RESEARCH PAPER

Enhancing Trust Through Personalized Interactions and Reciprocated Trust Factors in AI Applications

Dr. M. Sukanya[1*], Dr. A. Priya[2], Praveena Ayyasamy[3], Dr. S. R. Rajabalayanan[4], Aswathy P. B[5], Dr. M. Arunachalam[6], Saveetha R[7], Negalurmath Vinayakaswami[8]

[1*]Associate Professor, Department of Computer Science and Engineering, Kathir College of Engineering, Coimbatore, Tamil Nadu, India. Email: sukanmukesh@gmail.com

[2]Assistant Professor, Department of Computer Science and Business Systems, KIT - Kalaignarkarunanidhi Institute of Technology, Coimbatore, Tamil Nadu, India. Email: drpriyaa@kitcbe.ac.in

[3]Assistant Professor, Department of Computer Science and Engineering, Hindusthan Institute of Technology, Coimbatore, Tamil Nadu, India. Email: praveenaayyasamy@gmail.com

[4]Professor & Head, Department of Mechanical Engineering, Hindusthan Institute of Technology, Coimbatore, Tamil Nadu, India. Email: rajabalayanan@gmail.com

[5]Assistant Professor, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, India

[6]Professor, Sri Krishna College of Engineering and Technology, Coimbatore, Tamil Nadu, India. Email: dr.arunachalam13280@gmail.com

[7]Assistant Professor, Department of Computer Technology, Bannari Amman Institute of Technology, Sathyamangalam, Erode, Tamil Nadu, India. Email: savee13@gmail.com

[8]Assistant Professor, Department of Information Technology, VSB Engineering College, Coimbatore, Tamil Nadu, India. Email: negalurmathv@gmail.com.

* Corresponding Author: **Dr. M. Sukanya**

Received: 12th Feb 2026; Revised: 19th March 2026; Accepted: 30th March 2026; Available Online: 15th April 2026

Abstract - Even though AI often seems accurate, it can still make mistakes. This paper examines the productive use of AI in urban management and evaluates user trust in AI systems, particularly ChatGPT. It examines several ways in which AI experts, non-experts, and those in the energy domain use AI, as well as how they develop mistrust, doubt, or over-trust in the results produced by AI, which often suggests the dangers of these trust states. Both trust and distrust can affect AI-assisted decision-making, which can lead to unnecessary rejection of accurate AI suggestions, ultimately reducing the benefit of AI. This study explores an important gap in AI trust behaviors, which can be ignored by normal models. This was done by using the VIRTSI (Variability and Impact of Reciprocal Trust States Toward Intelligent Systems) theory to observe the evolution of human-AI trust through Deterministic Finite Automation (DFA) and measure trust actions using user-adapted confusion matrices. The results confirm that VIRTSI can monitor changes in trust. According to the study, energy experts tend to over trust AI because of its confident and seemingly reliable responses, while AI experts show mistrust because they are aware of AI's limitations. Non-experts show inconsistent trust, which highlights decision-making issues. In the end, it confirms VIRTSI as a key model for evaluating and improving confidence in AI-driven solutions, ensuring that AI systems are not only trusted but also used effectively and ethically in energy applications. Unlike other previous models of technology acceptance that merely focus on adoption, VIRTSI offers a continuous and statistical approach to trust measurement, identifying negative trust patterns and suggesting improvements. Unlike previous models of technology acceptance that merely focus on adoption.

Keywords: Urban management, AI, Human-AI trust, user models, AI systems, Language models.

How to cite this article: Sukanya M, Priya A, Ayyasamy P, Rajabalayanan SR, Aswathy PB, Arunachalam M, Saveetha R, Vinayakaswami N. Enhancing Trust Through Personalized Interactions and Reciprocated Trust Factors in AI Applications. Int J Drug Deliv Technol. 2026;16(5): 1160-1180. DOI: 10.25258/ijddt.16.5.109

1. INTRODUCTION

1.1 Background and Importance of Language Model: Its Significance in the Urban Energy Sector

Artificial intelligence (AI) has made a greater impact on today's businesses by improving data analysis and automating complex processes in organizations. Important developments include deep learning and machine learning, which made useful applications, such as improvements in deep learning methods and hybrid AI models [1]. These machine learning models and analyses influenced areas like healthcare, education, and businesses. Deep learning also benefits fields such as computer vision, natural language processing, and autonomous systems [2], [3]. The ability to handle difficult computational tasks in technical applications should be appreciated. Artificial intelligence (AI), information systems, and applications are more developed, which makes it easier to include AI in many kinds of fields. These developments promote better decision-making and automation while boosting AI's involvement in fields like autonomous systems and data analysis [4], [5]. Surveys on AI-based technologies provide many uses in several sectors as well as for future advancement [6], [7].

Moreover, changes in Knowledge-based Software Engineering are contributing to more efficient AI-driven decision-making processes and software system design, helping to solve increasingly complex and dynamic challenges [8]. Research in Smart Decision Technologies continues to provide valuable platforms for exploring advanced AI systems and handling difficult challenges [9]. AI helps in increasing carbon reduction in energy-intensive businesses by improving energy production, delivery, and consumption. It is important for helping the movement to greener, more sustainable energy systems [10]. AI technologies give new solutions to the difficult challenges of decarbonizing in the energy industry [11]. These developments are needed for improving grid management, like developing energy storage technologies as well as improving the utilization of renewable energy sources, which helps to support the global goal of reducing carbon emissions. In addition, AI supports industries in aligning their operations with the high carbon reduction targets set forth by the Paris Agreement [12]. The Paris Agreement highlights the critical need to keep global warming well below 2 degrees Celsius (United Nations, 2015), requiring new methods of reducing the effects of climate change [13]. AI may greatly help such attempts through using creative methods to improve demand responses and overall efficiency [14], as well as applying transfer methods of learning for solar power forecasting under data shortages, improving primary issues in renewable energy management[15]. The language model that is considered important today is ChatGPT by OpenAI [16], which is based on generative artificial intelligence and has great potential for urban energy. This tool is used by all urban energy consumers, including building owners, tenants, landlords, residential managers, and energy experts, as ChatGPT can offer both solutions and advice on complex topics because of its natural language fluency and vast knowledge base from huge data sets. ChatGPT helps users by providing easily available information and gives guidance on energy-saving techniques. But when AI is included in important decisions, the measure of accuracy of the information and trust that both expert and non-expert users place in these technologies is to be questioned. ChatGPT is used in many industries, such as business, education, and healthcare for various things. However, the accuracy of its responses and the efficiency of human-AI interactions might vary greatly across various fields, making it important to evaluate its performance on a domain-by-domain basis. For example, in the business sector, [17] an empirical study analyzed the benefits of ChatGPT for organizational performance, showing its importance in improving business operations. Also, in healthcare, [18] ChatGPT's performance in medical examinations, records, and education in Chinese reviews its abilities towards improving medical practices.

1.2 Application of Chat GPT and Trust Evaluation Across Domains

In education, [19] explored ChatGPT's role in resolving independent learning challenges, especially in mathematics showing its efficacy in educational environments. [20] tested ChatGPT's capabilities in the field of chemistry, searching if huge language models to understand complicated scientific topics. Reference [21] explores how ChatGPT could be utilized to improve learning in physics education. Similarly, [22] others study the function of ChatGPT in Intelligent Traveling, an important area in AI-driven autonomous systems, focusing on how it is used in interactive engines for intelligent driving technologies. The performance of this language model varies greatly depending on the field that it was applied to. So, these studies show how important it is to measure accuracy and engagement in different fields. The current work focuses mainly on generative AI systems, especially Large Language Models (LLMs) such as ChatGPT, rather than usual machine learning or deep learning methods. This research develops upon the initial research given in [23], which studied the interaction of non-expert stakeholders with AI in the energy urban area using the VIRTSI (Variability and Impact of Reciprocal Trust States towards Intelligent systems) framework [24]. While that study offered basic insights into how users interact with AI-driven tools and trust transitions, the current work expands the analysis by adding expert stakeholders from two categories, like AI experts and Energy Domain experts that helps in improving the VIRTSI model for a deeper evaluation. This paper tries to provide a clearer insight about trust assessment and its consequences for using AI in urban energy systems by looking at how both expert and non-expert users engage with AI. Mainly, it examines the relationship between three stakeholder groups, such as energy domain specialists, AI experts, and non-experts in either domain, in the energy sector by using the VIRTSI model and ChatGPT. The VIRTSI model is a useful model for this purpose, as it uses adapted confusion matrices to evaluate the efficacy of human-AI interaction, from over trust to distrust [24], recreating different levels of trust. This paper aims to prove by using finite state automation and confusion matrices to measure the trust in AI systems. Also, by focusing on stakeholder interaction with AI in the urban energy area, this research tries to evaluate how AI experts, energy sector experts, and non-experts trust the outputs produced by AI. Identifying the risk factors of trust and overconfidence in AI and how they affect AI-assisted decision-making in energy applications. Filling the gap between Traditional AI acceptance models by testing with the VIRTSI framework to monitor and tune trust constantly. Evaluate how well various user groups use AI, keeping in mind that people from different backgrounds may engage with AI at different degrees of performance.

2 Literature Review and Development hypothesis

2.1The Impact of Artificial Intelligence on Renewable Energy Optimization: A Systematic Review

AI has become an important tool for solving energy-related problems such as improving energy efficiency, measuring sustainability, and simplifying the inclusion of renewable energy sources. AI systems are being used more in many kinds of energy-related fields for automating energy-saving methods, improving resource management, and influencing policy development. AI is essential for improving energy efficiency in the building business. Reference [25] created an intelligent decision support model for evaluating ways to save energy in buildings. It enables finding the best methods for minimizing consumption of energy. This application expanded by establishing AI-based automation tools to manage the consumption of energy in tertiary sector buildings. These developments enable real-time monitoring and control and help in massive energy savings [26]. In addition, AI also assists in sustainable energy evaluations, particularly for rural areas. Principal Component Analysis (PCA) is applied to evaluate the energy sustainability of rural populations by Reference [27]. This method helps to create customized energy solutions for rural areas and offers statistical insight into the patterns of energy consumption. Another area where AI is useful is in the integration of renewable energy sources into the energy system. While [15] investigated the use of AI to determine the sustainability of renewable energy options using a new transfer learning technique, [28] reviewed the features and clients of nuclear power and renewable energy in the context of sustainable development, showing how AI models can help decide the most useful energy choices for the future.

Development of policies in the energy industry also benefits from AI. Reference [29] examined sustainable energy policy variables and gave AI-supported techniques for the improvement in policy creation and analysis. These techniques ensure that energy policies are successful in achieving both financial and sustainability goals. AI is applied increasingly to real-time energy management, particularly in hybrid systems. To improve power management in hybrid energy storage systems for plug-in hybrid electric vehicles, Reference [30] used reinforcement learning. Similarly, [31] used a reinforcement learning technique for the best control of hybrid AC-DC microgrids. These AI methods improve energy distribution networks' efficiency as well as productivity.

Used artificial neural networks to track energy conservation attempts but developed ensemble machine learning models for evaluating the energy savings of conservation efforts. These models provide an accurate estimate of energy savings and help in the effective conservation efforts [32], [33]. For example, it examined artificial intelligence methods for load demand forecasting, highlighting its importance in ensuring effective energy distribution and resource management [34]. In conclusion, AI is changing the energy sector by raising performance, boosting renewable energy integration, improving the development of policies, and optimizing energy management systems.

2.2 The Role of Transparency and Accountability in Building Trust in Personalized AI Systems

Like other industries, there is a rising concern about using AI in the energy sector. The European Commission High-Level Expert Group on AI has stressed that AI needs to be used in a safe and ethical manner. Trusting AI is a complex idea that is affected by both social and intellectual variables [35]. According to Source [36], mistrust of AI is different from mistrust of humans since AI systems provide specific challenges in building trust. Thus, developing trust in AI requires addressing both technological reliability and social- psychological aspects.Because of this, user simulation is important for trust, and enhances human-AI interaction. Understanding human cognitive processes is important, particularly for industries like energy, where AI must adapt to both expert and non-expert users. It also points out how specific AI systems may promote trust by changing users' decision-making processes [37]. The ability of Intelligent Tutoring Systems (ITS) is that machine learning customizes learning experiences [38], which helps users by providing user-friendly interfaces as well as customized information [39].Various techniques for user-friendly models exist. While fuzzy logic was used in [41] to explain users' levels of understanding, machine learning models have been used for the identification of emotions in speech [40]. AI-driven personalization, enabled through fuzzy logic and artificial intelligence (AI), has been proven to boost user happiness in educational situations [42]. In [43], similarity detection through choosing features was explored, as well as how AI reasoning helps decision-making, correcting errors, and adaptability [44][45].

These techniques improve user experiences by making sure artificial intelligence (AI) take into consideration their needs and abilities, especially proved in the developments in intelligent tutoring systems [46], [47]. These similar user modelling techniques can be used for human-AI interactions in energy systems, where trust in AI is important for both non-expert and expert stakeholders.Since the energy field faces a digital change, artificial intelligence (AI) systems are being used for many things, like to improve operations, to manage the balance between demand and supply, to predict usage of energy, and to connect renewable energy sources into the power system. Such applications are useful, but their efficiency depends on the trust that stakeholders—both expert and non-expert—place in them. This trust in AI is important, as there were high-stakes decisions and complexity of the systems involved. Many factors affect the trust in AI by the energy sector, such as the system's overall consistency, transparency, and clarity. Stability in these is vital, as decisions made by AI systems directly affect energy efficiency, cost, and even safety. For example, artificial intelligence is used in automated repair and electricity control to detect problems and prevent shortages. Failure of these systems might result in a major impact on both society and the economy. But people's views of consistency, transparency, and clarity are influenced by their individual experiences with AI, their level of knowledge in the field, their ability to confirm AI actions, and their understanding of AI.

2.3 The Role of the VIRTSI Model in Shaping Human Trust in Artificial Intelligence Systems

The study tries to solve the existing gap in cognitive trust modeling in human-AI interactions, especially in the energy domain. To help with this, the VIRTSI model, developed from previous studies [24], offers a strict statistical framework for understanding trust dynamics, particularly in the context of autonomous decision-making. Understanding human trust in AI requires a framework that captures the dynamic and context-dependent nature of trust. Traditional models view trust as a constant impression changed by system skills such as reliability, transparency, or usability. However, in high-stakes domains such as urban energy management, trust changes depending on real-time interactions and the reliability of AI outputs.

- **Four main trust states are identified by VIRTSI model**

Changes in the trust states: How relationships, situations, and system performance impact trust in intelligent systems (like AI, robots, or automated decision-making systems). Trust is not fixed; it can differ continually according to elements like stability, transparency, and past system behavior.

Influence of Trust in System Use and Efficiency: This study evaluates how changing the levels of trust influence users' decision-making, acceptance, and dependence while managing automated systems. Users might depend more on AI suggestions if trust grows; if it decreases, people might ignore or dismiss suggestions.

Stages of Trusting Each Other Using Intelligent Systems—Trust is not simply one-sided (people trusting AI); instead, AI systems show actions, which affect the user's trust. For example, AI systems that adapt, discuss decisions, or personalize experiences can create a feeling of common understanding, which helps in increasing trust among users.

All these states are evolving, suggesting that people may switch from one to another as they engage with AI over time. This method shows the importance for tracking not just fixed trust levels but also the amount and patterns of state changes, that have an impact on the accuracy of decisions.

3.METHODOLOGY

3.1 Stakeholder Groups:

The VIRTSI model that was used in this study is to monitor the changes in patterns of trust and to evaluate the consequences of potentially harmful states like mistrust and over trust. To evaluate human-AI interaction in the context of energy use, economical solutions, and renewable energy production, the study used a GAI system driven by large language models called ChatGPT.

No of participants: 10 energy experts, 10 AI experts, and 23 non-expert stakeholders

Non-expert participants (23) - Because non-experts are the main group who use artificial intelligence (AI) tools like ChatGPT for everyday energy-related decisions and, the number of non-expert users was purposely increased to better represent the opinions of the public. As more people are added from this group, more accurate analysis can be done on how common end users view the generative AI systems. The participants, who were a mix up of building managers and homeowners without any formal training in energy, were in charge of reviewing the results produced by AI.

Expert groups in AI (10)- As there were fewer qualified workers for maintaining a balanced mix across both energy and AI domains, the expert groups were limited to ten participants for each. The purpose of these expert participants was to provide accurate reviews and act as targets for evaluating the accuracy and quality of AI-generated responses. These people had at least two years of practical experience with AI technologies and university degrees in related subjects.

Energy Expert Stakeholders (10)- Every participant has at least two years of work experience in the energy industry and a university degree in an energy-related subject.

The mix of twenty-three ten and Ten participants were selected so as to create a balance between the breadth of general user input and the depth of knowledge, allowing the research to gather both ordinary user trust patterns and expert views.

Five types of human trust were the topic of the study: Trust- the maximum level of confidence about the system's durability and function. Distrust- a lack of trust due to previous experiences or knowledge. A large lack of trust due to a specific reason is known as mistrust. Over trust-When trust rises above its actual skills, safety or wellbeing can be affected.

3.2 Tasks, Data, and Questionnaire Structure

Using a 16-question survey to observe the ability and use of ChatGPT's answers on energy usage, other sources of energy were examined by the users. This assessment gave useful information about ChatGPT's use in providing complex data between expert and non-expert users, which made stakeholders either approve or reject the AI's answers based on their accuracy and relevancy that had been observed. The issues are identified based on the study group's energy experts' direct conversations with energy stakeholders, using Frequently Asked Questions (FAQs). Additionally, to create multiple trust state variations for users and to assess how their trust in ChatGPT changes during the period of the conversations, a number of important elements have been included when creating the questions.

Collection of data:

Using ChatGPT's past responses, a few questions were created to accept or oppose ChatGPT's answers, allowing people to think about how accurate it is.

Actual confirmation: tested how users respond to incorrect or unclear answers with accurate searches, which can show ChatGPT's errors, like producing mistakes.

Personal priority: ChatGPT was requested to put a value on answers for particular questions in order to see how users felt about its ability to make decisions and make judgments.

Simple but interesting questions: In order to show ChatGPT's accuracy and fluency and to increase user trust, some questions were created that were very simple to answer.

Questionnaire Structure

After participating in any of the other energy content, users were first asked to share their first ideas about trusting AI and ChatGPT, shown in Table 1. The goal of this stage was to set an example for participants' views on AI systems. Then the study was able to measure changes in views during initial participation. Because of this, the final testing gave important data on how using ChatGPT affected participants' trust in AI.

Table 1. Initial and final questions about trusting AI and ChatGPT.

OPTION	TRUST LEVEL
A	I trust it.
B	I trust it with doubts
C	I tend not to trust
D	I do not trust it
E	I do not know

Later, users were asked a series of questions about energy, and ChatGPT answered each one. They were asked to determine how accurate and helpful the AI's answers were. Participants choose whether to approve or reject ChatGPT's response to each question about energy. Before making their choice, participants additionally added if they confirmed the facts. Table 2 shows the multiple-choice answers for each question on the survey.

Table 2. Multiple choice options for each question of the questionnaire.

OPTION	EVALUATION CRITERIA
A	I accept ChatGPT's reply without validating it
B	I accept ChatGPT's reply after validating it
C	I reject ChatGPT's reply without

	validating it
D	I reject ChatGPT's reply after validating it

Users were asked to review their trust level in ChatGPT after completing the energy-related questions and examine their ChatGPT's responses. The study did not show any changes in trust during their interactions with the AI system because the final trust assessment used the same answers as the first assessment. Examples of the particular questions in the questionnaire are shown in Table 3.

3.3 Exploring the Impact of the VIRTSI Evaluation Framework on Stakeholder Engagement and Decision-Making Processes

This section explains how trust patterns and interactions are represented using the VIRTSI model. It also describes how the VIRTSI framework's DFAs and confusion matrices are used to recreate the questionnaire answers and also uses the VIRTSI 54 to show user responses to ChatGPT interactions. The data symbols and trust states explain how users' trust changes in reaction to their confirmation actions during ChatGPT interactions.

States of the VIRTSI Trust:

Trust (T): Trust and confirmation in proportion.

Over trust (O): Dependence too heavily

Unconditional (U-O): takes answers without verification.

Defective (D-O): Needs to make sure but are unable to.

Random (R-O): Has random trust.

Distrust (D): Negative opinion

Unconditional (U-D): ignores answers without taking them into considerations.

Defective (D-M): Makes a poor attempt at verification.

Justified (J-M): Rejects after a verification fail.

Random (R-M): Mistrusts without reason.

Symbols for Input:

Positive (P): Acceptance

P_sv: Not verified.

P_uv: Following a verification error.

P_cv: After the proper verification

Table 3. Examples of questions of the questionnaire.

Question	ChatGPT Reply (New Text)	Correctness of ChatGPT Reply according to Experts	Final Verdict
1. What are the most effective strategies for improving energy efficiency in residential buildings?	One of the most effective strategies for improving energy efficiency in residential buildings is enhancing thermal insulation. Proper insulation helps maintain stable indoor temperatures, reducing the need for heating and cooling systems. This results in significant energy savings and increased long-term efficiency. Improvements may include roof and wall insulation, high-performance windows, sealing air gaps, and using energy-efficient exterior	Mostly correct answer but includes subjective prioritization.	Correct

	materials.		
2. What is the typical annual electricity usage for a medium-sized household in a European city?	The annual electricity consumption of a medium-sized household in Europe depends on building quality, number of residents, and appliance efficiency. On average, the total may range between 12,000 and 25,000 kWh per year, including heating, cooling, water heating, lighting, and appliances.	Mostly correct answer but includes subjective parts in terms of generalization.	Correct
3. What are effective methods cities can use to mitigate urban heat island effects?	Cities can reduce urban heat islands by expanding vegetation, developing green roofs and parks, installing reflective surfaces, increasing shaded areas, and designing climate-responsive urban spaces. Using cool pavements and water-based cooling structures can also help lower outdoor temperatures in dense urban areas.	Mostly correct answer but includes subjective parts in terms of generalization.	Correct
4. Which of the mitigation methods is considered the most impactful?	Increasing vegetation and urban forests is commonly considered among the most impactful long-term solutions for cooling cities, as trees provide shade and reduce surface temperatures through evapotranspiration. Additional benefits include improved outdoor comfort and community resilience.	Partly correct answer but includes irrelevant parts not focused directly on heat reduction.	Incorrect (partly irrelevant information)
5. Why did you mention non-heat-related benefits such as visual or psychological comfort in your	You are right to point out that psychological or aesthetic benefits are not directly connected to temperature reduction. The answer should	Mostly correct answer but includes subjective parts in terms of prioritization.	Correct

previous thermal-reduction explanation?	emphasize functional cooling factors like shade coverage, evapotranspiration, and reduced heat absorption through vegetation density.		
14. Provide reliable academic references on renewable energy solutions for urban households.	Suggested references included books and research articles on renewable energy, solar systems, and home-based green solutions. However, some entries were incorrectly cited or not verifiable in academic databases.	There are correct references but also hallucinated references which do not exist. It is considered wrong.	Incorrect (Hallucinated References)

Table 4. Table showing VIRTSI framework's DFA

State	N_sv Without Verification	P_sv Without Verification	N_uvFailed Verification	P_uvFailed Verification	N_rv Successful Verification	P_cvSuccessful Verification
T						
UO	R_M	U O	R_M	D O	J M	T
DO	R_M	U O	D_M	D O	J M	T
RO	R_M	R O	D_M	D O	J M	T
UD	U_D	U O	D_M	R O	J M	T
DM	U_D	R O	D_M	D O	J M	T
JM	U_D	R O	D_M	D O	J M	T
RM	R_M	R O	R_M	R O	J M	T

Negative (N): Rejection:

N_sv: Without verification.

N_uv: After failed verification.

N_rv: After successful verification.

The VIRTSI DFA is summarized in Table 4.

4. RESULTS

4.1 Non-Expert Results

The research study explored three different stakeholder groups' basic levels of trust in AI-generated solutions in the energy sector: Non-Expert Energy Stakeholders, AI Experts, and Energy Expert Stakeholders. 30% of stakeholders who are not experts showed total trust in answers given by AI.

20% of respondents said that they had doubts but still trusted AI.
10% of respondents decided against artificial intelligence (AI).

20% of the respondents showed an absence of trust by dismissing the AI responses. Another 20% stated confusion, meaning they were unclear about their decision to trust the AI.
Conclusion: Non-expert stakeholders' answers show a wide variety of trust levels, with many of them either completely trusting in the AI or having concerns about it.

4.2 AI Experts Results

The AI answers were just entirely trusted by 30% of AI professionals.
A careful strategy was seen in the majority, 15%, which trusted the AI but had a few concerns.

7.5% of AI specialists said they didn't trust AI. A further 17.5% had absolutely no trust in the AI. There was a little percentage that was there but not identified for clarity, showing little trust or confusion (30%).

Conclusion: The data show that experts in AI maintain a critical but generally positive view of AI, with the majority of them trusting AI-generated solutions with a few doubts.4.3

Energy Expert Results:

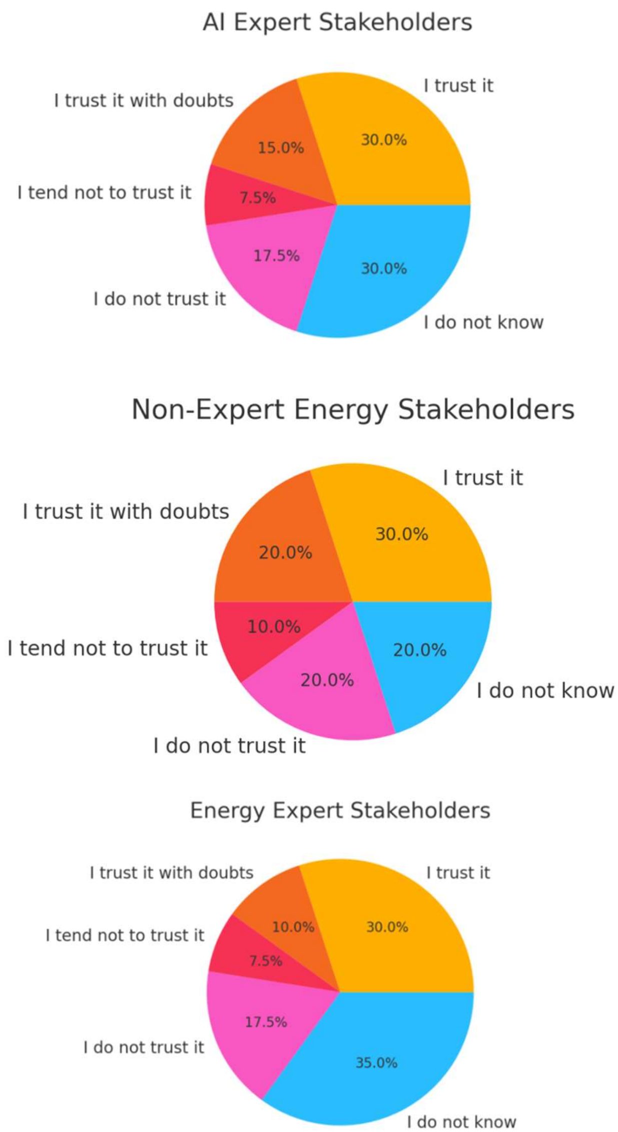

Figure 2. Initial Trust States of Expert and Non-Expert Energy Stakeholders to AI.

30% of energy experts answered they had total trust in the AI answers. 10% of the participants have some worries about the AI. 7.5% of the participants said they didn't trust the AI. 17.5% said they were totally mistrustful. 35% of the participants weren't sure if they should believe the AI or not.

Conclusion: The amount of trust between energy experts shows a more balanced views, with many of them showing complete trust while others expressing doubt or express mistrust. These findings explain how various stakeholder groups' opinions on trust in AI change depending on their amount of familiarity and experience with the technology. Three pie charts showing the trust patterns for Non-Expert Energy Stakeholders, AI Experts, and Energy Expert Stakeholders are used in Figure 2 to show the findings. As shown in Table 5, the confusion matrix using VIRTSI was created based on 322 responses that the 23 non-expert energy gave to the main section of the survey, which consisted of 14 questions about actual ChatGPT interactions with non-expert and expert stakeholders.

Table 5. The confusion matrix of non-expert, domain expert, and AI expert stakeholders according to VIRTSI DFAs

TOTAL INTERACTIONS WITH 23 NON-EXPERT ENERGY STAKEHOLDERS	
PERCENTAGES of NON-EXISTENT OR FAILED VALIDATION vs SUCCESSFUL VALIDATION in POSITIVE AND NEGATIVE ACCEPTANCE	**VIRTSI CONFUSION MATRIX VALUES (TP, FP, TN, FN)**
Total Interactions: 322	
(P_sv + P_uv) % = **50%**	**TP** = 160 **FP** = 80
P_cv % = **20%**	
(N_sv + N_uv) % = **20%**	**TN** = 50 **FN** = 32
N_cv % = **10%**	
TOTAL INTERACTIONS WITH 10 ENERGY-EXPERT STAKEHOLDERS	
PERCENTAGES of NON-EXISTENT OR FAILED	**VIRTSI CONFUSION**

VALIDATION vs SUCCESSFUL VALIDATION in POSITIVE AND NEGATIVE ACCEPTANCE	**MATRIX VALUES (TP, FP, TN, FN)**
Total Interactions: 140	
(P_sv + P_uv) % = **40%**	**TP** = 70 **FP** = 25
P_cv % = **35%**	
(N_sv + N_uv) % = **15%**	**TN** = 30 **FN** = 15
N_cv % = **10%**	

TOTAL INTERACTIONS WITH ALL EXPERT STAKEHOLDERS

PERCENTAGES of NON-EXISTENT OR FAILED VALIDATION vs SUCCESSFUL VALIDATION in POSITIVE AND NEGATIVE ACCEPTANCE	**VIRTSI CONFUSION MATRIX VALUES (TP, FP, TN, FN)**
Total Interactions: 140	
(P_sv + P_uv) % = **45%**	**TP** = 85 **FP** = 20
P_cv % = **30%**	
(N_sv + N_uv) % = **15%**	**TN** = 25 **FN** = 10
N_cv % = **10%**	

5.DISCUSSION

5.1Trust Patterns

A) Evaluating the Role of Trust Dynamics in the Energy Sector: Insights from Confusion Matrix Analytics

The discussion of the research's results is given in this section, with a focus on the patterns of trust that developed between expert and non-expert stakeholders. Also, it examines and contrasts confusion matrix measurements. We produce and review the next metrics for each of the three cEnergy Stakeholder Efficiency confusion matrices:

We produce and study the following metrics for each of the three cEnergy Stakeholder Efficiency confusion matrices:

1) Accuracy calculates the percentage of correctly classified cases related to the total. It shows how well VIRTSI can tell the difference between trust and mistrust that is required and those that are not. The formula is

$$\text{Accuracy} = \frac{\text{NumberOfCorrectPredictions}}{TotalNumberOfPredictions}$$

2)Precision (Positive Prediction Value): By measuring the number of genuine positives among all expected positives, precision (also known as positive prediction value) measures the accuracy of positive predictions. Higher precision in VIRTSI increases classification accuracy by reducing false positives. The formula used is

$$Precision = \frac{(TruePositives(TP))}{(TruePositives(TP) + FalsePositives(FP)}$$

3) Precision (Positive Prediction Value):calculates the percentage of true positives among all expected positives in order to measure the accuracy of positive predictions.

Higher precision in VIRTSI increases classification reliability by lowering the number of false positives. The formula is

$$Recall = \frac{(TruePositives(TP))}{(TruePositives(TP))\ (TruePositives(TP) + FalseNegatives(F}$$

4) The selection (specificity or true negative rate): Determines the precision of negative predictions by calculating the percentage of true negatives among all recommendations. Highly accuracy in VIRTSI means that false positives can be reduced by correctly separating wrong views. The formula is

$$Selectivity = \frac{TrueNegatives(TN)}{TrueNegatives(TN) + FalsePositives(FP)}$$

5) The chance of incorrect Alarm (False Positive Rate): It shows user accuracy and shows the percentage of real negatives that are incorrectly identified as positives.

TABLE6.TheconfusionmatrixmetricsofNon-Expert,DomainExpertandAIExpertStakeholdersAccordingtoVIRTSIDFAs.

Metric	Non-Expert Stakeholde	Energy-Expert Stakeholde	AI-Expert Stakeholders

	rs	rs	
Precision	0.6667	0.7368	0.8095
Recall (Sensitivity)	0.8333	0.8235	0.8947
Selectivity (True Negative Rate)	0.3846	0.5455	0.5556
False Alarm Rate (FAR)	0.6154	0.4545	0.4444
False Discovery Rate (FDR)	0.3333	0.2632	0.1905
Miss Rate (FNR)	0.1667	0.1765	0.1053
MCC	0.2455	0.3859	0.4857

By decreasing improper mistrust or trust in AI responses, reducing this value in VIRTSI helps with maintaining of system trust. The formula is

$$ProbabilityofFalseAlarm = \frac{FalsePositives(FP)}{FalsePositives(FP) + TrueNegatives(TN)}$$

6) False Discovery Rate (FDR): Finds the percentage of inaccurate positive predicts being used as a measure for accuracy. Improving FDR in VIRTSI ensures clear positive acceptances. The equation is:

$$FalseDiscoveryRate = \frac{FalsePositives(FP)}{FalsePositives(FP) + TruePositives(TP)}$$

7) Missing Ratio (False Negative Rate): Measure the percentage of real positives which the system misses. It gives view about sensitivity and the risk of neglecting real doubt or trust in VIRTSI. The formula is

$$MissRate = \frac{FalseNegatives(FN)}{FalseNegatives(FN)FalseNegatives(FN) + TruePositives(TP)}$$

8) Matthews Correlation Coefficient (MCC): A detailed result that begins with 1 to 1 and covers each variable in the confusion matrix. MCC checks the overall accuracy and correctness of classifications in VIRTSI. The equation is

$$MCC = \frac{TP - TN\ - FPFN}{\sqrt{((TP + FP)(TP + FN)(TN\ + FP)(TN\ + FN))}}$$

5.2A Framework for Understanding Human–AI Complementarity in Collaborative Work Environments and Error Interpretation

B) Evaluating the Effects of ChatGPT Engagement on Energy Stakeholder Collaboration: A Comprehensive Analysis

The final section gives a detailed study of the results, which shows both the possible positives and problems of using ChatGPT in the energy sector. It also shows the importance of human experts in AI to test and correct AI-generated content.

a) Results Analysis

1)Stakeholders with skills:

•High Recall (83.33%): They are more likely to trust AI-generated positive results as they are able to identify a key number of true positives.

• Poor performance (66.67%): But a high amount of errors leads to a lower accuracy, showing a high level of trust in the AI.

• Low Selection (38.46%): They are not very successful at observing situations where mistrust or trust do not belong since they are not capable of correctly identifying real negatives.

• High False Alarm Rate (61.54%): Because many negatives are incorrectly presented as positives, this further increases an attraction towards over trust.

• Moderate FDR (33.33%) and Moderate Miss Rate (16.67%): These values show inconsistent decision patterns.

• Low MCC (0.2455): This indicates limited balanced classification performance.

2) Stakeholders with ability in energy:

• High Precision (73.68%): As they are less likely to lack trust in AI-generated responses because they have trust in their positive estimations.

• High Recall (82.35%): They correctly identify most of the true positives but can miss some, meaning an extra careful approach.

• Moderate Selectivity (54.55%): As compared to non-experts, they are better at identifying real negatives.
• Moderate False Alarm Rate (45.45%): Suggests a more balanced decision pattern than non-experts.
• Moderate FDR (26.32%) and Moderate FNR (17.65%): Reflect controlled misclassification levels.
• Medium MCC (0.3859): A balance plan with a good overall assessment can be seen.

3) Stakeholders with AI expertise:

• High Precision (80.95%): AI experts are accurate in their positive reports, which shows a careful but successful use of AI, compared to energy experts.
• Moderate Recall (89.47%): A large number of true positives are collected, but there is a slightly visible miss that shows there is a chance of mistrust in AI findings.
• High Selectivity (55.56%): AI experts are better at finding real negatives correctly, which reduced the false positive rate.
• Lower False Alarm Rate (44.44%): Indicates more careful acceptance of AI-generated predictions.
• Low FDR (19.05%) and Low Miss Rate (10.53%): These reinforce their selective but accurate judgment.
• Highest MCC (0.4857): This shows good performance during classification and the ideal balance in general between accuracy and recall.

b) An Analytical Study of Complementarity Between Artificial Intelligence experts and Domain Experts

The analysis of the confusion matrix metrics for AI experts and domain experts (Energy-Experts) reveals a complementary behavior in how they interact with AI-generated predictions, each bringing unique strengths and potential biases to the decision-making process. This complementarity is rooted in their respective expertise and how they perceive and trust AI outputs.

1)Precision vs. Recall:

•AI Specialists: AI experts show high precision (80.95%), indicating as they are highly accurate in their positive predictions. So, they are usually correct if they decide to trust an AI-generated solution. Their recall (89.47%) is also very strong, showing they correctly identify most true positives while still applying caution.It also suggests that AI experts are usually more careful and essential, maybe as a result of their in-depth knowledge of AI's rules. They could dismiss even AI-generated solutions, which may be true because they are more alert of the issues when the AI can fall down.

•Domain Specialists (Energy-Experts): As compared to AI experts, domain specialists have a somewhat lower precision (73.68%) but a high recall (82.35%), which means they capture almost all of the true positives. This behavior shows that domain experts are ready to give up more kinds of positive predictions produced by AI, which can result in more false positives. People can be less likely to think that the use of AI can help them in the workplace due to their excellent domain knowledge, which makes them trust AI predictions more.

Reason for Balance:

• The AI specialist's worry arises as they have a deep understanding of AI's limitations. They have knowledge of all of the technical details, and they understand AI can make mistakes in difficult situations. Because of this, they trust less in AI recommendations, which results in a decrease in false positives but more false negatives.
• On the other hand, domain specialists are comfortable about their particular skills as well as how AI can support their area-specific decision-making. They can be less likely to accept AI outputs due to their experience with energy-related issues, even if this occasionally results in overtrust (false positives).

2) Selection vs. Wrong Alarm Rate:

• AI Experts: They have a low false alarm rate (44.44%), but a moderate selectivity (55.56%) shows that they can find true negatives correctly. This shows their safe behavior, which makes them believe AI less. But in some cases, AI's expectations may result in incorrect or negative choices.
•Domain Experts: Due to their lower level of selectivity (54.55%), domain experts are less accurate in correctly recognizing situations in which mistrust or trust is not needed, which leads to an increasing false alarm rate (45.45%).

Reason for balance:

• AI experts usually check AI predictions carefully to make sure that only the most trusted ones are accepted, protecting from over trust. This understanding of the AI drawbacks and their effects

on behavior when they depend more on AI.
• Because AI has been successfully applied to well-defined activities that they are experienced with, domain experts may have a more positive view of the abilities of AI within their own industry. This can end in an increased amount of false positives when people's trust in AI beats its real performance, especially in complex or unclear situations.

3) Missed Rate as well as False Discovery Rate (FDR):

• AI Experts: Both lower FDR (19.05%) show how careful and selective their approach is; still, they accept an AI-generated positive prediction when they are usually correct. But the higher miss rate (10.53%) shows that they rarely fail to detect true positives while still being cautious about AI errors.

• Domain Experts: Their FDR (26.32%) is slightly greater, which shows that they accept false positive predictions more. But they need to make sure that more true positives are recorded by accepting some false positives if needed, which can be seen in their reduced miss rate (17.65%).

Reason for balance:

• While it requires being less diverse (higher miss rate), AI experts are going to give priority to the accuracy of the recommendations they approve. Their goal is to reduce the risk of acting on incorrect data by making sure that, when people trust AI, it is very likely to be right.

• Driven by the positive benefits that AI can provide in their field, domain experts want to use AI to collect as many accurate predictions as possible due to their decreased miss rate. Even if they sometimes make mistakes, their clever use of AI for better decision-making can be seen in the ability to accept a greater FDR.

A Balanced Technique:

The same behavior between domain experts and AI experts shows how important it is to consider these points about human-AI engagement. To make sure that AI is not overtrusted, especially in sensitive or high-risk situations, the experts use an important, data-driven way to maintain accuracy and reduce false positives. When comparing domain experts with AI experts, they mostly have less trust in AI predictions, as they show more false negatives. By using their deep domain knowledge on AI as a tool for improving decision-making, domain experts (energy experts) bring a more open and realistic approach that helps in collecting more positives. Considering those higher numbers of false positives, there can be a minor desire for domain experts to overtrust AI predictions.Using these methods can result in a more strong and equal decision-making process where each group's capabilities help offset each other's disadvantages. In order to use AI's potential while carefully managing its limits, this combination can improve the total effectiveness and trust of human-AI interactions.

5.3 Contribution & Novelty of VIRTSI

Many important results and suggestions for managing informative and accurate human-AI interactions have been generated from the VIRTSI model and the results obtained in the field study using ChatGPT.
A. The Impact of VIRTSI on User Experience in AI-Driven Platforms: Insights and Implications
Implementation, management, and ethical issues are all affected by the complicated and complex matter of trust in artificial intelligence (AI). Issues about transparency, accountability, and trust sometimes weaken trust in AI, which makes it difficult for people and organizations to fully integrate AI technologies [51]. The feeling of confidence is an important variable in the implementation of AI in SMEs, as beliefs on the use of AI are affected by safety issues and avoiding risk [52]. Also, public trust in the management of AI is important as different opinions of AI's role in decision-making show the importance of clear rules and regulations [53]. Trust dynamics in AI-driven chatbots also show that conditions, the performance of machines, and user experience all affect trust, which needs constant research to improve AI-human interactions [54]. In terms of philosophy, as AI without moral and emotional intelligence, trust in AI can often confused with dependence, which increases questions about if AI is truly regarded as trustworthy [55]. [56] suggests that examining AI to be accurate involves the risk of transforming it and transferring moral duty away from politicians and businesses. To make AI systems are trustworthy and responsible, it is also important to

find a balance between advances in technology, legal monitoring, and ethical issues.
The VIRTSI method is an important method over other standard methods like the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI).
As it provides a planned, numerical, and flexible way for trust assessment in human-AI interactions. Rather than using finite state automation and confusion matrices to track changes in trust, using the VIRTSI method gives a more complex analysis of trust evolution than these past designs, which mainly focus on adoption and spreading. In AI-driven systems, where trust changes regularly and the relationship is affected by system performance, errors, and user experience instead of a single model, this method is particularly important. The increased TAM framework used by [48] to look at college students' adoption of AI chatbots shows how important expected value, ease of use, and engagement are in building trust.In the same way, study on the virtual world use [49] expands TAM to include social and psychological concepts like emotional connection and social presence. Whereas this study identifies elements that affect initial acceptance, it does not provide a method to measure how consumers' trust changes when they come across errors in AI-driven environments. VIRTSI, on the other hand, is more suitable for examining trust in difficult, changing digital ecosystems as it gives an approach for studying changes in trust over time. Interaction technological elements like engagement and learning effect are included in the i-TAM model [57]. As this method improves our knowledge of AI engagement, it cannot differentiate between trust in artificial intelligence (AI)decisions that are necessary and those that are not. studies [58] use the Technology Acceptance Model (TAM) to explore how people develop trust in ChatGPT, mainly for ethical concerns and ease of use. While useful, that work
does not explain what happens to trust when the system makes mistakes or when users change their expectations. This is where the VIRTSI model adds value. By tracking trust as it rises, falls, and stabilizes over time, VIRTSI offers a clearer picture of how people actually respond to AI behaviour. Reference [59] also discusses trust in relation to ChatGPT, especially in higher-education settings. Their findings underline the importance of security and transparency, but they do not provide a way to measure trust at different levels or observe how it shifts. VIRTSI helps bridge this gap by offering a structured way to examine how trust develops and changes, giving researchers a more complete view of user experience.A multi-layer system for trust in human-AI interactions is offered in Reference [50], in a concentrate on legal and ethical issues. If their theoretical approach offers a useful concept basis, it lacks of an actual, systematic method to measure changes in trust. By offering a numerical, state-based methods, VIRTSI applies this trust model and increases its value to real-world AI systems that need dynamic trust tests.

VIRTSI id different from these present as it provides a multi-state, error-aware examination of trust, which is important in high-risk AI applications like managing energy, healthcare, and finance. A more accurate and useful evaluation of trust in AI systems can be given by its ability to track trust transitions in real-time, taking user errors into account and adjust to differences in system performance.

B. The Interaction Between Energy Stakeholder Groups and AI Technologies: Implications for Future Energy Policies

The energy sector's trust in artificial intelligence (AI) systems is affected by a number of important elements, such as system's clarity, transparency, and stability. Because AI decisions impact cost control, safety procedures, and energy efficiency, accuracy is important. For example, AI is necessary for automated service and energy grid management, where it is used to identify patterns and avoid possible failures. These systems' failure may have several impacts. It not only impacts current operations but also other neighborhoods and businesses that depend on a constant supply of electricity.But technical features like security, transparency, and meaning are not the only factors that affect the trust in artificial intelligence (AI) systems. It also has a major impact by the personal interactions that stakeholders' experts not have with AI such as field of experience, their capacity to analyze replies given by AI carefully, and overall knowledge of AI technologies. The level of adjustment in AI responses and the quality of human-AI engagement tools also have an impact on these factors.The conclusions of the present research tested the way energy stakeholders interact with ChatGPT in the energy field, which gives useful data about the trust states and confusion matrices of both expert and non-expert stakeholders. Those can be improved by the VIRTSI method. It is found that AI experts commonly show higher levels of mistrust, as they have knowledge of AI's disadvantages, such as errors, incorrect data, and a lack of experience in the energy sector. But experts in the energy sector sometimes underestimate AI. As a result of the professional quality and accuracy of AI-generated answers, even though those answers are incomplete.Particularly, a number of ChatGPT's logical comments were not entirely accurate. All stakeholder participants agreed that they would trust AI, but with errors, because the AI managed to provide useful context ignoring this. This shows that even while they may not completely trust artificial intelligence (AI), they somehow value the information that these systems provide. The results indicate the importance of a deeper plan for human-AI engagement in the energy industry. The combined knowledge of AI experts as well as those in the energy domain is important for successful use of AI technology in energy management.

5.4 Feasibility, Scalability, Challenges

A organized approach for studying and recreating confidence patterns in human-AI interaction in energy management is given by the VIRTSI framework. It also improves AI system design to be more effective and consistent with human decisions by imitating trust state phases. But there are still issues with execution, flexibility, and efficiency when applying this model in real energy-related uses.VIRTSI offers an accurate description of how energy experts connect with AI-driven systems for decision-making by using DFA to evaluate and display trust relations. VIRTSI helps in identifying negative trust states, such as excess belief in AI-generated energy estimations or excessive mistrust that lead to poor energy options, by using trust assessment factors, such as confusion matrices and accuracy evaluations. The ability to adjust to various AI-driven energy-related uses, including consumption planning, smart grids, and energy use improvement, affects how useful it is in real energy networks.

a) Addressing Adaptation and Scalability Issues

VIRTSI has to encourage a large variety of AI uses in the energy industry, from power distribution control to renewable energy integrating, to allow them to be used at large. The accuracy of trust analysis must be maintained between different types of users, such as grid operators, policy makers, and consumers with a variety of AI skills. In order to enable real-time monitoring of trust-state transitions and ensure that AI suggestions are correctly connected with human decision-making in changing energy situations, the system must also be highly effective in computing.

b)Identifying Challenges and Future Improvements

The ability of VIRTSI to completely evaluate the impact of trust-based choices is one of its drawbacks in energy applications. The missing method in this is to analyze the long-term effects of trust-related evaluation errors, but it successfully imitates human acceptance or rejection of AI-driven suggestions. For example, mistrusting without any reason may result in poor energy use and lost improvement options, while a lack of trust in incorrect AI predictions may lead to high energy usage. To measure the effects of mistrust or overtrust on conservation and energy savings, future research is to focus on adding consequence-based assessments, adding decision sensitivity to trust-state modeling, and improving confusion matrices.The effect of these trust-related decisions has to be examined in present and future research, The goal of developing these methods that determine the value of these mistakes in true energy management situations. Article [60] published the first results from this work, offering early ideas on how trust gaps affect AI adoption and decision-making outcomes. These results are going to improve the VIRTSI framework so that it accurately describes the impacts of behaviors connected to trust in AI-assisted managing energy. VIRTSI improves trust analysis, evaluation, and reducing tools to help create AI systems that are not only technically strong but also legally as well as social aware. But in order to overcome problems with scalability and maintain its efficiency in improving savings and conservation, its successful use in energy systems needs continuous improvements

6.CONCLUSION

6.1 Summary of Findings

In relation to how expert and non-expert stakeholders interact with AI, this study focused on a new way to build trust in AI-powered urban energy management. Mainly, on how expert and non-expert stakeholders interact with AI. Artificial intelligence (AI) offers more creativity and flexibility in problem-solving than previous methods, resulting in a new perspective. But it can also produce incorrect answers, so users should interact with it carefully rather than carelessly. So trust in AI needs to be correctly balanced by comparing the benefits with its drawbacks.

a) Importance of VIRTSI for analysis

In AI-driven decision-making situations the VIRTSI model gives a more accurate and creative way to find trust behavior than the traditional models like the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI), which mostly focus on the original use and diffusion. VIRTSI models trust as a development that is affected by continuous human-AI contact instead of as a fixed idea. In AI applications like huge language models like ChatGPT, a complex and modern generative AI tool, this view gives a clearer picture of trust behavior.By combining both Finite State Automation (FSA) with user-adapted Confusion Matrices VIRTSI gives an organized method for measuring trust changes. It also allows a complete evaluation on how users interact with AI-based energy solutions. In energy management, where actions are affected by consumer opinions of trust and honesty in along with the accuracy of AI-generated suggestions, this detailed approach is important. In order to prevent both blind dependence on AI and the insufficient refusal of its recommendation. Because they can result in errors, improper management of energy resources, and a failure to use all of the benefits that AI can offer—it is important to differentiate between trust, overtrust, mistrust, and distrust.

b) Trust behavior differences

The study also gives the importance of adding error-aware evaluation systems that can help to take note of both human trusting errors and AI mistakes. By identifying these users who are improperly refusing correct AI outputs or incorrectly accepting false ones, it gives a clear idea of how to improve AI trust measurement. The use of VIRTSI in high-stakes energy situations shows its importance for decreasing the risks of trust errors and ensuring that artificial intelligence is used effectively without losing decision quality.

6.2 Future Work / Recommendations

The study explains the unique changes that are required for better human-AI interaction along with measuring trust state. The specific approaches in both human training and AI adaptation are shown by differences in how to use and also about possible improper use of ChatGPT among AI specialists, energy domain experts, and non-experts. By making sure that their interactions match with AI, their specific needs, and their levels of expertise, stakeholders need unique trust measurement methods. For example, rather than basic AI literacy, AI experts, who have a more technical understanding, should need training on identifying and reducing AI bias. But when consider other side even though they are knowledgeable in energy-related ideas, experts in the energy sector may find it challenging to review AI-generated energy ideas objectively.

a) Evaluating Current Limitations: A Comprehensive Analysis of Potential Improvements in Ongoing Research Work

For those who have little experience particularly non-experts with both AI and energy management, The training solutions that improve the ability to differentiate between accurate and inaccurate AI outputs are useful for them. Similarly, AI itself has to be improved such that it reacts to each stakeholder type in a manner that is suitable to their levels of technical knowledge, expectations, and trust behaviors. For example, when chatting with AI professionals, ChatGPT's responses can be changed into technical explanations and system clarity while reducing difficult concepts and giving confirmation techniques for non-experts. Errors and excessive trust can be reduced by making sure AI adjusts its answers to user skills, that leads to better energy-related decision-making. With the improvement in trust modeling, review, and prevention techniques, this study improves AI systems so that they can align with the way humans think. This also makes sure that it allows better cooperation between stakeholders and

AI-powered energy-related decision-making tools. Future research must focus on including the effects of trust-based choices. Even though the VIRTSI model is an important step in understanding human-AI relations. This will also make sure that the use of AI in energy systems remains both ethical and practical.

REFERENCES

[1] G. A. Tsihrintzis, M. Virvou, and I. Hatzilygeroudis, ''Editorial: Special issue on selected papers from the 33rd annual IEEE interna- tional conference on tools with artificial intelligence (ICTAI-2021),'' Int. J. Artif. Intell. Tools, vol. 32, no. 5, Aug. 2023, Art. no. 2302003.

[2] G. A. Tsihrintzis, M. Virvou, and L. C. Jain, ''Introduction to advances in machine learning/deep learning-based technologies,'' in Advances in Machine Learning/Deep Learning-based Technologies. Switzerland: Springer, 2022, pp. 1–5.

[3] G. A. Tsihrintzis and L. C. Jain, Machine Learning Paradigms—Advances in Deep Learning-Based Technological Applications. Cham, Switzerland: Springer, 2020.

[4] N. G. Bourbakis, G. A. Tsihrintzis, and M. Virvou, in Proc. 13th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Corfu, Greece. Dordrecht, The Netherlands: Springer, Jul. 2022. https://doi.org/10.1109/IISA56318.2022

[5] G. A. Tsihrintzis, M. Virvou, and I. Hatzilygeroudis, ''Special collection of extended selected papers on novel research results presented in the 12th international conference on information, intelligence, systems and applications (IISA2021), 12–14 July 2,'' Intell. Decis. Technol., vol. 15, no. 4, pp. 641–643, 2021.

[6] G. A. Tsihrintzis, M. Virvou, and G. Phillips-Wren, ''Surveys in artificial intelligence-based technologies,'' Intell. Decis. Technol., vol. 13, no. 4,
pp. 393–394, Feb. 2020.

[7] I. C. Dimitriou, A. Arsenopoulos, G. P. Trachanas, E. Sarmas, and
V. Marinakis, ''Assessing the adoption level of solar PV installations, on district scale of urban environment,'' Renew. Energy, vol. 237, Dec. 2024, Art. no. 121676.

[8] G. A. Tsihrintzis, M. Virvou, and T. Saruwatari, ''Special collection of extended selected papers on 'Novel research results presented at the 14th international joint conference on knowledge-based software engineering (JCKBSE2022), 22–24 August 2022, Larnaca, Cyprus https://easyconferences.eu/jckbse2022/,''' Intell. Decis. Technol., vol. 16, no. 4, pp. 715–716, Dec. 2022.

[9] G. A. Tsihrintzis, G. Phillips-Wren, and L. C. Jain, ''Intelligent decision technologies: An international journal (IDT) heading into its 18th year: A short note from the editors-in-chief,'' Intell. Decis. Technol., vol. 18, no. 1, pp. 1–7, Feb. 2024.

[10] P. Skaloumpakas, E. Sarmas, M. Rachmanidis, and V. Marinakis, ''Reshaping the energy landscape of Crete through renewable energy valleys,'' Sci. Rep., vol. 14, no. 1, p. 8038, Apr. 2024.

[11] E. Papadis and G. Tsatsaronis, ''Challenges in the decarbonization of the energy sector,'' Energy, vol. 205, Aug. 2020, Art. no. 118025.

[12] C. Bataille, M. Åhman, K. Neuhoff, L. J. Nilsson, M. Fischedick,
S. Lechtenböhmer, B. Solano-Rodriquez, A. Denis-Ryan, S. Stiebert,
H. Waisman, O. Sartor, and S. Rahbar, ''A review of technology and policy deep decarbonization pathway options for making energy-intensive industry production consistent with the Paris agreement,'' J. Cleaner Prod., vol. 187, pp. 960–973, Jun. 2018.

[13] J. Tollefson and K. R. Weiss, ''Nations adopt historic global climate accord: Agreement commits world to holding warming'well below'2 [degrees] C,'' Nature, vol. 582, no. 7582, pp. 315–317, 2015.

[14] V. Michalakopoulos, E. Sarmas, I. Papias, P. Skaloumpakas, V. Marinakis, and H. Doukas, ''A machine learning-based framework for clustering res-idential electricity load profiles to enhance demand response programs,'' Appl. Energy, vol. 361, May 2024, Art. no. 122943.

[15] E. Sarmas, N. Dimitropoulos, V. Marinakis, Z. Mylona, and
H. Doukas, ''Transfer learning strategies for solar power forecasting under data scarcity,'' Sci. Rep., vol. 12, no. 1, pp. 1–13, Aug. 2022.

[16] OpenAI et al., ''GPT-4 technical report,'' 2023, arXiv:2303.08774.

[17] M.-N. Chu, ''Assessing the benefits of ChatGPT for business: An empirical study on

organizational performance,'' IEEE Access, vol. 11, pp. 76427–76436, 2023.

[18] H. Wang, W. Wu, Z. Dou, L. He, and L. Yang, ''Performance and exploration of ChatGPT in medical examination, records and education in chinese: Pave the way for medical AI,'' Int. J. Med. Informat., vol. 177, Sep. 2023, Art. no. 105173.

[19] P.-H. Li, H.-Y. Lee, Y.-P. Cheng, A. I. Starčič, and Y.-M. Huang, ''Solving the self-regulated learning problem: Exploring the performance of ChatGPT in mathematics,'' in Proc. Int. Conf. Innov. Technol. Learn. Cham, Switzerland: Springer, Jan. 2023, pp. 77–86.
pp. 73–125, Apr. 2023.

[20] C. M. Castro Nascimento and A. S. Pimentel, ''Do large lan- guage models understand chemistry? A conversation with ChatGPT,''

[21] Y. Liang, D. Zou, H. Xie, and F. L. Wang, ''Exploring the potential of using ChatGPT in physics education,'' Smart Learn. Environ., vol. 10, no. 1,

[22] Y. Gao, W. Tong, E. Q. Wu, W. Chen, G. Zhu, and F.-Y. Wang, ''Chat with ChatGPT on interactive engines for intelligent driving,'' IEEE Trans. Intell. Vehicles, vol. 8, no. 3, pp. 2034–2036, Mar. 2023.

[23] G. A. Tsihrintzis, E. Sarmas, V. Marinakis,
D. Panagoulias, E.-A. Tsihrintzi, and M. Virvou, ''Evaluating non-expert stakeholder interaction with artificial intelligence on energy urban domain using VIRTSI: The case of ChatGPT,'' in Proc. 15th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Jul. 2024, pp. 1–10.

[24] M. Virvou, G. A. Tsihrintzis, and E.-A. Tsichrintzi, ''VIRTSI: A novel trust dynamics model enhancing artificial intelligence collaboration with human users—Insights from a ChatGPT evaluation study,'' Inf. Sci., vol. 675, Jul. 2024, Art. no. 120759.

[25] E. Sarmas, V. Marinakis, and H. Doukas, ''A data-driven multicriteria decision making tool for assessing investments in energy efficiency,'' Oper. Res., vol. 22, no. 5, pp. 5597–5616, Nov. 2022.

[26] E. Sarmas, N. Dimitropoulos, S. Strompolas, Z. Mylona, V. Marinakis,
A. Giannadakis, A. Romaios, and H. Doukas, ''A web-based building automation and control service,'' in Proc. 13th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Jul. 2022, pp. 1–6.

[27] H. Doukas, A. Papadopoulou, N. Savvakis, T. Tsoutsos, and J. Psarras, ''Assessing energy sustainability of rural communities using principal component analysis,'' Renew. Sustain. Energy Rev., vol. 16, no. 4,
pp. 1949–1957, May 2012.

[28] C. Karakosta, C. Pappas, V. Marinakis, and J. Psarras, ''Renewable energy and nuclear power towards sustainable development: Characteristics and prospects,'' Renew. Sustain. Energy Rev., vol. 22, pp. 187–197, Jun. 2013.

[29] K. D. Patlitzianas, H. Doukas, A. G. Kagiannas, and J. Psarras, ''Sustainable energy policy indicators: Review and recommendations,'' Renew. Energy, vol. 33, no. 5, pp. 966–973, May 2008.

[30] R. Xiong, J. Cao, and Q. Yu, ''Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle,'' Appl. Energy, vol. 211, pp. 538–548, Feb. 2018.

[31] J. Duan, Z. Yi, D. Shi, C. Lin, X. Lu, and Z. Wang, ''Reinforcement- learning-based optimal control of hybrid energy storage systems in hybrid AC–DC microgrids,'' IEEE Trans. Ind. Informat., vol. 15, no. 9,
pp. 5355–5364, Sep. 2019.

[32] E. Sarmas, N. Dimitropoulos, V. Marinakis, A. Zucika, and H. Doukas, ''Monitoring the impact of energy conservation measures with artificial neural networks,'' in Proc. ECEEE Summer Study, Jul. 2022, pp. 571–579.

[33] E. Sarmas, E. Spiliotis, N. Dimitropoulos, V. Marinakis, and H. Doukas, ''Estimating the energy savings of energy efficiency actions with ensemble machine learning models,'' Appl. Sci., vol. 13, no. 4, p. 2749, Feb. 2023.

[34] M. Q. Raza and A. Khosravi, ''A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings,'' Renew. Sustain. Energy Rev., vol. 50, pp. 1352–1372, Oct. 2015.

[35] European Commission High-Level Expert Group on AI. (2019). Ethics Guidelines for Trustworthy AI. Accessed: Oct. 18, 2024. [Online]. Available: https://digital-

strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[36] K. T. Bochniarz, S. K. Czerwiński, A. Sawicki, and P. A. Atroszko, ‘‘Attitudes to AI among high school students: Understanding distrust towards humans will not help us understand distrust towards AI,’’ Personality Individual Differences, vol. 185, Feb. 2022, Art. no. 111299.

[37] M. Virvou, ‘‘The emerging era of human-AI interaction: Keynote address,’’ in Proc. 13th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Jul. 2022, pp. 1–10.

[38] M. Virvou, E. Alepis, G. A. Tsihrintzis, and L. C. Jain, Machine Learning Paradigms: Advances in Learning Analytics. Cham, Switzerland: Springer, 2020.

[39] M. Virvou and G. A. Tsihrintzis, ‘‘Is ChatGPT beneficial to education? A holistic evaluation framework based on intelligent tutoring systems,’’ in Proc. 14th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Jul. 2023, pp. 1–8.

[40] A. S. Lampropoulos and G. A. Tsihrintzis, ‘‘Evaluation of MPEG-
7 descriptors for speech emotional recognition,’’ in Proc. 8th Int. Conf. Intell. Inf. Hiding Multimedia Signal Process., Jul. 2012,
pp. 98–101.

[41] S. Papadimitriou, K. Chrysafiadi, and M. Virvou, ‘‘FuzzEG: Fuzzy logic for adaptive scenarios in an educational adventure game,’’ Multimedia Tools Appl., vol. 78, no. 22, pp. 32023–32053, Nov. 2019.

[42] K. Chrysafiadi, M. Virvou, G. A. Tsihrintzis, and I. Hatzilygeroudis, ‘‘Evaluating the user’s experience, adaptivity and learning outcomes of a fuzzy-based intelligent tutoring system for computer programming for academic students in Greece,’’ Educ. Inf. Technol., vol. 28, no. 6,
pp. 6453–6483, Jun. 2023.

[43] D. N. Sotiropoulos, A. S. Lampropoulos, and G. A. Tsihrintzis, ‘‘MUSIPER: A system for modeling music similarity perception based on objective feature subset selection,’’ User Model. User-Adapted Interact., vol. 18, no. 4, pp. 315–348, Sep. 2008.

[44] M. Virvou, ‘‘Automatic reasoning and help about human errors in using an operating system,’’ Interacting with Comput., vol. 11, no. 5, pp. 545–573, May 1999.

[45] M. Virvou and K. Kabassi, ‘‘Adapting the human plausible reasoning theory to a graphical user interface,’’ IEEE Trans. Syst., Man, Cybern., A, Syst. Hum., vol. 34, no. 4, pp. 546–563, Jul. 2004.

[46] J. Greer and M. Mark, ‘‘Evaluation methods for intelligent tutoring systems revisited,’’ Int. J. Artif. Intell. Educ., vol. 26, no. 1, pp. 387–392, Mar. 2016.

[47] T. Paul and M. K. Rohil, ‘‘Advanced intelligent tutoring systems: Featuring the learning management systems of the future,’’ in Proc. Int. Conf. Com- put. Intell. Mach. Learn. Cham, Switzerland: Springer, Jan. 2024,
pp. 453–463.

[48]X. Lin, ‘‘Factors influencing college students’ use of AI chatbots for learning-empirical study based on TAM extended model,’’ in Proc. 5th Int. Conf. Artif. Intell. Electromech. Autom. (AIEA), Jun. 2024, pp. 151–159.

[49]R. Wu and Z. Yu, ‘‘Investigating Users’ acceptance of the metaverse with an extended technology acceptance model,’’ Int. J. Hum.-Comput. Inter- act., vol. 40, no. 19, pp. 5810–5826, Oct. 2024.

[50]A. Ferrario, M. Loi, and E. Viganò, ‘‘In AI we trust incremen- tally: A multi-layer model of trust to analyze human-artificial intelli- gence interactions,’’ Philosophy Technol., vol. 33, no. 3, pp. 523–539, Sep. 2020.

[51] J. Paliszkiewicz and J. Gołuchowski, Trust and Artificial Intelligence: Development and Application of AI Technology. New York, NY, USA: Taylor & Francis, 2024.

[52] M. S. Alzboon, H. M. Al-Shorman, S. M. N. Alka’awneh, S. G. Saatchi,
M. Alqaraleh, E. I. M. Samara, M. E.-S. Wahed, S. I. Mohammad,
A. M. Al-Momani, and A. A. A. Haija, ‘‘The role of perceived trust in embracing artificial intelligence technologies: Insights from SMEs,’’ in Intelligence-Driven Circular Economy: Regeneration Towards Sustain- ability Social Responsibility. Cham, Switzerland: Springer, Jan. 2025,
pp. 1–15.

[53] P. Robles and D. J. Mallinson, ‘‘Artificial intelligence technology, public trust, and effective

governance,'' Rev. Policy Res., vol. 42, no. 1, pp. 11–28, Jan. 2025.

[54] S. W. T. Ng and R. Zhang, ''Trust in AI chatbots: A systematic review,''
Telematics Informat., vol. 97, Feb. 2025, Art. no. 102240.

[55] J. M. Durán and G. Pozzi, ''Trust and trustworthiness in AI,'' Philosophy Technol., vol. 38, no. 1, pp. 1–31, Mar. 2025.

[56] M. Ryan, ''In AI we trust: Ethics, artificial intelligence, and reliability,''
Sci. Eng. Ethics, vol. 26, no. 5, pp. 2749–2767, Oct. 2020.

[57] M. Nilashi and R. A. Abumalloh, ''I-TAM: A model for immersive tech- nology acceptance,'' Educ. Inf. Technol., vol. 2024, pp. 1–29, Oct. 2024.

[58] L. S. Ningsih, M. Iqbal, and L. Marlina, ''ChatGPT app trust level mea- surement (artificial intelligence) use technology acceptance model (TAM) among the campus community,'' in Proc. Int. Conf. Artif. Intell., Navig., Eng., Aviation Technol. (ICANEAT), 2024, vol. 1, no. 1, pp. 524–533.

[59] M. F. Shahzad, S. Xu, and I. Javed, ''ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone,'' Int. J. Educ. Technol. Higher Educ., vol. 21, no. 1, p. 46, Jul. 2024.

[60] M. Virvou and G. A. Tsihrintzis, ''Impact of consequenses on human trust dynamics in artificial intelligence responses,'' in Proc. 15th Int. Conf. Inf., Intell., Syst. Appl. (IISA), Jul. 2024, pp. 1–6.