’s decisions.	0.767 (27.094)	0.000	Decker et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 9	I consider transparency in the origin and processing of data to be key for equity in AI.	0.801 (39.930)	0.000	González-Argote et al. (2025)
Awareness of Fairness and Data Justice	AFDJ 10	I support the publication of institutional reports on detected biases and improvements implemented in educational algorithms.	0.779 (35.175)	0.000	Pham et al. (2025)
Factor 4	Code	HAIC. Human–AI Creative Collaboration. Students’ capacity to use AI as a creative partner for ideation, problem-solving, experimentation, reflective improvement, and innovation-oriented knowledge production. Cronbach’s Alpha (≥ 0.70) = 0.942; rho_A (Dijkstra–Henseler’s ≥ 0.70) = 0.943; rho_c (Composite Reliability ≥ 0.70) = 0.950; AVE (≥ 0.50) = 0.656.	Outer loading ***(t-value)***	*p* - Value	Associated references
Human–AI Creative Collaboration	HAIC 1	I use AI as a starting point to generate ideas that I later develop personally.	0.739 (27.678)	0.000	Georgieva & Georgiev (2025)
Human–AI Creative Collaboration	HAIC 2	I combine my own contributions with AI suggestions to create more innovative outcomes.	0.812 (40.894)	0.000	Rafner et al. (2025)
Human–AI Creative Collaboration	HAIC 3	I analyze how AI responses influence my creative process.	0.795 (34.688)	0.000	Wang et al. (2025)
Human–AI Creative Collaboration	HAIC 4	I learn new ways of solving problems when interacting with AI.	0.829 (43.662)	0.000	Wang et al. (2025)

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Human–AI Creative Collaboration	HAIC 5	I consider AI a creative partner that complements my human abilities.	0.801 (36.297)	0.000	Salma et al. (2025)
Human–AI Creative Collaboration	HAIC 6	Collaboration with AI inspires new perspectives or approaches that I would not have had alone.	0.784 (32.013)	0.000	Rafner et al. (2025)
Human–AI Creative Collaboration	HAIC 7	I use AI to experiment with different creative styles or solutions.	0.840 (47.686)	0.000	Georgieva & Georgiev (2025)
Human–AI Creative Collaboration	HAIC 8	I reflect on how my work improves through interaction with AI.	0.817 (40.091)	0.000	Wang et al. (2025)
Human–AI Creative Collaboration	HAIC 9	I adjust AI proposals to align them with my own creative vision or purpose.	0.836 (50.771)	0.000	Salma et al. (2025)
Human–AI Creative Collaboration	HAIC 10	In creative projects, I combine my human decisions with AI's generative capabilities to achieve original outcomes.	0.841 (50.968)	0.000	Rafner et al. (2025)
Factor 5	Code	MTPP. Metacognitive Transparency in Prompting Practices. Students' capacity to plan, document, monitor, adjust, and reflect on prompting practices to improve learning, transparency, and responsible AI interaction. Cronbach's Alpha (≥ 0.70) = 0.918; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.923; rho_c (Composite Reliability ≥ 0.70) = 0.932; AVE (≥ 0.50) = 0.577.	Outer loading ***(t-value)***	*p* - Value	Associated references
Metacognitive Transparency in Prompting Practices	MTP P1	I systematically record the prompts I use in order to learn from my own process.	0.680 (22.064)	0.000	Haidar et al. (2025)
Metacognitive Transparency in Prompting Practices	MTP P2	I adjust my prompts when I detect that AI responses do not meet my learning objectives.	0.766 (30.472)	0.000	Haidar et al. (2025)
Metacognitive Transparency in Prompting Practices	MTP P3	I analyze changes in AI responses to understand how my requests affect the results.	0.772 (31.853)	0.000	Tsakeni et al. (2025)
Metacognitive Transparency in Prompting Practices	MTP P4	I reflect on the clarity and precision of my prompts before submitting them.	0.794 (39.200)	0.000	Haidar et al. (2025)
Metacognitive Transparency in Prompting Practices	MTP P5	I document the reasoning I follow when modifying a prompt or interpreting a response.	0.714 (22.127)	0.000	Tsakeni et al. (2025)
Metacognitive Transparency in Prompting Practices	MTP P6	I compare different versions of the same prompt to identify which one produces more useful results.	0.702 (20.172)	0.000	Waaler et al. (2025)
Metacognitive Transparency	MTP P7	I evaluate whether my prompting strategies contribute to a deeper understanding of the topic.	0.816 (44.317)	0.000	Tsakeni et al. (2025)

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in Prompting Practices					
Metacognitive Transparency in Prompting Practices	MTP P8	I plan the structure and purpose of the prompt before beginning my interaction with AI.	0.823 (47.701)	0.000	Miao & Cukurova (2024)
Metacognitive Transparency in Prompting Practices	MTP P9	I review the coherence between my initial objectives and the results obtained from AI.	0.776 (35.589)	0.000	Wang & Wang (2025)
Metacognitive Transparency in Prompting Practices	MTP P10	At the end of the activity, I reflect on what I learned from the process of interacting with AI.	0.741 (28.494)	0.000	Haidar et al. (2025)
Factor 6	Code	**CAITIZEN**. AI-assisted Sustainable Citizenship. Students' capacity to participate responsibly in AI-mediated societies by integrating critical literacy, ethics, fairness, creativity, metacognition, innovation, and social sustainability. Cronbach's Alpha (≥ 0.70)= 0.910; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.912; rho_c (Composite Reliability ≥ 0.70) = 0.925; AVE (≥ 0.50) = 0.553.	Outer loading ***(t-value)***	*p* - Value	Associated references
AI-assisted Sustainable Citizenship	CAIT IZEN 1	I identify myself as part of a society that coexists daily with artificial intelligence.	0.712 (25.165)	0.000	Mejía-Trejo (2025[a])
AI-assisted Sustainable Citizenship	CAIT IZEN 2	I consider it important to understand how AI influences my rights and responsibilities as a citizen.	0.740 (25.552)	0.000	Mejía-Trejo (2025[a])
AI-assisted Sustainable Citizenship	CAIT IZEN 3	I believe that everyone should participate in public decisions related to the use of AI.	0.719 (24.341)	0.000	Decker et al. (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 4	I am interested in AI being used transparently by governments and institutions.	0.742 (27.335)	0.000	Papagiannidis et al. (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 5	I think that access to AI knowledge is a form of citizen empowerment.	0.731 (29.056)	0.000	Southworth et al. (2023)
AI-assisted Sustainable Citizenship	CAIT IZEN 6	I am concerned that AI may reinforce inequalities if inclusive policies are not implemented.	0.658 (18.382)	0.000	González-Argote et al. (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 7	I trust that informed citizenship can guide the ethical development of AI.	0.779 (34.155)	0.000	Gunasekara et al. (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 8	I am willing to learn continuously in order to adapt to an AI-driven society.	0.750 (24.031)	0.000	Córdova-Esparza (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 9	I believe that being a citizen in the AI era implies actively collaborating in its regulation and oversight.	0.795 (37.653)	0.000	Papagiannidis et al. (2025)
AI-assisted Sustainable Citizenship	CAIT IZEN 10	I value the importance of combining technological innovation with collective responsibility and social sustainability.	0.795 (39.014)	0.000	Mejía-Trejo (2025[a])

Notes:

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- **CAIL.** Critical Artificial Intelligence Literacy; **EAR.** Ethical Awareness and Responsibility; **AFDJ.** Awareness of Fairness and Data Justice; **HAIC.** Human–AI Creative Collaboration; **MTPP**. Metacognitive Transparency in Prompting Practices; **CAITIZEN**. AI-assisted Sustainable Citizenship. The items were conceptually adapted from the qualitative **CAITIZEN** model and supported by specialized literature. The associated references indicate conceptual support and do not imply that the items were directly copied from previous scales.
- Indicators with outer loadings between **0.40** and **0.70** were retained when reliability, **AVE**, and theoretical relevance supported their inclusion.
- **rho_A**. Dijkstra–Henseler's rho_A is a reliability coefficient used to assess internal consistency in PLS-SEM. Values above 0.70 indicate acceptable reliability.
- **rho_C**. Composite Reliability assesses the internal consistency of construct indicators. Values between 0.70 and 0.90 are considered satisfactory. Values above 0.95 may suggest indicator redundancy or common method bias (Hair et al., 2022).
- **AVE** (Average Variance Extracted). An **AVE** > 0.50 indicates that a construct explains more than 50% of the variance in its observed indicators, thereby supporting convergent validity (Fornell & Larcker, 1981).
- Indicators are according to Likert Scale 1-7 (1. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. I do not know ; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree).
- Regarding saturated model fit, the **SRMR** value was **0.048** below the recommended threshold of **0.08**, indicating acceptable approximate fit and supporting the continuation of the **PLS-SEM** assessment.

Source: Own elaboration using SmartPLS 4.1.1.8

5.1.2. Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait–Monotrait (**HTMT**) ratio. As shown in **Table 3**, the square roots of the **AVEs** (diagonal values) are greater than the inter-construct correlations, satisfying the Fornell-Larcker criterion. Additionally, all **HTMT** values are below the conservative threshold of 0.85 (Henseler et al., 2015), confirming discriminant validity.

Table 3. CAITIZEN measurement model discriminant validity

Fornell & Larcker Criteria (Diagonal= Root Square -**AVE**-) for discriminant validity **HTMT Criteria Ratio<= 0.85<=0.90 for convergent validity**						
Construct	**AFDJ**	**CAIL**	**CAITIZEN**	**EAR**	**HAIC**	**MTPP**
AFDJ	0.762	**0.794**	**0.824**	**0.827**	**0.788**	**0.763**
CAIL	0.718	0.722	**0.679**	**0.834**	**0.694**	**0.732**
CAITIZEN	0.759	0.614	0.743	**0.712**	**0.820**	**0.744**
EAR	0.766	0.759	0.661	0.745	**0.712**	**0.716**
HAIC	0.735	0.637	0.765	0.673	0.810	**0.752**
MTPP	0.708	0.665	0.695	0.669	0.713	0.760

Notes:
HTMT. The Heterotrait–Monotrait ratio of correlations assesses discriminant validity by evaluating whether constructs are empirically distinct. Values below 0.85 indicate adequate discriminant validity under a conservative criterion, whereas values below 0.90 may be acceptable for conceptually related constructs (Henseler et al., 2015). Bootstrapping can be used to test whether HTMT confidence intervals include the value of 1.0, providing additional statistical evidence for discriminant validity. Franke and Sarstedt (2019) compare HTMT with other discriminant validity procedures and support its use as a more reliable approach than traditional criteria.
Source: Own elaboration using SmartPLS 4.1.1.8

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5.1.3. Collinearity Assessment

Before assessing the structural paths, collinearity among predictor constructs was examined using the **inner variance inflation factor (VIF)** values obtained from the **PLS-SEM Algorithm** in **SmartPLS**. The results ranged from **1.000** to **3.269**, remaining below the commonly accepted threshold of **5.0** and also below the more conservative reference value of **3.3**. Therefore, collinearity did not represent a critical issue in the structural model, and the path coefficients could be interpreted without evidence of problematic predictor redundancy. See **Table 4.**

Table 4. CAITIZEN collinearity assessment of the CAITIZEN structural model

Structural path	Inner VIF	Assessment
AFDJ -> CAITIZEN	3.269	Acceptable
CAIL -> AFDJ	1.000	Acceptable
CAIL -> EAR	1.000	Acceptable
CAIL -> HAIC	1.000	Acceptable
CAIL -> MTPP	1.000	Acceptable
EAR -> CAITIZEN	2.663	Acceptable
HAIC -> CAITIZEN	2.664	Acceptable
MTPP -> CAITIZEN	2.485	Acceptable

Note. VIF = variance inflation factor. Values below 5.0 indicate absence of critical collinearity; values below 3.3 also satisfy a more conservative reference criterion (Hair et al., 2022).
Source: Own elaboration using SmartPLS 4.1.1.8.

5.2 Structural Model Assessment

To evaluate the structural model of the **CAITIZEN** framework, the recommended **PLS-SEM** criteria were applied (Hair et al., 2022). First, multicollinearity was examined using the inner Variance Inflation Factor (**VIF**). All **VIF** values were below the conservative threshold of 3.3, indicating no critical collinearity among the predictor constructs and supporting the stability of the path estimates.

After confirming the absence of collinearity problems, the structural relationships were assessed through path coefficients, bootstrapping, confidence intervals, significance levels, and effect sizes. The results generated with **SmartPLS 4.1.1.8** are presented in **Figure 2** and **Table 5**. These results show the empirically validated relationships of the extended **CAITIZEN** framework, in which **CAIL** functions as the foundational antecedent of **EAR, AFDJ, HAIC, and MTPP**, while **AFDJ, HAIC, and MTPP** significantly predict **AI**-assisted Sustainable Citizenship. The path from **EAR to CAITIZEN** was retained in the model but was not statistically significant. This structural assessment supports the explanatory capacity of the model and confirms that AI-assisted

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sustainable citizenship is mainly shaped by applied capacities related to fairness awareness, human–AI creative collaboration, and metacognitive prompting practices. **See Table 5.**

Table 5. Structural model assessment of the CAITIZEN framework: hypothesis testing and effect sizes

Hypotheses	β Paths	* β Path [*t-value; p-value*]	Result	*Interval	f^2 Effect Size (pls-algorithm)	
				95% CI [2.5%; 97.5%]	(0.02<=; 0.15 <=0.35)	Effect (Small; Medium; Large)
H1a: *"**CAIL** positively and significantly predicts **EAR**."*	**CAIL -> EAR**	0.760 [28.411; 0.000]	Accepted	[0.700; 0.807]	1.371	**Large**
H1b: *"**CAIL** positively and significantly predicts **AFDJ**."*	**CAIL -> AFDJ**	0.720 [24.144; 0.000]	Accepted	[0.655; 0.774]	1.079	**Large**
H1c: *"**CAIL** positively and significantly predicts **HAIC**."*	**CAIL -> HAIC**	0.640 [17.726; 0.000]	Accepted	[0.560; 0.703]	0.692	**Large**
H1d: *"**CAIL** positively and significantly predicts **MTPP**."*	**CAIL -> MTPP**	0.664 [20.186; 0.000]	Accepted	[0.593; 0.722]	0.789	**Large**
H2: *"**EAR** positively and significantly predicts **CAITIZEN**."*	**EAR -> CAITIZEN**	0.045 [0.880; 0.379]	**Rejected**	[**-0.056**; **0.144**]	0.002	**Small**
H3: *"**AFDJ** positively and significantly predicts **CAITIZEN**."*	**AFDJ -> CAITIZEN**	0.333 [5.498; 0.000]	Accepted	[0.215; 0.450]	0.106	**Small**
H4: *"**HAIC** positively and significantly predicts **CAITIZEN**."*	**HAIC -> CAITIZEN**	0.376 [7.071; 0.000]	Accepted	[0.269; 0.479]	0.166	**Medium**
H5: *"**MTPP** positively and significantly predicts **CAITIZEN**."*	**MTPP -> CAITIZEN**	0.159 [3.516; 0.000]	Accepted	[0.070; 0.249]	0.032	**Small**

Notes:

- **CAIL.** Critical Artificial Intelligence Literacy; **EAR.** Ethical Awareness and Responsibility; **AFDJ.** Awareness of Fairness and Data Justice; **HAIC.** Human–AI Creative Collaboration; **MTPP**. Metacognitive Transparency in Prompting Practices; **CAITIZEN**. AI-assisted Sustainable Citizenship.
- Bootstrapping results are reported as two-tailed t-values and p-values using bias-corrected 95% confidence intervals [2.5%; 97.5%], based on 5,000 subsamples and a 0.05 significance level.
- f^2 effect size. 0.02, 0.15, and 0.35 are interpreted as small, medium, and large (Cohen, 1992)
- Hypothesis acceptance or rejection was determined based on the significance of the bootstrapped path coefficients, whereas f^2 values were used only to interpret effect size magnitude.

Source: Own elaboration using SmartPLS 4.1.1.8

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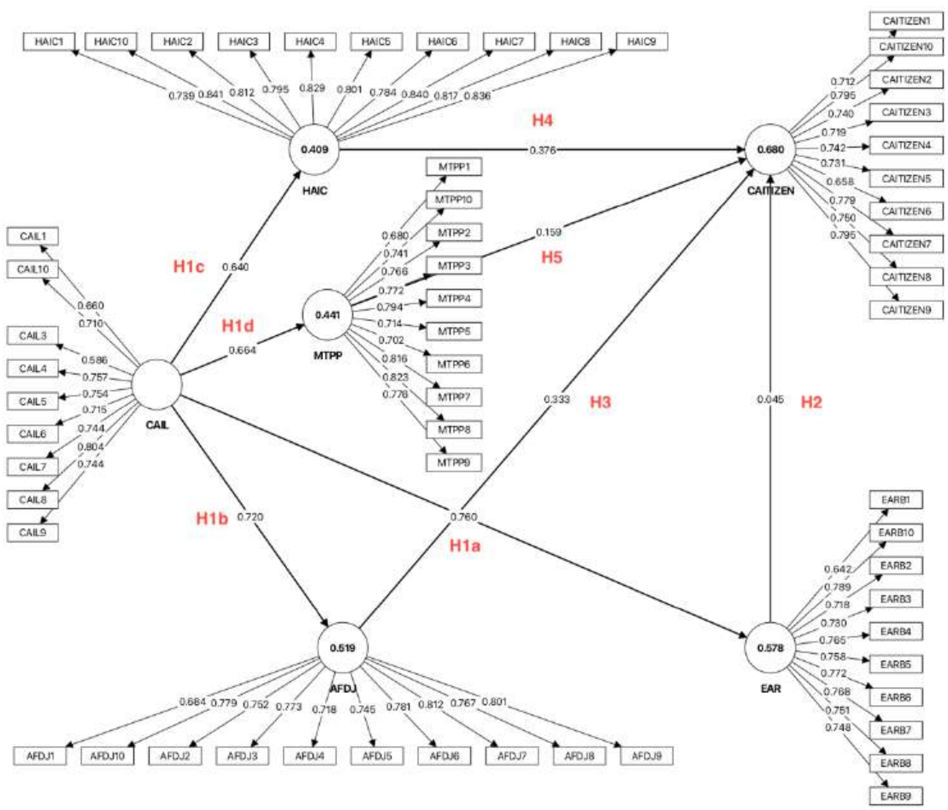
The empirical structural model is presented in **Figure 2** to visually summarize the validated relationships of the extended **CAITIZEN** framework. The figure shows **CAIL** as the foundational antecedent of **EAR, AFDJ, HAIC, and MTPP**. The path from **EAR to CAITIZEN** is retained in the model but was not statistically significant. The coefficients displayed in the figure indicate the strength and direction of each structural relationship, whereas the values inside the endogenous constructs represent their explained variance. This visualization complements the hypothesis testing results by showing which relationships were empirically supported and how the constructs interact within the extended model. The strongest effects are observed from **CAIL** toward the proximal capacities, confirming its role as the structural literacy foundation of the model. In contrast, **CAITIZEN** is mainly shaped by applied and actionable dimensions, particularly **HAIC, AFDJ, and MTPP** suggesting that sustainable **AI**-assisted citizenship depends not only on ethical awareness, but also on creative agency, fairness-oriented judgment, and reflective prompting practices.

Figure 2. The CAITIZEN ex-post PLS-SEM structural model results with validated paths and effect sizes



Source: Own elaboration using SmartPLS 4.1.1.8.

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5.3. Predictive Relevance

Predictive relevance was assessed using **PLSpredict** in **SmartPLS 4.1.1.8**, focusing on the ten indicators of **CAITIZEN**, understood as **Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked Formation**. **Q²_predict** values greater than zero indicate predictive relevance, while lower **RMSE** values indicate better predictive performance. The **PLS-SEM** model was compared with the linear model benchmark (**LM**). See **Table 6**.

Table 6. PLSpredict assessment for CAITIZEN

Indicator	Q²_predict	PLS-SEM RMSE	LM RMSE	PLS-LM RMSE	Assessment
CAITIZEN1	0.217	1.353	1.370	-0.017	PLS better
CAITIZEN2	0.186	1.226	1.249	-0.023	PLS better
CAITIZEN3	0.157	1.305	1.324	-0.019	PLS better
CAITIZEN4	0.151	1.383	1.394	-0.011	PLS better
CAITIZEN5	0.185	1.299	1.321	-0.022	PLS better
CAITIZEN6	0.150	1.462	1.475	-0.013	PLS better
CAITIZEN7	0.215	1.307	1.331	-0.024	PLS better
CAITIZEN8	0.214	1.220	1.237	-0.017	PLS better
CAITIZEN9	0.247	1.178	1.192	-0.014	PLS better
CAITIZEN10	0.309	1.136	1.149	-0.013	PLS better

Note. CAITIZEN: Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked Formation. **Q²_predict** > 0 indicates predictive relevance. **RMSE** = root mean squared error; **LM** = linear model benchmark. Negative **PLS-LM RMSE** values indicate that **PLS-SEM** produced lower prediction errors than LM. Source: Own elaboration using SmartPLS 4.1.1.8**.**

As shown in **Table 6**, all **Q²_predict** values were positive and all **PLS-LM RMSE** differences were negative. Therefore, the extended **CAITIZEN** model demonstrates high out-of-sample predictive power for **Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked Formation**.

6. Discussion

The results provide empirical support for the **extended CAITIZEN model** as an **explanatory-predictive framework** for **AI-assisted sustainable citizenship in higher education**. The findings confirm that **Critical Artificial Intelligence Literacy (CAIL)** operates as the **foundational antecedent** of **Ethical Awareness and Responsibility (EAR)**, **Awareness of Fairness and Data Justice (AFDJ)**, **Human–AI Creative Collaboration (HAIC)**, and **Metacognitive Transparency in Prompting Practices (MTPP)**. The strongest structural effects are observed from **CAIL toward the four proximal capacities**, indicating that students' ability to **understand,**

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evaluate, verify, and responsibly use AI systems enables more specific forms of **ethical, fairness-oriented, creative, and metacognitive engagement**.

The interpretation of **effect sizes (f^2)** further clarifies the relevance of the structural results. The effects of **CAIL on EAR (f^2 = 1.371), AFDJ (f^2 = 1.079), HAIC (f^2 = 0.692), and MTPP (f^2 = 0.789)** are **large**, confirming that **critical AI literacy is the strongest formative foundation of the model**. At the CAITIZEN level, **HAIC shows a medium effect (f^2 = 0.166)**, making **human–AI creative collaboration** the strongest direct actionable mechanism for forming AI-assisted sustainable citizenship. **AFDJ (f^2 = 0.106)** and **MTPP (f^2 = 0.032)** show **small but meaningful effects**, suggesting that fairness awareness and prompt transparency contribute directly, although more moderately. In contrast, **EAR has a negligible effect (f^2 = 0.002)**, reinforcing that ethical awareness alone does not directly translate into sustainable AI-assisted citizenship unless it becomes actionable through fairness, creativity, and metacognitive practices.

The predictive relevance results strengthen this interpretation. **All Q^2_predict values for CAITIZEN indicators are positive**, and **all PLS-LM RMSE differences favor the PLS-SEM model**. Therefore, the model does not only explain relationships among constructs; it also shows **predictive capacity** for the **CAITIZEN** indicators. Overall, the findings indicate that **AI-assisted sustainable citizenship is not produced by technical AI use alone**. It emerges from the interaction between **critical literacy** and **applied capacities** that connect **fairness, creativity, metacognition, responsibility, and sustainable innovation** in higher education.

6.1. Theoretical Contribution

The extended **CAITIZEN** model contributes theoretically by transforming a **qualitative ethical–cognitive–social framework** into an **empirically validated explanatory-predictive structure**. The original **CAITIZEN** framework identified **Critical Artificial Intelligence Literacy**, **Ethical Awareness and Responsibility**, **Awareness of Fairness and Data Justice**, **Human–AI Creative Collaboration**, and **Metacognitive Transparency in Prompting Practices** as relevant dimensions of **AI-assisted sustainable citizenship**. The present study advances that conceptual foundation by specifying and testing the **internal structural logic** among those dimensions. In doing so, it moves **CAITIZEN** from **conceptual identification** to **empirical explanation**.

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The first theoretical contribution is the positioning of **CAIL as a foundational literacy layer**. The large effects of **CAIL on EAR, AFDJ, HAIC, and MTPP** show that critical AI literacy is not merely one isolated component of AI citizenship; rather, it functions as the **cognitive and evaluative condition** that enables other capacities. Students who understand AI systems, evaluate their outputs, recognize their limitations, and verify information are better positioned to develop **ethical responsibility**, **fairness awareness**, **creative collaboration**, and **metacognitive transparency**. Thus, the model theorizes AI-assisted citizenship as a **literacy-enabled process**, not as a simple consequence of AI access or use.

The second contribution concerns the distinction between **normative awareness** and **actionable capacity**. **EAR is significantly enabled by CAIL, but it does not directly predict CAITIZEN** and shows a negligible direct effect. This result refines responsible AI theory by suggesting that **ethical awareness may operate as a necessary orientation but not as a sufficient direct mechanism**. Sustainable AI-assisted citizenship appears to depend more strongly on capacities that can be enacted in practice. The medium effect of **HAIC** indicates that **creative human–AI collaboration** is a central theoretical mechanism, while the small effects of **AFDJ** and **MTPP** confirm that fairness judgment and reflective prompting also contribute to the formation of **CAITIZEN.**

The third contribution is the integration of **multidisciplinarity into a measurable structural model**. **CAITIZEN** articulates **education, artificial intelligence, ethics, data justice, creativity, metacognition, innovation, and sustainable development**. The model therefore expands AI literacy theory by connecting **individual competence** with **civic formation** and **sustainable innovation**. It also contributes to innovation studies by framing **AI-assisted citizenship as a social and conceptual innovation** aligned with **quality education** and **institutional transformation**. Finally, the positive predictive results support the **theoretical robustness of CAITIZEN** as a measurable construct for studying **sustainable AI-mediated citizenship in higher education**.

6.2. Practical Contribution

The extended **CAITIZEN** model offers practical value for **universities, educators, curriculum designers, institutional leaders, and policymakers** seeking to guide **responsible AI adoption in higher education**. The results indicate that AI education should begin with **Critical Artificial**

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Intelligence Literacy, because **CAIL** shows **large effects** on the ethical, fairness-oriented, creative, and metacognitive capacities required for sustainable citizenship. Therefore, institutional AI strategies should not be limited to **technical training, productivity improvement, or tool adoption**. They should include systematic formation in **how AI systems work**, **how outputs should be verified**, **how bias may emerge**, **how privacy and digital rights are protected**, and **how AI use can be made transparent and accountable**.

The significant effect of **AFDJ on CAITIZEN**, although small, shows that **fairness and data justice must become explicit curricular and institutional priorities**. Universities should train students to identify **algorithmic bias**, **unequal data representation**, **opacity**, **discrimination**, and **unfair automated decisions**. This implies incorporating **algorithmic fairness modules**, **case-based learning**, **data justice discussions**, and **institutional protocols** for evaluating AI systems used in academic contexts. Even a small direct effect is practically relevant because fairness awareness addresses risks that can affect equity, trust, and responsible participation in AI-mediated environments.

The medium effect of **HAIC on CAITIZEN** shows that AI-assisted citizenship requires **creative agency**. Students should learn to use AI as a **co-creative partner** without surrendering **authorship, judgment, or responsibility**. Educational practice can include activities in which students **compare AI-generated outputs**, **revise them critically**, **justify their creative decisions**, and **document how human agency shaped the final product**. This promotes **responsible innovation** rather than passive dependence on **AI** systems.

The significant but small effect of **MTPP** highlights the importance of **prompt transparency**. Universities should teach students to **plan, document, monitor, adjust, and evaluate their prompting practices**. **Prompt logs, reflective reports, disclosure statements, and iterative prompt analysis** can become practical tools for **academic integrity** and **responsible AI use**. Finally, the negligible direct effect of **EAR** suggests that **ethical campaigns and declarations are insufficient if they are not connected to observable practices**. Institutions should translate ethical principles into measurable competencies such as **bias detection**, **prompt traceability**, **responsible disclosure**, **output verification**, and **human accountability**. In this sense, **CAITIZEN can serve as a diagnostic and formative tool** to assess student readiness, guide

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teacher training, design AI policies, and monitor institutional progress toward **responsible AI-assisted sustainable citizenship**.

7. CONCLUSION

This section summarizes how the study addresses the research question, the hypotheses, the main findings, and the final scope of the research. The conclusion emphasizes the contribution of the extended **CAITIZEN** model as a quantitative re-specification of the qualitative framework proposed by Mejía-Trejo (2025a), highlighting its value for multidisciplinarity, innovation, and sustainable development in higher education.

7.1. How the Research Question and Hypotheses Are Addressed

This study addresses the research question by empirically examining how Critical Artificial Intelligence Literacy (**CAIL**), Ethical Awareness and Responsibility (**EAR**), Awareness of Fairness and Data Justice (**AFDJ**), Human–AI Creative Collaboration (**HAIC**), and Metacognitive Transparency in Prompting Practices (**MTPP**) explain **CAITIZEN**, understood as Citizenship Assisted by Artificial Intelligence for Sustainable, Ethical, and Networked Formation.

The results confirm that **CAIL** positively and significantly predicts **EAR, AFDJ, HAIC, and MTPP;** therefore, **H1a, H1b, H1c, and H1d** are accepted. These findings establish **CAIL** as the foundational antecedent of the extended model. In the second structural stage, **AFDJ, HAIC, and MTPP** positively and significantly predict **CAITIZEN**; therefore, **H3, H4, and H5** are accepted. However, **EAR** does not significantly predict **CAITIZEN**; therefore, **H2 is rejected**. This result indicates that ethical awareness is relevant, but it requires translation into actionable capacities such as fairness judgment, creative collaboration, and metacognitive prompting.

7.2. Research Findings

The main finding is that the extended **CAITIZEN** model advances the original qualitative framework by explaining the internal structural logic among its dimensions. The model does not only identify five components of **AI**-assisted sustainable citizenship; it shows how they interact. **CAIL** operates as the literacy foundation that enables ethical, fairness-oriented, creative, and

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metacognitive capacities. In turn, **AFDJ, HAIC, and MTPP** function as proximal mechanisms that directly shape **CAITIZEN.**

The theoretical contribution is that the study provides new knowledge on AI-assisted citizenship as a multidimensional, literacy-enabled, justice-oriented, creative, and reflective construct. This supports the integration of **AI** literacy, responsible **AI**, data justice, human–AI collaboration, metacognition, innovation, and sustainable development. The practical contribution is that the model offers universities a measurable framework for designing **AI** curricula, institutional AI policies, responsible prompting practices, fairness education, and innovation-oriented citizenship formation. The positive PLSpredict results further support the model's out-of-sample predictive relevance.

7.3. Final Scope of the Research

The scope of this research is centered on higher education students who use **AI** tools in academic, creative, and decision-making contexts. The study contributes to **SDG4** by supporting quality education through critical and responsible **AI** competencies, and to **SDG9** by promoting innovation-oriented learning and institutional transformation. However, the results are limited by the use of a non-probabilistic sample, the predominance of undergraduate students, the cross-sectional design, and the absence of experimental or longitudinal evidence.

Future research should test the extended **CAITIZEN** model in different universities, countries, disciplines, and educational levels. Comparative, longitudinal, and mixed-method studies may examine whether the rejected path from **EAR** to **CAITIZEN** becomes significant in other contexts or when mediated by fairness, creativity, or metacognitive practices. Overall, the study confirms that **CAITIZEN** is not only a qualitative conceptual model, but an empirically validated innovation for understanding and forming sustainable **AI**-assisted citizenship in higher education.

The extended **CAITIZEN** model complements the original qualitative model by moving from conceptual substantiation to empirical validation. While the qualitative study established **CAITIZEN** as an ethical–cognitive–social system composed of **CAIL, EAR, AFDJ, HAIC, and MTPP**, the extended model specifies how these dimensions operate structurally. Its main contribution is to demonstrate that **CAIL** functions as the foundational antecedent of the model, whereas **AFDJ, HAIC, and MTPP** act as the direct actionable mechanisms that predict AI-assisted

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sustainable citizenship. Thus, the extended model does not replace the original CAITIZEN framework; it advances it by providing explanatory hierarchy, effect-size interpretation, predictive relevance, and practical priorities for higher education institutions

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