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A Quantitative Study on IoT User Opinion Using SPSS Methodology

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Abstract

This excerpt provides a clear overview of the IoT user experience research study. The research design appears to be well-structured, focusing on five fundamental dimensions that are important for understanding user adoption and acceptance of IoT technologies. The choice of variables is particularly thoughtful – ease of use and usefulness are consistent with established technology acceptance models such as the TAM (Technology Acceptance Model), while security concerns address one of the most important barriers to IoT adoption. Reliability and satisfaction round out the framework by capturing both technology performance and overall user perception. However, there are a few methodological considerations to note: Sample size limitation: With only five users, this appears to be a pilot study or exploratory research. While SPSS can technically analyze small datasets, the statistical power would be very limited, and the findings would not be generalizable to the wider population. Statistical approach: A combination of descriptive statistics, histograms, and Pearson correlations are appropriate for this type of exploratory analysis, although correlations should be interpreted with caution given the sample size. Although small in sample size, this type of study can provide valuable insights for initial product development, identify potential issues early in the design process, or inform larger-scale research designs. For future iterations, expanding the sample size, incorporating qualitative methods (interviews or focus groups), and considering additional variables such as privacy concerns or behavioral intent could strengthen the research framework and provide more robust insights into IoT user experiences. Findings revealed that usability and satisfaction received the highest mean scores, indicating strongly positive user experiences. Ease of use and reliability were also rated highly, while security concerns showed high variability across participants. The correlation matrix demonstrated strong positive relationships between satisfaction, usefulness, and ease of use, indicating that these factors are interdependent and important for improving IoT user experience. Conversely, security concerns showed weak or negative correlations, highlighting the need for improved security communication or features in IoT systems. This research demonstrates the effectiveness of SPSS in identifying patterns and supports the data-driven development of user-centric IoT solutions.

Keywords: Internet of Things (IoT), SPSS, User Experience, Ease of Use, Security Concern, Usefulness, Reliability, Satisfaction, Data Analysis, Communication

Introduction

The Internet of Things (IoT) extends digital connectivity beyond conventional devices such as laptops and mobile phones to include everyday objects, including home appliances, cars, fitness trackers, and manufacturing equipment. These networked objects create an intelligent ecosystem by communicating with users and central management systems, facilitating automated processes and informed decision-making based on collected data. By integrating sensors, applications, and network capabilities into physical objects, IoT improves monitoring, management, and performance optimization in personal, commercial, and industrial settings [1]. This integration of tangible and virtual parts drives technological advancements, increases operational productivity, and enhances user convenience in many sectors, such as healthcare, agriculture, logistics, and connected homes. The independent and integrated operation of these connected devices enables IoT to deliver personalized solutions, create more responsive environments, streamline systems, and fundamentally change how different sectors operate and function [2]. The Internet of Things (IoT) facilitates improved management and efficiency in both personal and industrial domains. By connecting the physical and digital worlds, it drives technological advancement, improves operational efficiency, and brings greater convenience to sectors such as healthcare, agriculture, transportation, and smart homes [3]. One of the defining strengths of IoT is its ability to transform human interactions with the environment. Users can remotely monitor, control, and receive real-time updates from connected devices via apps and dashboards [4]. This capability has accelerated IoT integration in consumer markets, including smart homes, wearable's, and connected vehicles. In healthcare, IoT-connected medical devices support remote patient monitoring, improve treatment outcomes, and help reduce hospital visits. In agriculture, IoT tools help with crop monitoring, optimize irrigation, reduce resource waste, and promote sustainable farming practices [5]. As IoT continues to expand into new sectors, the growing number of connected devices is creating vast datasets that are fueling the development of artificial intelligence and machine learning. These data-driven insights enable more accurate decision-making, predictive maintenance, and personalized services. IoT is transforming the way individuals and businesses operate [6]. By embedding connectivity in everyday objects, it is improving automation, user experience, and operational efficiency across industries. However, as this rapidly growing ecosystem evolves, it also presents challenges that must be addressed to unlock its full potential. Unlike conventional computing systems, IoT extends connectivity to common objects — including home appliances, transportation systems, wearables, and industrial equipment — enabling them to collect, transmit, and efficiently share data [7]. This acronym effectively explains the transformative impact of IoT across multiple sectors through real-time data processing and automated decision-making capabilities. The examples provided demonstrate the versatility of IoT well. Smart home applications showcase consumer-facing IoT, where personalization and convenience drive adoption. The industrial use case highlights the role of IoT in predictive maintenance and operational efficiency – a particularly compelling application as it directly leads to cost savings and reduced operational disruptions [8]. Key strengths of the analysis: The paragraph correctly identifies the underlying technologies that enable IoT expansion. The reference to various wireless protocols (Wi-Fi, Bluetooth, cellular) acknowledges that different IoT applications require different connectivity solutions based on range, power consumption, and data requirements. Technology infrastructure: Emphasis on cloud computing and data storage improvements is critical – IoT is generating massive amounts of data that require scalable processing and storage solutions [9]. Edge computing, although not mentioned here, is also becoming increasingly important for reducing latency in time-critical applications. Industry Impact: The breadth of industries mentioned reflects the cross-sector applicability of IoT, although each faces unique implementation challenges and opportunities. Areas for Expansion: This paragraph would benefit from acknowledging some of the challenges along with the opportunities, such as interoperability between different IoT platforms, cyber security vulnerabilities, and the complexity of managing heterogeneous device ecosystems. Additionally, mentioning emerging technologies such as 5G networks and edge computing will provide a more complete picture of the technological foundation of IoT. [10]. In healthcare, IoT-connected devices have revolutionized patient care by providing doctors with real-time health metrics, enabling remote monitoring, and allowing early intervention in medical issues. In agriculture, IoT solutions help monitor soil health, manage water use, monitor crop conditions, and promote more sustainable and efficient farming practices [12]. The continued growth of IoT is closely linked to the increasing importance of data analytics and machine learning. As IoT devices generate ever-increasing amounts of data, analyzing this information becomes essential to uncover meaningful insights. These insights support better decision-making, help predict trends, and allow both businesses and individuals to streamline operations and improve outcomes [14]. While the Internet of Things (IoT) holds significant promise, it faces significant challenges – particularly in cyber security, data protection and interoperability. The highly connected architecture of IoT devices increases their vulnerability to cyber-attacks, raising serious concerns about the protection of users' sensitive information. In addition, the lack of global standards and protocols across devices and platforms can hinder smooth communication and integration [18]. As IoT becomes more embedded in everyday life, it is essential to address these issues. IoT is a transformative and rapidly evolving technology that connects everyday objects to the Internet, opening up new opportunities for automation, improved performance, and data-driven decision-making [18]. While its continued development promises to revolutionize many industries and improve the quality of everyday life, these advances must be balanced with efforts to overcome the technological and security hurdles that come with it. Unlike conventional Internet-connected devices such as smartphones and laptops, IoT extends connectivity to a wide range of objects such as home appliances, vehicles, wearable technology, and industrial machinery. By integrating sensors, applications, and communication networks, IoT devices can autonomously collect and share data, enabling intelligent interactions using minimal human input [20].

Material and Method

Input Parameters: User type, Device type, Use purpose, Frequency, Technology knowledge

User type reflects the identity or role of the user, such as student, professional, or retiree. It helps to classify behavioural patterns, needs, or expectations from the technology being used.

Device type identifies the primary device used - smartphone, laptop, tablet, etc. Since some tasks are device-specific, this affects user interaction styles and accessibility.

Use purpose explains the reason the user engages with the technology. This can include learning, work, entertainment, or communication. Understanding the purpose helps align features or services with user goals.

Frequency describes how often the user accesses the computer - daily, weekly, monthly, or infrequently. This indicates the level of engagement and helps determine the need for updates, notifications, or support frequency.

Technology knowledge measures the user's comfort and skill level with the technology. Categories such as Beginner to Expert provide insight into training needs, interface design preferences, and expected troubleshooting behavior.

Evaluation Parameters: Ease of Use, Security Concern, Usefulness, Reliability, Satisfaction

Ease of use refers to how simple and intuitive a system or device is for the user. A high ease of use rating indicates that minimal effort is required to learn or operate the technology.

Security concerns refer to a user's awareness or concern about data security, privacy, and system vulnerabilities. High concerns can affect trust and usage behavior, especially for online services.

Usability measures how useful or practical the user finds the technology to be in meeting their needs. This directly impacts continued use and user engagement.

Reliability refers to the consistency and stability of the system over time. A reliable device or application frequently performs without errors or crashes, increasing user trust.

Satisfaction captures the user's overall experience and emotional response. It is often the result of a combination of factors such as ease of use, usefulness, and reliability, and is a key measure of user retention and feedback.

SPSS method: Data Entry and Production: Responses from five participants were entered into SPSS. Variables were defined with appropriate measurement levels (e.g., ordinal or scale), and missing values were checked. Descriptive Statistics: SPSS was used to calculate measures such as mean, standard deviation, range, median, and percentages. These provided a general summary of how users rated each variable. Histogram Analysis: Frequency distributions were visualized using histograms enclosed by normal curves, allowing for the shape of the distribution (e.g., skewness, spread) and user rating patterns to be assessed. Correlation Matrix: SPSS calculated Pearson correlation coefficients to examine relationships between variables. For example, strong positive correlations between satisfaction, usefulness, and ease of use revealed interdependence. Interpretation: SPSS results were interpreted to draw conclusions about user perceptions and system performance. This structured method provided both statistical insight and visual clarity to support decision making. First, data entry and coding were carried out. Five responses were entered into the SPSS dataset. Each variable was defined with the correct labels, measurement levels (scales), and value assignments, ensuring that SPSS could perform accurate calculations. Second, descriptive statistics were calculated to understand central tendency and dispersion. Values such as mean, median, mode, standard deviation, skewness, and kurtosis provided insight into how participants rated each factor. For example, usefulness and satisfaction had the highest mean values, indicating strong positive feelings, while safety concern showed the most variability. Third, frequency distributions were visualized using histograms with superimposed normal curves. These visualizations helped assess the shape of the distribution—whether the responses were symmetrical, skewed, or tightly clustered. Most variables, especially usefulness and satisfaction, were skewed to the left, indicating a concentration of higher ratings. Next, a correlation matrix was created using Pearson's r to assess the strength and direction of the relationships between the variables. Strong positive correlations were found between satisfaction, usefulness, and ease of use, highlighting their influence on user satisfaction. In contrast, security concerns had weak or negative correlations, indicating that security issues are not directly correlated with user satisfaction in this model.

Result and Discussion

TABLE 1. Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.671	.771	5

Cronbach's alpha is a statistical measure that assesses the internal consistency or reliability of a scale or questionnaire. It indicates how closely the items in a test are related as a group, with values ranging from 0 to 1. In this case, the original Cronbach's alpha is .671, which falls below the generally accepted .70 threshold for adequate reliability. However, the standardized version shows .771, which exceeds the acceptable level. This improvement occurs because standardization removes the influence of different item variances and focuses only on the correlations between items. The scale has 5 items. While the original alpha indicates questionable reliability, the standardized alpha indicates good internal consistency. This suggests that the items measure the same underlying construct but may have different sizes or variances. Researchers may consider this scale acceptable for research purposes, although item refinement may further improve reliability. The standardized alpha provides a more precise estimate when the items have different measurement scales.

TABLE 2. Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Ease of Use	5	2	3	5	21	4.20	.374	.837	.700	-.512	.913	-.612	2.000
Security Concern	5	3	2	5	17	3.40	.510	1.140	1.300	.405	.913	-.178	2.000
Usefulness	5	1	4	5	23	4.60	.245	.548	.300	-.609	.913	-3.333	2.000
Reliability	5	2	3	5	21	4.20	.374	.837	.700	-.512	.913	-.612	2.000
Satisfaction	5	2	3	5	22	4.40	.400	.894	.800	-1.258	.913	.313	2.000
Valid N (list wise)	5												

The table summarizes the responses of 5 participants on five user experience variables. Ease of use and reliability both have a mean of 4.20, indicating generally high but slightly varying ratings. Their negative slope (-0.512) indicates that most users rated them highly. Security concern has a low mean of 3.40 and a high variance (1.30), indicating a high degree of disagreement among users. Usefulness has the highest mean (4.60), the lowest standard deviation (0.548), and is negatively skewed (-0.609), indicating that most users found the system very useful. Its kurtosis (-3.333) indicates that the responses are tightly clustered around the mean. Satisfaction has a high mean of 4.40 and shows moderate stability with a slight leftward skew (-1.258), indicating strong user approval. Overall, the data shows generally positive responses, with usefulness and satisfaction rated very high, while safety concerns revealed greater variability and slightly lower confidence among users.

TABLE 3. Frequencies Statistics

		Ease of Use	Security Concern	Usefulness	Reliability	Satisfaction
N	Valid	5	5	5	5	5
	Missing	0	0	0	0	0
Median		4.00	3.00	5.00	4.00	5.00
Mode		4[a]	3	5	4[a]	5
Percentiles	25	3.50	2.50	4.00	3.50	3.50
	50	4.00	3.00	5.00	4.00	5.00
	75	5.00	4.50	5.00	5.00	5.00

This table presents the central tendency and distribution of five key user experience variables based on 5 valid responses. The mean scores show that users generally rated ease of use and reliability at 4.00, security concern at 3.00, and both usefulness and satisfaction at the highest value of 5.00 – indicating strong overall satisfaction and usefulness. The mode (most frequent value) supports these findings, with usefulness and satisfaction again receiving scores of 5 most often. The percentile values further show how the responses are distributed. For example, the 75th percentile for ease of use, reliability, usefulness, and satisfaction is 5.00, indicating that at least 25% of users gave it a high rating. In contrast, security concern shows more moderate responses, with a 25th percentile of 2.5 and a 75th percentile of 4.5, indicating more variability and slightly less confidence in computer security.

Histogram Plot:

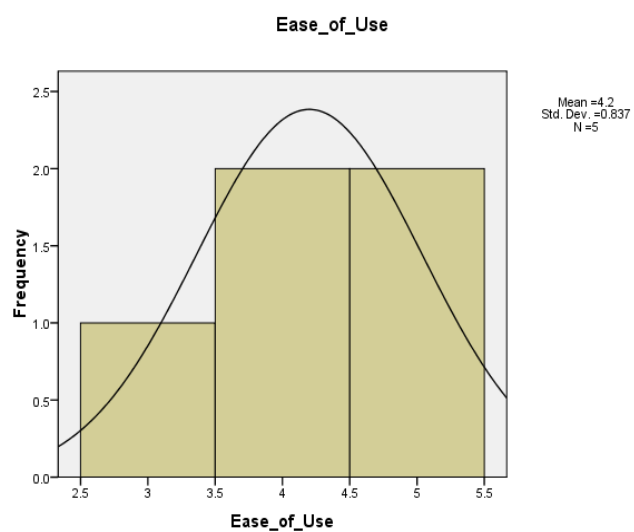

FIGURE1. Ease of Use

The histogram illustrates the distribution of responses for Ease_of_Use based on 5 participants. The values range from 3 to 5, with a mean of 4.2 and a standard deviation of 0.837, indicating moderate variation. The shape of the histogram, along with the superimposed normal curve, indicates a slightly left-skewed distribution, in which most participants rated the ease of use positively. Two users rated it 4, two rated it 5, while only one user gave it a low score of 3. This clustering toward the high end supports the idea that the system is generally easy to use. Although the small sample size (N = 5) limits statistical generalizability, the bell-shaped curve approximates normality.

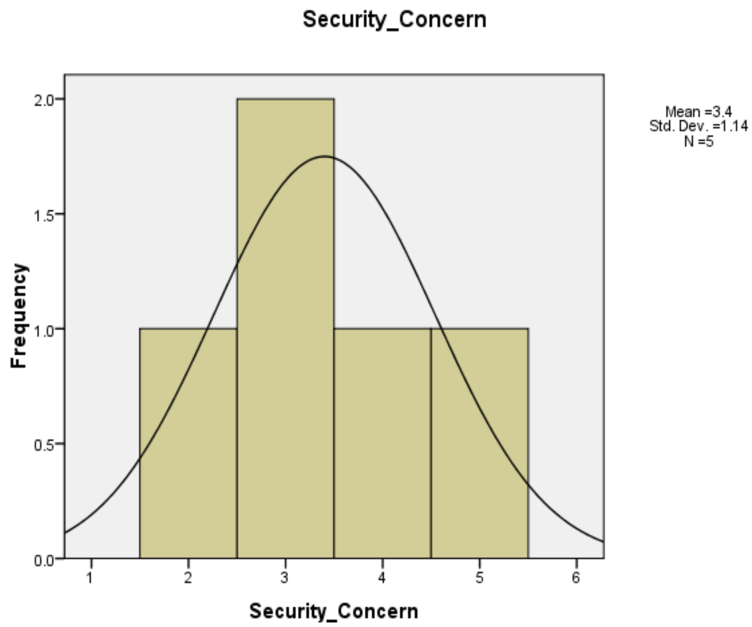

FIGURE 2. Security Concern

The histogram for Security_Concern shows a wide spread compared to the other variables, with responses ranging from 2 to 5. The mean is 3.4, and the standard deviation is 1.14, indicating moderate variation in user concerns about security. The frequency is highest at a rating of 3, indicating that most users had neutral to slightly concerned views. The bell curve is very symmetrical, indicating a normal distribution despite the small sample size (N = 5). This indicates varying levels of confidence in computer security, with no extreme skew.

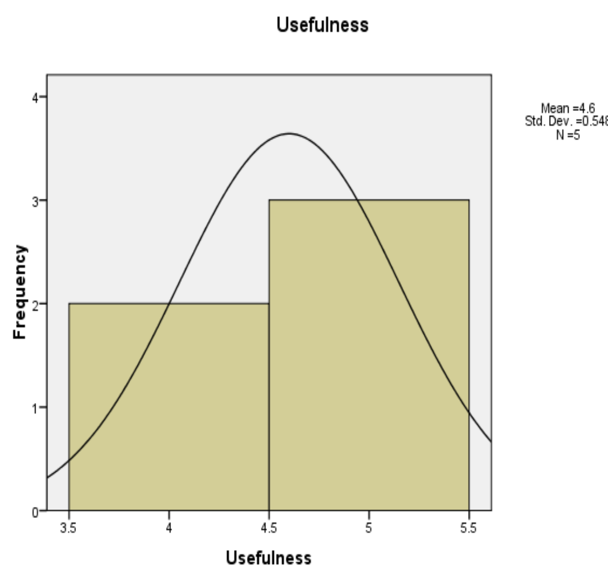

FIGURE3. Usefulness

The histogram for usability indicates that users generally found the system to be very useful. The mean rating is 4.6, and the standard deviation is relatively low at 0.548, indicating strong agreement among users. Most responses are clustered between 4.5 and 5.0, with a higher frequency at the upper end. The shape of the curve is slightly tilted to the left, reinforcing that users consistently rated the system as very useful. With N = 5, this small sample still indicates a positive perception of the practical value of the system.

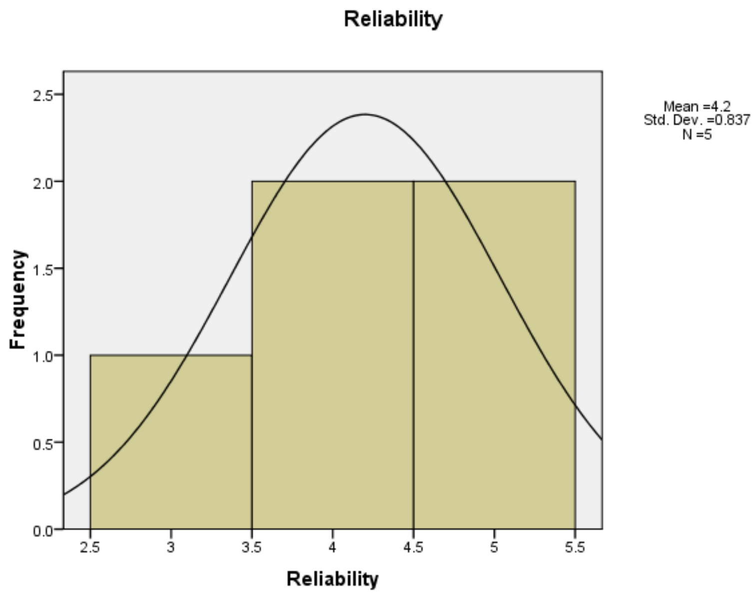

FIGURE4. Reliability

The reliability graph reflects favorable user opinions, with most responses falling between 4 and 5 ratings. The mean score of 4.2 and the standard deviation of 0.837 indicate a moderate level of agreement among participants. While two users rated the reliability high, one gave a low rating near 3, indicating little variation in perception. The overall distribution appears closer to normal, with a slight skew to the left.

FIGURE5. Satisfaction

The histogram for satisfaction shows a strong positive response, with most users rating it at 5. The mean is 4.4 and the standard deviation is 0.894, indicating generally high but slightly varying levels of satisfaction. Three participants rated satisfaction at the highest level, while one gave a low score around 3, indicating a slight expression. The distribution is slightly skewed to the left, showing that most ratings are in the high range.

TABLE 4. Correlations

	Satisfaction	Reliability	Usefulness	Security Concern	Ease of Use
Satisfaction	1.000	.535	.919	-.441	.869
Reliability	.535	1.000	.764	.419	.643
Usefulness	.919	.764	1.000	-.080	.764
Security Concern	-.441	.419	-.080	1.000	-.367
Ease of Use	.869	.643	.764	-.367	1.000

The table presents the correlation coefficients between the five variables. Satisfaction is strongly positively correlated with usefulness (0.919) and ease of use (0.869), indicating that when users find the system more useful and easy to use, their satisfaction increases. Reliability also shows moderate positive correlations with satisfaction (0.535) and usefulness (0.764). In contrast, security concern has weak or negative correlations with most variables, including a negative correlation with satisfaction (-0.441), indicating that high concern about security may slightly reduce satisfaction.

Conclusion

This study highlights the value of using SPSS to assess user perceptions of Internet of Things (IoT) technologies. Through descriptive statistics and correlation analysis, it was clear that usefulness, ease of use, and satisfaction are closely linked and significantly impact the overall user experience. Users generally found IoT systems to be useful and easy to interact with, which positively impacted their satisfaction levels. However, the findings also underscored mixed perceptions regarding security concerns. While not all users considered security to be a critical issue, the variation in responses suggests that IoT developers and providers need to address user trust and data security more proactively. The relatively low correlation between security and satisfaction suggests that even if users are satisfied with the functionality, unresolved security concerns can still impact long-term engagement and trust. The use of SPSS proved to be a useful and practical tool for analysing small sample datasets. It provided both quantitative clarity and visual representation, allowing for deeper insights into how users interact with IoT systems. This approach can be scaled up to larger studies and further extended to assess other user-centric metrics such as affordability, adaptability, and data transparency. Using SPSS methodology in IoT research provides a structured way to measure user feedback and uncover key factors that influence user experience. This helps developers and stakeholders create more responsive, secure, and user-friendly IoT environments, contributing to wider adoption and improved satisfaction among end users.

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