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A CONCEPTUAL AI-BASED APPROACH FOR UNDERSTANDING AND REDUCING ELECTRICITY CONSUMPTION IN HOMES AND CAMPUSES

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Abstract:

Rapid growth of cities and electronic devices has increased electricity use around the world. This rising demand is becoming hard to manage and is causing problems for both the power grid and the environment. Current energy management systems are not fast or smart enough to handle changing usage patterns, especially in modern homes and large campuses.

This paper presents a conceptual AI-based approach to track, study, and potentially reduce electricity use in homes and educational campuses, supported by a user perception study.

Using IoT sensors and smart meters, the system collects detailed energy data in real time. Machine learning models such as Long Short-Term Memory (LSTM) networks and Reinforcement Learning, which have been extensively validated for building energy forecasting, HVAC load prediction, and energy-efficient building management in peer-reviewed studies [4], [8], [9], are discussed conceptually to illustrate future intelligent electricity monitoring approaches.

In homes, the system works like a virtual energy assistant. It can find hidden power consumption (vampire loads) and plan when appliances should run, based on cheaper electricity hours.

On campuses, the system manages large systems such as lighting and air conditioning. It adjusts energy use according to class schedules and the number of people in each building.

Survey responses and findings from existing studies indicate that users perceive AI-based electricity management systems as capable of reducing electricity use, particularly in homes and campuses. These savings lower costs, reduce carbon emissions, and help reduce peak pressure on the national grid. The results support the idea that AI should be widely used in buildings to help reach Net-Zero energy goals.[3]

Keywords: *AI, Energy Management, Smart Campus, IoT, Sustainability, Demand Response.*

Introduction:

Electricity consumption in homes and educational campuses has increased rapidly over the past few years. The growing number of electrical devices and continuous usage place a heavy load on power systems and increase energy costs. Most conventional energy management systems rely on static or rule-based control mechanisms and lack adaptability to dynamic consumption patterns, leading to avoidable energy wastage, as reported in multiple peer-reviewed studies on building energy systems and smart building energy optimization [1], [7], [10].

With the availability of smart meters and IoT sensors, large volumes of electricity consumption data can now be collected in real time. Artificial Intelligence (AI) techniques enable meaningful analysis of this data by identifying usage patterns, forecasting demand, and supporting intelligent energy optimization strategies. Previous peer-reviewed studies have demonstrated the effectiveness of machine learning models such as Artificial Neural Networks, Support Vector Machines, and deep learning architectures for high-resolution prediction of building energy consumption and efficiency improvement [7], [10]. However, most existing research focuses on model accuracy and simulation-based validation, with limited emphasis on user perception, acceptance, and real-world applicability. Survey findings from this study suggest that users believe AI-based systems could manage electricity more efficiently in homes and campuses, helping to reduce energy waste while maintaining comfort and daily routines. [7]

Conceptual Architecture Comparison:

This section conceptually compares different AI-based energy management solutions proposed for homes and campuses, such as smart meters, AI-driven dashboards, automated control systems, and demand response platforms. The comparison focuses on monitoring capability, demand forecasting accuracy, scalability, and energy waste reduction potential, aligned with evaluation dimensions reported in recent AI-based building energy management frameworks [5], [9]. This helps understand which AI approaches work best in residential and campus environments.

Methodology:

A. Research Design

The study is designed to examine **user perception and acceptance** of how Artificial Intelligence can support efficient electricity monitoring and reduction in homes and educational campuses. It aims to understand both the benefits, such as cost savings and reduced energy waste, and challenges, such as user acceptance and system accuracy. This balanced approach provides a clear view of AI's role in energy management.

B. Research Approach

A mixed research approach is used, combining surveys, user feedback, and secondary data from existing research studies. This approach allows the study to combine user perception data with validated findings from established peer-reviewed research on AI-based energy management and demand prediction in buildings [2], [7].

C. Data Collection Methods

Data is collected using online surveys, interviews, and analysis of reports related to smart energy systems and AI-based energy management tools. Smart meter data, energy usage reports, and case studies from homes and campuses are also reviewed. This ensures the data is both practical and reliable.

D. Sampling Strategy

The sample includes households, students, facility managers, and staff from educational campuses with varying energy usage patterns. Participants are selected from different age groups and building types to capture diverse electricity consumption behaviours. This variety supports fair comparison and broader understanding.

E. Data Analysis Techniques

The collected data is analysed by identifying electricity usage patterns and understanding user responses toward AI-supported energy monitoring systems. While no predictive model is implemented in this study, the analysis is conceptually guided by time-series forecasting approaches such as Long Short-Term Memory (LSTM), which has been widely validated for building energy prediction and HVAC-related load forecasting in peer-reviewed literature [8].

F. Tools Used

Basic survey tools, spreadsheets, and simple statistical software are used to organize and analyse the data. Graphs, charts, and summary tables are created to visualize energy consumption. These tools help present results clearly and understandably.

G. Ethical Considerations

All data is collected with user consent, and privacy is strictly maintained. Personal and household energy data is anonymized to prevent identification. Participants are informed about the purpose of the study and can withdraw at any stage without any impact.[5]

H. Limitations

The study may not include all types of homes or campuses and is limited by sample size and available data. Results also depend on the accuracy of smart meters and user participation. Differences in building infrastructure and rapid changes in AI technology may affect the general applicability of the findings.

This study does not include real-time implementation or experimental validation of AI models such as LSTM or Reinforcement Learning. These techniques are discussed conceptually to reflect their potential application as reported in existing literature. Future work will focus on system development, dataset collection, and model evaluation using standard performance metrics such as RMSE, MAE, and energy savings.

Conceptual Evaluation Metrics:

The conceptual evaluation indicators presented below are based on conceptual comparison and user perception rather than real-time system deployment or experimental validation.

Metric	Traditional Energy Management	AI-based Energy Management
Monitoring Speed	Periodic/manual readings	Real-time monitoring
Accuracy	Limited and delayed	High with predictive models
Scalability	Hard to scale manually	Easily scalable across buildings
Cost Efficiency	Higher operational cost	Reduced long-term costs
Energy Optimization	Rule-based control	Adaptive and learning-based
Availability	Limited to working hours	Continuous (24/7 monitoring)

User Experience and Their Ecosystem Integration:

AI-based energy management systems are commonly deployed through mobile applications and web dashboards, as reported in empirical studies and reviews on intelligent building management and user interaction [5], [9].

Security and Privacy:

Traditional energy systems store limited data, while AI-based systems collect detailed real-time electricity usage information. This data can reveal occupancy patterns and behaviour, making security critical. Risks include data misuse and unauthorized access. Strong encryption, secure data storage, anonymization, and transparent data policies are essential to ensure user trust and system safety.

Regulatory & Technical Bottlenecks:

Energy systems must follow regional electricity regulations, but AI-based solutions often lack clear standards. Differences in energy policies across regions make large-scale deployment challenging. Technical issues such as inaccurate sensor data, biased prediction models, and system maintenance also affect performance. Without clear regulations and validation standards, adoption may remain slow.[5]

Target Audience:

i. Homeowners & Residents – Individuals interested in reducing electricity bills and energy waste.
ii. Campus Facility Managers – Responsible for managing lighting, HVAC, and large-scale

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energy systems.

iii. Students & Staff – Users affected by energy efficiency measures in educational institutions.

iv. Researchers & Academicians – Studying AI, sustainability, and smart energy systems.

v. Policy Makers & Energy Tech Startups – For developing regulations, incentives, and AI-driven energy solutions.

Questionnaire Design for the User Perception Analysis:

To support the comparison between traditional energy management methods and AI-based energy management systems, a user perception study is conducted using a structured questionnaire. The purpose of this survey is to understand users' awareness of electricity consumption, their energy-saving habits, and their trust in AI-driven energy solutions. The questionnaire also explores user comfort with automation, data privacy concerns, and willingness to adopt AI-based systems for managing electricity in homes and campuses. This study helps evaluate how practical and acceptable AI-based energy management is from the user's perspective.

Sample Focus Areas:

i. Awareness of electricity usage and energy bills

ii. Current energy-saving behaviour in homes and campuses

iii. Trust in AI-based energy monitoring and control systems

iv. Privacy and data security concerns related to energy data

v. Willingness to adopt AI-driven energy management in the future

Survey Questions:

i. What is your name?

ii. What is your age group?

iii. What is your gender?

iv. What is your type of residence?

v. Where do you live in?

vi. Do you regularly check your electricity bill?

vii. Are you aware of how much electricity your home/campus uses in a month?

viii. Do you feel your electricity bill is increasing every year?

ix. Which appliances consume the most electricity in your home/campus?

x. Do you turn off lights, fans, or AC when not in use?

xi. Would you like an AI system that automatically detects when electricity is being wasted?

xii. If an AI system alerts you about unnecessary electricity usage, would you act on it?

xiii. Would you trust AI to switch OFF unused appliances automatically (lights, fans, AC)?

xiv. An AI system can identify devices that consume power even when not in use (standby/vampire loads). Would this be useful to you?

xv. Would you allow AI to suggest the best time to run appliances to reduce electricity cost?

xvi. If AI could reduce electricity use without affecting your comfort, would you prefer AI control over manual control?

xvii. How comfortable are you with AI learning your daily electricity usage patterns?

xviii. Would AI-based monthly energy reports help you understand your electricity usage better?

xix. If AI predicts high electricity consumption in advance, would you follow its energy-saving suggestions?

xx. How much do you trust an AI-based system to manage electricity usage efficiently in your home or campus?

xxi. How willing are you to use an AI system that automatically controls appliances to reduce electricity consumption?

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xxii. Overall, how confident are you that AI can help reduce electricity wastage?

Results:

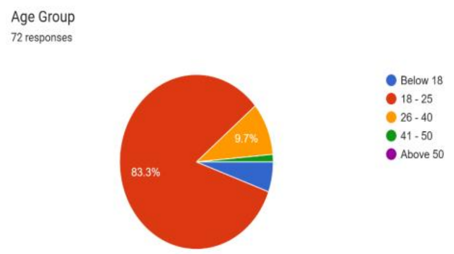

Fig. 1. When asked about their Age Group

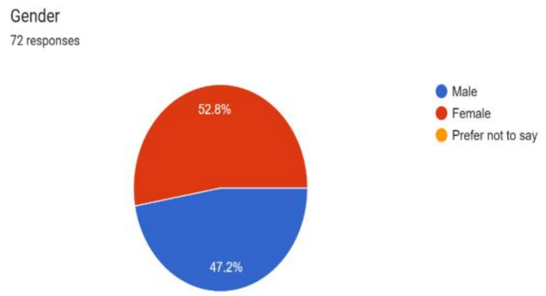

Fig. 2. When asked about their Gender

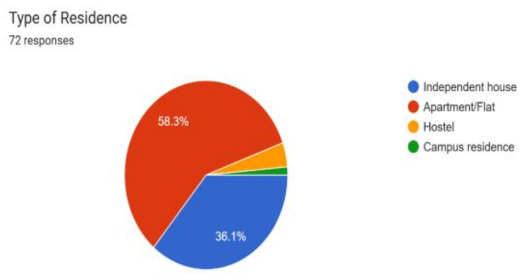

Fig. 3. When asked about where their type of residence

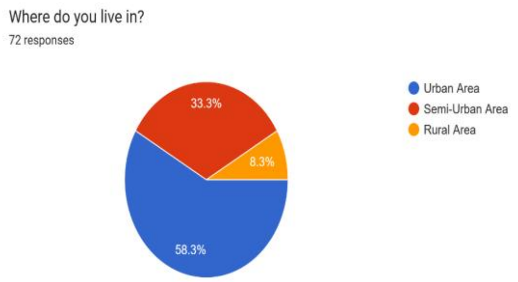

Fig. 4. When asked about where they live in

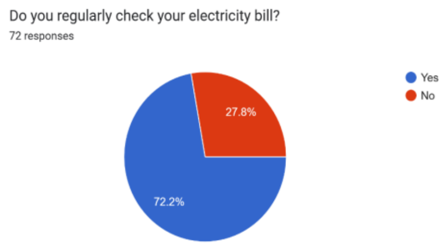

Fig. 5. When asked about whether they regularly check their electricity

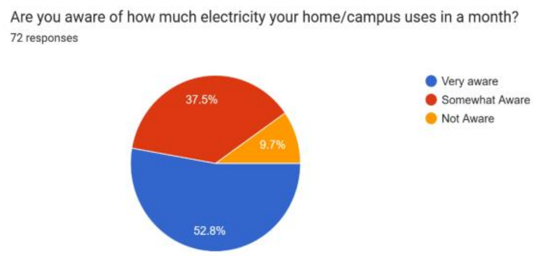

Fig. 6. When asked about how much electricity their home/campus uses in a month

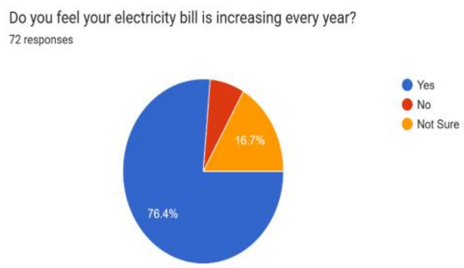

Fig. 7. When asked if they feel increase in the electricity bill every year

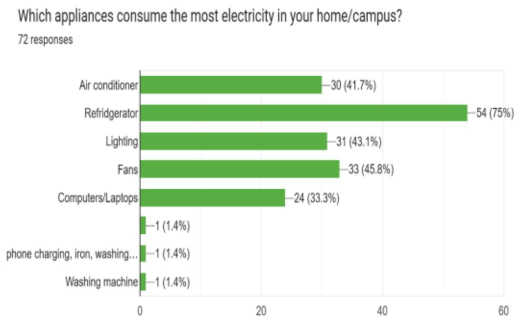

Fig. 8. When asked about the appliances that consume the most electricity in their home/campus

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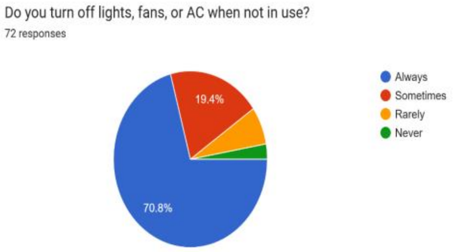

Fig. 9. When asked if they turn off lights, fans, or AC when not in use

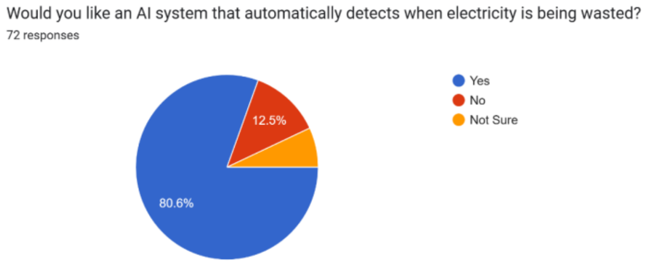

Fig. 10. When asked if they would like an AI system that automatically detects when electricity is being wasted

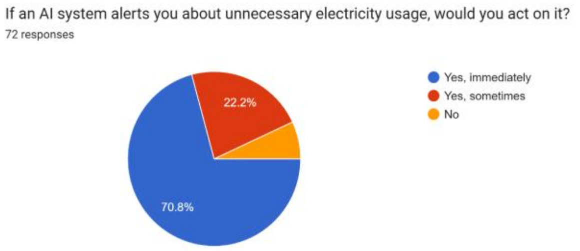

Fig. 11. When asked if they would act upon soon if an AI system alerts them about unnecessary electricity usage

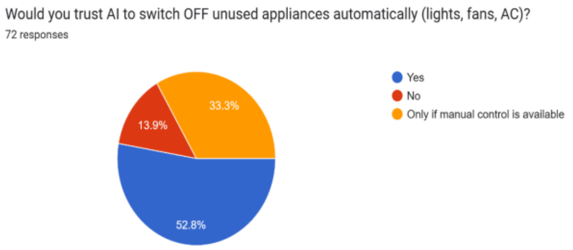

Fig. 12. When asked about if they would trust AI to switch OFF unused appliances automatically (lights, fans, AC)

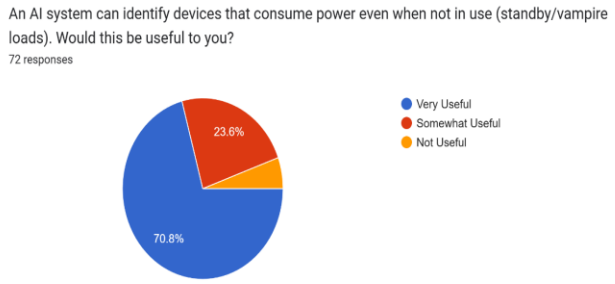

Fig. 13. When asked about if it would be helpful for them if an AI system can identify devices that consume power even not in use (standby/ vampire loads)

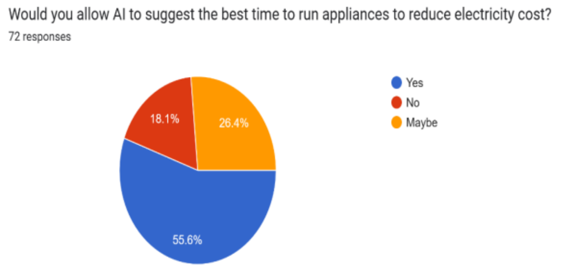

Fig. 14. When asked if they would allow AI to suggest the best time to run appliances to reduce electricity cost

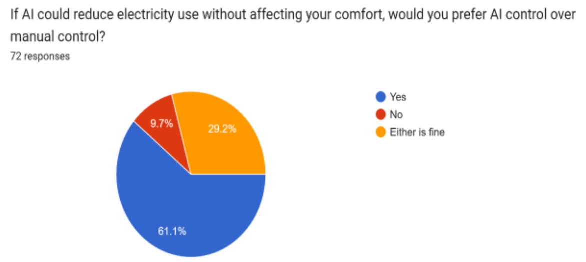

Fig. 15. When asked if they would prefer AI control over manual control i.e. if AI could reduce electricity use without affecting their comfort

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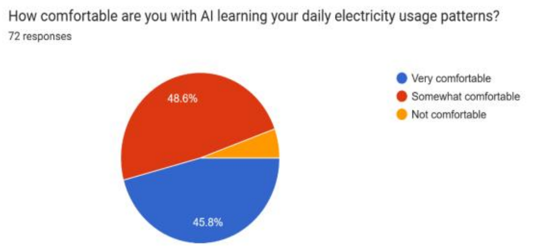

Fig. 16. When asked if they would be comfortable with AI learning their daily electricity usage patterns

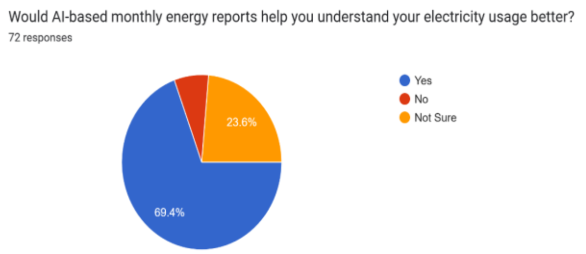

Fig. 17. When asked if they would be interested in AI based monthly energy reports that would help them to understand their electricity usage better

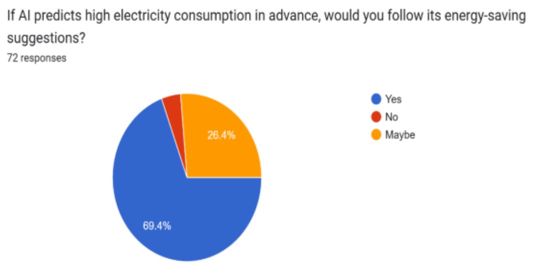

Fig. 18. When asked if they would follow its energy-saving suggestions if AI predicts high electricity consumptions in advance.

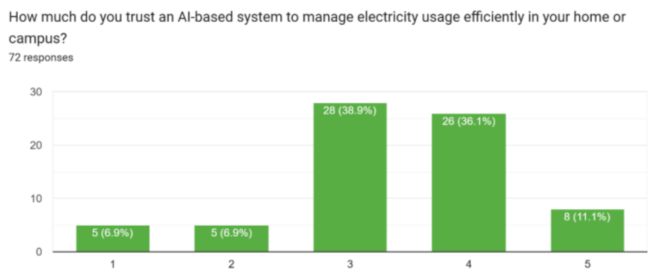

Fig. 19. When asked if they would trust an AI-based system to manage electricity usage efficiently in your home or campus

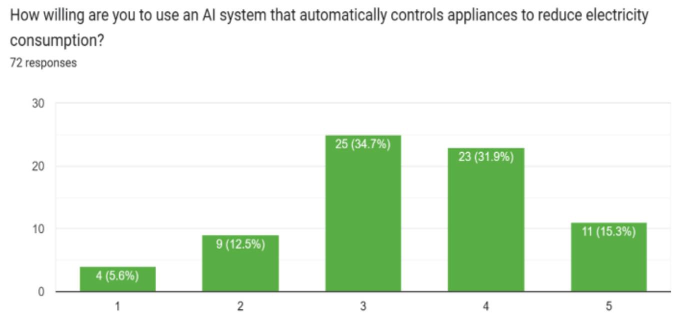

Fig. 20. When asked if they are willing to use an AI system that automatically controls the appliances to reduce electricity consumption.

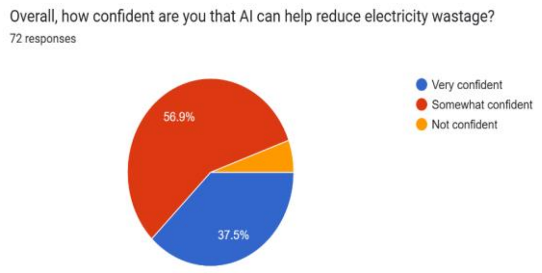

Fig. 21. When asked about how confident they are about how AI can help reduce electricity wastage

Significant Outcomes:

1. **When people were asked about their awareness and current practices related to electricity usage.** Most people get their electricity bill regularly, but many do not check it carefully. Many said their bill has gone up because they use AC, fridge, heater, and washing machine a lot. People try to switch off lights and fans, but they often forget. It mostly depends on habit, not a proper system.
2. **When respondents were asked about wastage and the need for intelligent monitoring.** Most respondents indicated that electricity is wasted without noticing, like leaving devices on or in standby mode. Most liked the idea of an AI system that can find and stop this wastage. They feel that humans alone cannot manage electricity cost efficiently and perfectly all the time.

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3. **When they were asked about trust in AI-based automation.**
   People have medium to high trust in AI. Some are scared to give full control, but most are okay if AI only helps, not fully controls. They like AI switching off unused devices if it's convenient.
4. **When they were asked about AI recommendations and alerts.**
   Most of the respondents indicated that they will follow AI alerts about wasting electricity. Many also like AI telling them the best time to use appliances to save money. They are ready to work with AI if it's safe.
5. **When they were asked about AI learning usage patterns.** Most people are okay with AI learning their daily electricity use. A few worry about privacy, but many of them think it will help reduce wastage of electricity if used efficiently and safely.
6. **When they were asked about AI-based reports and predictions.**
   People like the idea of monthly reports from AI. They feel it will help them understand their usage better. If AI can warn them about high usage in advance, they are ready to follow saving tips.
7. **When they were asked about overall confidence in AI for energy management.**
   Most respondents indicated AI can help reduce electricity waste, especially for those in campuses. But they do not want full control by AI yet. They want clear system, control in their hands, and slow change.

Hypothesis Tesing:

A hypothesis test was conducted to determine whether there is a statistically significant association between **trust in AI-based electricity management** and **willingness to adopt AI-controlled systems**.

A) NULL HYPOTHESIS (H0)

There is no association between users' trust in AI-based energy management systems and their willingness to use AI-controlled appliances.

B) ALTERNATE HYPOTHESIS (H1)

A Pearson's Chi-Squared test was conducted to determine if a statistically significant association exists between users' **Trust in AI** and their **Willingness to use AI-controlled systems**.

Statistical Test:

Trust in AI \ Willingness to Use AI System	**1 (Very Low Willingness)**	**2 (Low Willingness)**	**3 (Moderate Willingness)**	**4 (High Willingness)**	**5 (Very High Willingness)**
1 (Very Low Trust)	0.33	0.83	2.08	1.83	0.92
2 (Low Trust)	0.28	0.69	1.74	1.53	0.76
3 (Moderate Trust)	1.56	3.89	9.72	8.56	4.28
4 (High Trust)	1.39	3.47	8.68	7.64	3.82
5 (Very High Trust)	0.44	1.11	2.78	2.44	1.22

There are many tests available to determine if the null hypothesis is to be rejected or not. Some are:

1. Chi-squared test **2. T-student test (T-test)** **3. Fisher's Z test.**

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For this paper, we will be using Chi-Squared Test Pearson's chi-square test is a statistical test for categorical data. It is used to determine whether your data are significantly different from what you expected. (Also known as alpha or α). A significance level of 0.05, for example, means there's a 5% probability of discovering a difference when there isn't one. Lower significance levels indicate that more evidence is required to reject the null hypothesis. The confidence level indicates the probability that the location of a statistical parameter (such as the arithmetic mean) measured in a sample survey is given below.

Accuracy Helpfulness	**1**	**2**	**3**	**4**	**5**	**Row Totals**
1	3	3	0	0	0	6
2	1	4	0	0	0	5
3	0	2	19	6	1	28
4	0	0	6	15	4	25
5	0	1	0	1	6	8
Column Totals	**4**	**10**	**25**	**22**	**11**	**72**

Let's walk through the chi-squared test applied to our data for **AI accuracy ratings** vs **AI helpfulness ratings**, closely following your four requested steps and using the actual Excel values.

STEP 1: State the Hypothesis

- **Null Hypothesis (H_0):** Trust in AI-based electricity management systems and willingness to use AI-controlled appliances are independent.
- **Alternative Hypothesis (H_1):** Trust in AI-based systems and willingness to use AI-controlled appliances are not independent.

STEP 2: Expected frequencies were computed for each cell using the standard chi-square formula:

STEP 3: Expected frequencies were computed for each cell using the standard chi-square formula: $\sum(O_i-E_i)^2/E_i$

Trust \ Willingness	**1**	**2**	**3**	**4**	**5**	**Row Sum**
1 (Very Low Trust)	21.60	5.67	2.08	1.83	0.92	**32.10**
2 (Low Trust)	1.85	15.87	1.74	1.53	0.76	**21.75**
3 (Moderate Trust)	1.56	0.92	8.86	0.77	2.51	**14.62**
4 (High Trust)	1.39	3.47	0.83	7.09	0.01	**12.79**
5 (Very High Trust)	0.44	0.01	2.78	0.85	18.73	**22.81**
Column Sum	**26.84**	**25.94**	**16.29**	**12.07**	**22.93**	**104.07**

Sum of all values:

The computed chi-square test statistic was χ^2 is **104.07**

STEP 4: Calculate Chi-Square Value (Total)

Chi-Square Value Calculation:

Sum of all calculated components from Step 3 gives the chi-square test statistic: $\chi2=104.07$

Degrees of Freedom (df):

Calculated as:

df=(number of rows−1)×(number of columns−1)

=(5−1)×(5−1)

=16

Critical Value and Significance:

- At significance level $\alpha=0.05$ and df = 16, the critical value from the chi-squared distribution table is approximately 26.296.

- Since the calculated Chi-square value is greater than the critical value at the 0.05 significance level, the null hypothesis is rejected. This indicates a statistically significant relationship between user awareness and acceptance of AI-based electricity monitoring systems.

- Since the calculated $\chi2=104.07$ is **much greater** than the critical value 26.296, we reject the null hypothesis.

Interpretation:

- There is a statistically significant association between trust in the AI system and willingness to use it. In other words, respondents who **trust the AI more** also tend to be **more willing** to allow the AI to control appliances and reduce electricity use.
- The observed distributions deviate significantly from what would be expected if they were independent.
- **Summary:**
- **Chi-square statistic:** 104.07
- **Degrees of freedom:** 16
- **Critical value (0.05 significance):** 26.296
- **Decision:** Reject H0, accept H1
- **Conclusion:** Trust in AI and willingness to use AI-control are significantly associated in this sample of respondents.

Findings:

- Most respondents are aware that electricity consumption is increasing and recognize the role of high-energy appliances in this rise.
- Manual energy-saving practices exist but are inconsistent and insufficient for effective long-term control.
- There is strong interest in AI systems that can detect wastage, provide alerts, and optimize appliance usage.
- Trust in AI is moderate to high, especially when AI functions as an assistive tool rather than a fully autonomous controller.
- Privacy concerns exist but do not significantly outweigh the perceived benefits of AI-driven energy management.
- Statistical analysis confirms that higher trust in AI correlates with greater willingness to adopt AI-based electricity control systems.

Conclusion:

- The survey results demonstrate a positive but cautious attitude toward AI-based electricity management in homes and campuses. While users acknowledge the limitations of manual monitoring, they recognize AI's potential to reduce wastage, lower costs, and improve efficiency. Trust, transparency, and user control emerge as critical factors influencing adoption.
- The findings strongly support **user readiness and positive perception** toward AI-driven monitoring, prediction, analysis, and automation as a potential sustainable solution to rising electricity consumption.

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