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Impact of cost perception and environmental concern on environmental attitudes toward green energy adoption

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Abstract

Renewable energies are considered expensive, especially solar energy, which requires heavy investments, and the cost of panels is often a constraint that limits attitudes towards it. This study reports a structural equation model (SEM) to analyze information collected through a questionnaire administered to homeowners in Ciudad Juárez, Mexico. The SEM quantifies the relationships between cost perception (PCO), environmental concern (ECO), and environmental attitudes (ENA) through three hypotheses, generating equations that are later used through system dynamics (SD) to examine behaviors over ten years. The results show a direct and positive impact of PCO on ECO and ENA. In addition, a gradual increase in favorable attitudes towards renewable energy technologies was observed. However, the need to interpret these results cautiously is highlighted because of the complexity of attitude change and variability in the time required to achieve a desired change. These findings highlight the importance of addressing cost perception as a critical factor for promoting pro-environmental attitudes among university students.

Keywords: Environmental behavior; environmental attitudes; system dynamics; SEM.

1. Introduction

Renewable energy (RE) has emerged as a promising solution for addressing climate change and reducing the dependence on fossil fuels. Policy creation and media distribution of information often emphasize RE as an environmental or "green" issue motivated by global climate change and the need to reduce greenhouse gases (Olson-Hazboun et al., 2016).

However, the transition to clean and sustainable energy sources depends not only on technological advances and government policies but also on society's perception of their costs and the benefits they reap (Zerinou et al., 2020). In addition, studies have shown that sociodemographic factors influence a population's environmental attitudes (ENA) and environmental behaviors. The importance of RE is highlighted by the increasing energy demand, environmental impacts, climate change, greenhouse gas emissions, and socioeconomic development (Akhoondi et al., 2021). In this regard, the relationship between the perceived costs of RE, environmental concerns (ECO), and ENAs plays a crucial role in adopting and accepting these technologies.

Perception of costs (PCO) of renewable energy refers to how people perceive the costs associated with using renewable energy sources, such as solar, wind, hydro, and geothermal, compared to traditional energy sources, such as coal, oil, or natural gas (Li et al., 2019).

Environmental concern (ECO) is a topic of growing importance today, reflecting people's awareness and sensitivity to environmental issues as well as the level of environmental awareness and sensitivity that motivates people to opt for renewable energy sources instead of traditional energy sources. Furthermore, they can be interpreted as people's concerns about the impacts of climate change, air, water, and soil pollution caused by the use of fossil fuels, and concerns about the limitations of natural resources (Arshad et al., 2021).

The beliefs, values, and willingness of the community towards the use and adoption of ERs in the context of environmental protection and sustainability (Pan et al., 2018). These ENAs can vary from person to person and are influenced by several factors, including beliefs about the importance of environmental protection, perceptions of the effectiveness of ERs, economic and social considerations, and confidence in technology and innovation (Tomsana et al., 2020). ENAs can influence individual and collective behavior concerning energy and the environment as well as government policies and decisions regarding the transition to a more sustainable energy system.

Although Mexico has experienced significant growth in the RE sector in recent years, it has also faced challenges in terms of cost perception, attitudes, education, public awareness, and policies, which are necessary to encourage investment in clean energy and drive a faster transition to a more sustainable energy system in the country. Therefore, although Mexico has high untapped potential regarding the ECO, PCO, and ENA of REs, no articles emphasize these variables. This study reports a structural equation model (SEM) that integrates three variables. Using the SEM results, a system dynamics (SD) model was developed to understand how these relationships and behaviors evolve, providing a more complete view of how a system changes and responds to different influences. A more holistic and complete view of how different factors interact and how phenomena develop over time can be obtained using SEM to understand the relationships between variables and SD in order to model a system’s temporal dynamics and feedback. Thus, the results of this study provide a quantitative understanding of the impact of cost on the Mexican population and their behavior over time regarding investments in solar energy.

The rest of the article is organized as follows: Section two focuses on a review of the literature, discussing the background, and how the variables are related, and proposes the hypotheses to subsequently design the structural equation model, section three focuses on the methodology used, explaining the process for obtaining SEM and system dynamics data, and finally, the results and conclusions obtained are presented.

2. Literature review and hypotheses

2.1. Relationship of PCO to ECO

PCO and ECO are closely related and can influence each other in several ways; for example, how society views the costs of REs can be influenced by environmental concerns (Kar et al., 2024). Government policies and incentive programs can influence perceptions of RE costs and ECO; for example, subsidies and support policies can make RE more accessible and affordable, thus strengthening the link between ECO and clean energy adoption (Solaymani, 2021).

On the other hand, a lack of equitable access to renewable technologies and regulatory or financial barriers can hinder the relationship between cost perception and environmental concern. Concerns about energy costs, climate change, and fossil fuel depletion have led many countries to switch to renewable energy sources, such as photovoltaic systems, because of their cost-effectiveness and environmental friendliness (Alasali et al., 2022).

In addition, the link between perceptions of RE costs and ECOs can be strengthened by the availability of accurate information and education on the subject. When people have access to clear and understandable data on the costs and benefits of RE compared with traditional energy sources, they can make informed decisions and align their environmental values with their actions (Wall et al., 2021). Consequently, we propose the following hypothesis:

H1. The perception of the cost of renewable energy directly and positively affects environmental concerns.

2.2. Relationship of PCO with ENA

Studies have shown that factors such as environmental concerns, awareness of renewables, and beliefs about the benefits of renewables play an essential role in influencing consumers' intention to adopt renewable energies (Wall et al., 2021). In addition, environmental attitudes have been found to positively affect the intention to adopt renewable energy technologies and support renewable energy policies.

Hast et al. (2015) analyzed consumers' attitudes toward green energy in China and their willingness to purchase it. They indicated that price and equipment issues are barriers to purchasing RE, demonstrating a direct relationship between cost perception and villagers' attitudes. On the other hand, Lucas et al. (2021) studied how to improve public attitudes towards renewable energies. As a result, there is resistance in the population, but it is decreasing daily, and citizen support is achieved through the purchase of RE. However, it is necessary to increase awareness of these technologies.

In addition, understanding residents' perceptions of renewable energy investment, the availability of renewable energy sources, climate change, and environmental conservation can lead to more efficient and sustainable implementation of renewable energy policies (Kiprop et al., 2019). Studies have also indicated that economic growth positively impacts the development of environmental awareness regarding the use of renewable energy and alternative fuels (Ceran, 2020). Therefore, we propose the following hypothesis:

H2. Perception of the cost of renewable energy directly and positively affects environmental attitudes.

2.3. ECO's relationship with ENA

Environmental concerns are central to shaping individuals' attitudes toward environmental issues, and research indicates a positive correlation between environmental concerns and attitudes. Environmental concerns encompass people's perceptions and convictions regarding the impact of human activities on the natural environment and their willingness to protect it (Borusiak et al., 2021). Cognitive and affective processes influence these concerns (Davis et al., 2019). Studies have shown that environmental concerns can lead to the development of favorable attitudes toward green products and behaviors (Cheung et al., 2015).

In addition, environmental concerns have been shown to affect individuals' attitudes toward specific environmental behaviors such as green purchasing behavior. Factors such as social influence, concern for self-image in environmental protection, and perceived environmental responsibility can be affected by environmental concerns and subsequently influence green purchasing behavior (Lee, 2008).

Likewise, as mentioned in the Unified Theory of Acceptance and Use of Technology (UTAUT), the intention to use and, in turn, the use of technology is determined by factors related to behavior and the environment. Thus, analyzing people's social context provides optimal ways to evaluate the interaction between environmental concerns and attitudes toward renewable energy (Palos-Sanchez et al., 2019).

In addition, environmental concerns have been found to positively influence attitudes and subjective norms, which impact intentions related to environmental behaviors, such as food waste separation (Ng et al., 2021). Additionally, renewable energy adoption is closely linked to environmental concerns, as consumers with significant environmental concerns tend to favor renewable energy adoption (Kar et al., 2024). Therefore, we propose the following hypothesis:

H3. Environmental concerns have a direct and positive effect on environmental attitudes.

Figure 1 illustrates the proposed model in which the proposed variables and hypotheses are related.

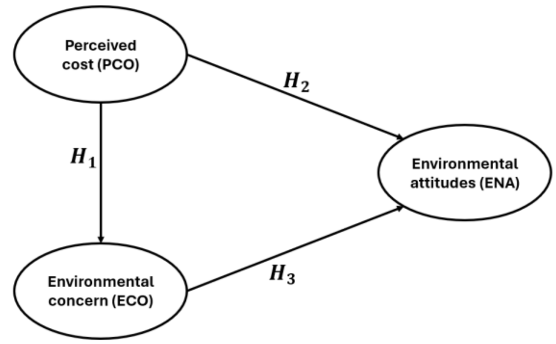

Figure 1. Proposed model

3. Methodology

Two stages were developed to carry out this research: the first corresponds to structural equation modeling to identify the relationships, and the second corresponds to system dynamics to model the impact over time.

3.1. Structural Equation Modeling

3.1.1. Questionnaire design and application

A literature review was conducted to identify previous studies that analyzed the same variables, which made it possible to identify the items, which was a rational validation. Subsequently, a preliminary questionnaire was developed consisting of two sections: the first focused on obtaining demographic information, with the answers being optional, and the second focused on the items of the variables analyzed, in which their answers were mandatory. Responses were recorded on a five-point Likert scale, where 1 = never, 2 = rarely, 3 = frequently, 4 = always, and 5 = always (Vonglao, 2017).

The questionnaire was administered through Google Forms to facilitate access to the respondents and ensure that they completed the total number of responses. A link with access to the questionnaire was sent by e-mail to people working in the maquiladora industry in Ciudad Juarez, Mexico. Once the period for receiving responses had elapsed, the platform was closed, and a database was downloaded in CSV format. This database was initially analyzed in Excel and subsequently exported to SPSS V.25 software for statistical analysis.

3.1.2. Debugging and validation of information

Extreme values were identified for information purification, and each item in the second section of the questionnaire was standardized. The median replaced values higher than four in absolute values (extreme values) (Hoffman, 2019)In addition, the deviation of each response obtained identified uncommitted respondents; if the result was less than 0.5, the case was discarded.

The following indices were used to validate the latent variables.

- R^2 and adjusted R^2 measure parametric predictive validity, and values greater than 0.02 are expected.
- Q^2 is expected to measure nonparametric predictive validity and values similar to R^2 are expected.
- Cronbach's alpha and the composite validity index were expected to measure internal validity and values equal to or greater than 0.7, respectively.
- The average variance extracted (AVE) to measure discriminant and convergent validity and values equal to or greater than 0.5 and 0.7, respectively, are expected.

  - The variance inflation index (VIF) measures collinearity, and values less than 3.3 are expected.

3.1.3. Structural Equation Modeling

Structural equation modeling (SEM) is used to statistically test the relationships between variables (hypotheses) because it allows the analysis of when they play independent and dependent roles. Furthermore, the partial least squares (PLS) approach was chosen because it is recommended when information is obtained from small samples or when there is no normal distribution (Kock, 2019).
WarpPLS v.8 software was used to evaluate the structural equation model with a confidence level of 95%, and the following efficiency indices were analyzed:

- The average path coefficient (APC), whose associated p-value must be less than 0.05, has predictive validity.
- The average R-squared (ARS) and average adjusted R-squared (AARS) were used to measure predictive validity; the p-value was expected to be less than 0.05.
- The average block VIF (AVIF) and average full collinearity VIF (AFVIF) measure multicollinearity and are expected to be less than 5.
- The GoF index measures the fit of the data to the model and is expected to be greater than 0.36.

3.1.4. Model effects

Within the model, direct, indirect, and total effects were evaluated. The first is the direct effect that validates the hypothesis, represented by a standardized β value that indicates the standard deviation that the dependent variable changes when the independent variable changes by one unit. In addition, the indirect effects that occur through mediating variables are evaluated and are especially useful when the direct effects are not statistically significant. Standardized β values also represent this; in this study, only the sum of these values is reported. Finally, the total effect is obtained, which is the sum of the direct and indirect effects. In addition, for each dependent variable, the R value² was estimated as a measure of the variance explained by the independent variable in the dependent variable.

3.2. System Dynamics

System dynamics (SD) was introduced by Forrester (1994) as a method for modeling and analyzing the behavior of complex social systems, especially in an industrial context. In this sense, SD is a rigorous system description method that facilitates feedback analysis, usually using a continuous simulation model of the effects of system structure and alternative control policies on the behavior of the system (Wolstenholme, 1982). As mentioned above, SEM is a technique based on modeling relationships between observed and latent variables that allows theories to be tested on how different variables are associated. Although it may include time variables, it generally focuses more on static models that analyze causal relationships at a given time. On the other hand, SD focuses on modeling complex systems through feedback loops and accumulation flows and provides insight into how system elements interact over time and how trends develop. In this sense, SD can generate new questions or hypotheses about causal relationships that can be tested using SEM.

SD has been used to estimate the probability of human error (Angelopoulou et al., 2019) and to support transportation and logistics problems in oil companies, where it has demonstrated its extensive predictive capabilities (Elena & Daniil, 2020). To implement the SD model, a series of six steps was established, which are described below in the methodology development in this research.

3.2.1. Step 1. System description

One of this research's objectives is to measure perceived cost's impact on environmental concerns and attitudes; therefore, the structural equation models are presented in Figure 1. The model in Figure 2 is a regressive model to achieve model feedback in a causal loop model to show cause-and-effect relationships between variables to understand the behavior of the system over time and, in turn, show positive or reinforcing feedback loops and negative flows indicating equilibrium (Rockow et al., 2019). These loops consist of nodes representing variables, and arrows indicating their causal relationships.

3.2.2. Step 2. Converting description to level and rate equations

Once the causal loop model was defined, a mathematical representation of the model was created, including equations describing the relationships between variables to simulate the SD model. An equation was established for each variable and its effect.

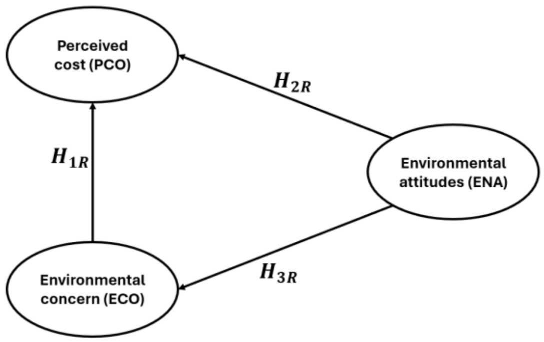

Figure 2. Feedback regression model

3.2.3. *Step 3. Simulate the Model*

Once the consistency of the variables and units of measurement within the model were reviewed, the simulation was carried out, establishing initial values of 0.1 for each of the variables, which assumes a perceived cost, concern, and environmental attitude of 10% to observe the behavior of the variables over time. The simulation was conducted for ten years.

4. Results

4.1. Demographic data

The questionnaire was administered in digital format using Google Forms. At the end of the application period, 511 responses were obtained, of which 211 were women and 297 men, and three people decided not to answer this question. In addition, 369 people were still students, and 142 were engineers working in maquiladora companies in Ciudad Juárez.

Likewise, the participants reported that the careers they developed were industrial engineering (182 responses), followed by mechanical engineering (63 responses). In addition, of the 142 active engineers, 88 participants worked in a large industry and 21 in a medium-sized company. The industrial sector with the largest number of responses was the automotive sector (77 participants), followed by the medical sector (34 participants).

4.2. Validation of the variables and the model

Table 1 shows the validation indices of the variables and shows that the R-squared, adjusted R-squared, and Q-squared values have good parametric and nonparametric predictive validity. In addition, the Cronbach's alpha and composite reliability indices were above 0.8, indicating strong internal validity. AVE also exceeded 0.5, suggesting adequate convergent validity. Finally, the VIFs were less than five, which rules out collinearity problems. In summary, the results support the interpretation of PLS-SEM.

Table 1. Validation of variables

Index	PCO	ECO	ENA
R-squared		0.169	0.364
Adj. R-squared		0.167	0.362
Composite reliability.	0.819	0.902	0.947
Cronbach's alpha	0.705	0.854	0.934
Avg. Var extract AVE	0.531	0.696	0.718
Full Collin VIF	1.256	1.476	1.549
Q-squared		0.167	0.366

The results in Table 2 suggest that the model is interpretable, given that the p-values in APC, ARS, and AARS are less than 0.01, indicating good predictive validity. In addition, the AVIF and AFVIF values were below 3.3, with specific values of 1.198 and 1.427, respectively, which rules out collinearity problems. The GoF index was 0.416, indicating an appropriate data fit to the model.

Table 2. Model fit and quality indices

Average path coefficient (APC)	0.373 p<0.001
Average R-squared (ARS)	0.266 p<0.001
Average adjusted R-squared (AARS)	0.264 p<0.001
Average block VIF (AVIF)	1.198, ideally <= 3.3
Average full collinearity VIF (AFVIF)	1.427, ideally <= 3.3
Tenenhaus GoF (GoF)	0.416, large >= 0.36

4.3. Results of direct, indirect, and total model effects and validation of hypothesis

Figure 3 illustrates the model evaluated to validate the hypotheses and Figure 4 shows the results of the feedback model. For each relationship, a β value and its associated p-value are illustrated along with the value of the effect size (ES). For each dependent variable, the value of R2 as a measure of the explained variance is also illustrated.

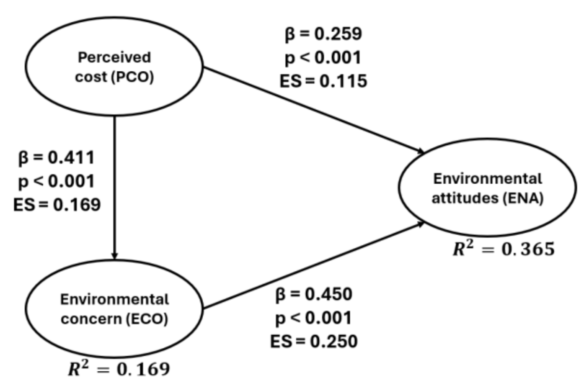

Figure 3. Model evaluated

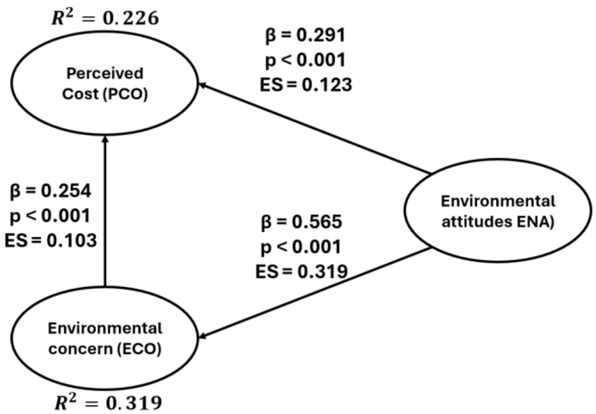

Figure 4. Evaluated regression model

A summary of the hypotheses is presented in Table 3, showing the standardized β values, the corresponding p-values, and the conclusions derived from these for each hypothesis. According to the p-values, all relationships between the variables were statistically significant, confirming the acceptance of the hypotheses. For example, the relationship PCO→ECO indicates that when the variable PCO increases its standard deviation by one unit, Echo does so by 0.411 units, with a 99.9% confidence level.

Table 3. Direct effects

Hypothesis	β(p-value)	Conclusion
PCO→ECO	0.411 (p<0.001)	Accept
PCO→ENA	0.260 (p<0.001)	Accept
ECO→ENA	0.450 (p<0.001)	Accept

In this case, there was only an indirect effect between PCO→ENA through ECO, which was statistically significant (β=0.185, p<0.001). Table 4 shows the total effects, which are statistically significant. In this case, the ratio of ECO→ENA is the highest because it is the only one that includes an indirect effect.

Table 4. The sum of indirect effects

Total Effects			
PCO	PCO	ECO	ENA
ECO	0.411(p<0.001) EN=0.169		
ENA	0.444 (p<0.001) EN=0.196	0.450 (p<0.001) ES=0.250	

4.4. Initial parameters in SD

Figure 5 shows the CLD of the SD model, which was integrated with the SEM models shown in Figures 3 and 4. This CLD is formed by three loops that represent each of the variables represented by red squares. A variable called the desire level was added for each latent variable, which measures the level that each variable is expected to reach. In this case, these variables are expected to reach a value of one, which represents 100%. The gap variables measure the difference between the desired and reached levels at a specific time. For example, if there is an attitude level of 20% at a certain point, the gap variable has a value of 0.8. Water tanks represent the adjustments to be made in the activities of each tool, which are fed by the weights of the indicators, gaps, and the *desired level* for each variable. All of these are auxiliary variables because the water reservoir is fed by other variables that directly affect them. To run the simulation, the initial parameters were set to a *desired level* of 0.1. The simulation was conducted for 10 years.

Once the causal loop model was defined, a mathematical representation of the model was created, including equations describing the relationships between the variables. The proposed equations are as follows.

PCO is the variable that measures the costs of technology acquisition and is defined by

$$\boldsymbol{PCO_t} = \boldsymbol{PCO_{t=0}} + \int_0^t (\boldsymbol{APCO})\, \boldsymbol{dt} \qquad (1)$$

Where:
A: Adjustment of activities.
G: represents the difference between the desired and executed levels.
w: represents the weights of the indicators for each LV.
APCO represents the adjustment to the PCO variable. It is the sum of the product of each regression coefficient (RC) of ECO and ENA multiplied by the PCO indicators (w), that is, PCO1, PCO2, PCO3, and PCO4.

GPCO represents the difference (gap) between the desired PCO level and the level reached at a given instant. The equations for the three variables were established similarly.

$$* \boldsymbol{APCO} = \boldsymbol{GPCO}\left[(\boldsymbol{RC_{ECO \to PCO}} * \boldsymbol{ECO}) * \sum_{i=1}^{4} \boldsymbol{wPCO_i} + (\boldsymbol{RC_{ENA \to PCO}} * \boldsymbol{ENA}) * \sum_{i=1}^{4} \boldsymbol{wPCO_i}\right] \qquad (2)$$

$$\boldsymbol{ECO_t} = \boldsymbol{ECO_{t=0}} + \int_0^t (\boldsymbol{AECO})\, \boldsymbol{dt} \qquad (3)$$

$$AECO = GPCO\left[(RC_{PCO\rightarrow ECO} * PCO) * \sum_{j=1}^{4} wECO_i + (RC_{ENA\rightarrow ECO} * ENA) * \sum_{i=1}^{4} wECO_i\right] \tag{4}$$

$$ENA_t = ENA_{t=0} + \int_0^t (AENA)\, dt \tag{5}$$

$$AENA = GEAN[(RC_{PCO\rightarrow ENA} * ENA) * \textstyle\sum_{k=1}^{4} wENA_i + (RC_{ECO\rightarrow ENA} * ECO) * \sum_{i=1}^{4} wENA_i] \tag{6}$$

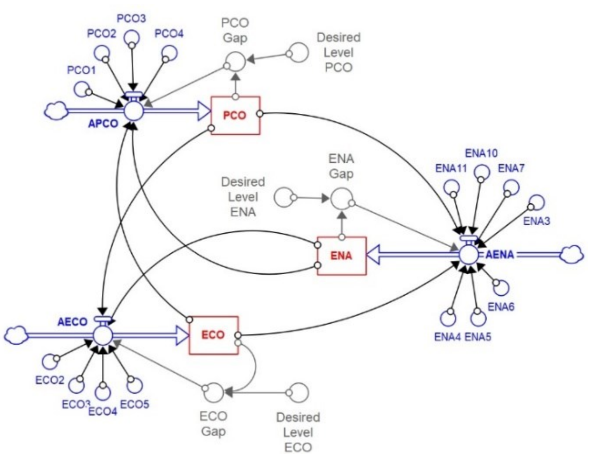

Figure 5. The simulation model was constructed using Stella Architect ® Software.

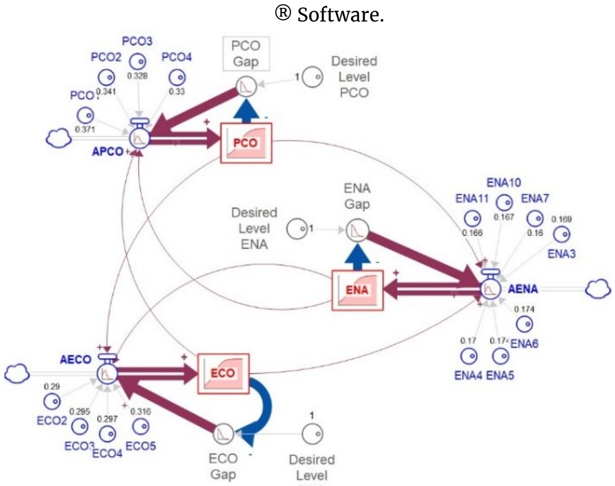

Figure 6. Simulated model

4.5. Evaluation of the simulation model

Figure 6 shows positive (red arrow) and negative (blue arrow) flows. As for positive influences. The Gap in each variable directly influences the water reservoirs, that is, the latent variables. If this Gap increases, the adjustments should increase. In the negative influence, if the application level increases, the gap decreases, that is, the higher the application level, the lower the desired level. Click here to observe the simulation's behavior for each scenario: https://exchange.iseesystems.com/public/roberto-diaz/environmental-attitude.

Figure 7 shows the simulation results for ten years. The x-axis shows the simulation period in years and the y-axis shows the level of attainment for each variable. The initial value for each variable was set at 0.1; practically, for this simulation period, 100% was reached for each variable. At the beginning of the year, the population shows a growing interest in the three variables, giving rise to the interaction and development of plans that are related in favor of renewable energies. Over the years, people have interacted 100% with the variables, that is, the perception of costs, environmental concern, and attitudes about green energies are an issue that develops in people's daily lives.

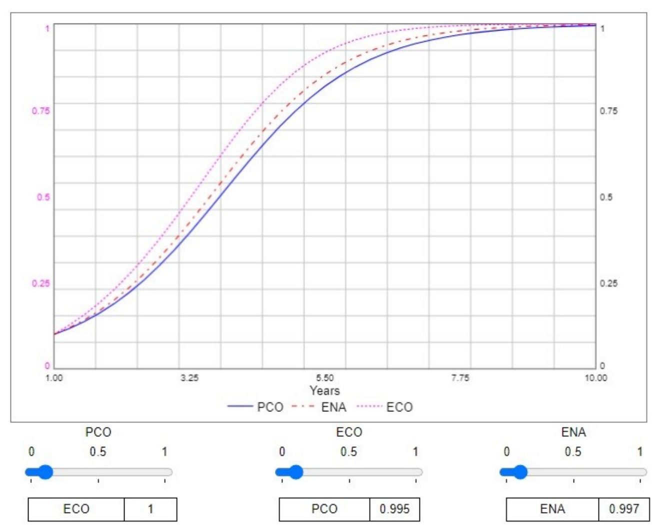

Figure 7. Simulation results

5. Conclusions

Based on the results obtained from the structural equation and system dynamics models, the following conclusions can be drawn:

The items related to the cost of acquiring technologies for renewable energy generation suggest that, according to the participants' perceptions, cost directly and positively affects both environmental concern and attitude. This indicates that the lower the perceived cost associated with adopting renewable technologies, the higher the concern for and favorable attitudes toward these technologies.

The items related to environmental concerns indicate that this variable directly and positively affects environmental attitudes. This highlights the importance of environmental concerns as a significant predictor of attitudes and behaviors toward adopting renewable energy technologies. Participants who are more concerned about environmental issues tend to have more positive attitudes toward adopting renewable technologies.

The relationship between cost, environmental concern, and attitude highlights the interconnectedness and complexity of these factors in forming environmental attitudes and behaviors. While cost may directly influence environmental concern and attitude, environmental concern may indirectly affect the relationship between cost and environmental attitude.

While there is potential for an increase in the adoption of renewable technologies among university students over time based on perceived costs and their impact on environmental concerns and attitudes, it is critical to interpret these results with caution. Achieving 100% change in environmental attitudes is a challenging and complex goal that can be affected by several external and internal factors. Therefore, it is crucial to recognize the limitations and assumptions inherent in the models and consider that the results may vary, requiring a continuous and long-term focus on promoting sustainable behaviors and environmental awareness.

The present study provides a comprehensive view of how perceived costs and environmental concerns interact to influence attitudes toward renewable technologies and establish a framework for future research. Future research should further explore the external and internal factors that may mediate or moderate this relationship, such as government policies, awareness campaigns, and the evolution and accessibility of technology. Furthermore, it is important to investigate how these dynamics manifest in different cultural and economic contexts to develop more effective and contextualized strategies.

Finally, this study contributes significantly to environmental education and the promotion of renewable technologies by providing a solid empirical basis and innovative methodological approach.

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