Proposed Model for Asset Lifecycle Management through the Internet of Things

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Abstract: Given the profound and extensive developments in information technology across the business landscape, the domain of asset and resource management within large-scale manufacturing corporations is also expected to undergo significant transformation. As asset management is one of the core and enduring managerial functions in large organizations, and as top executives consistently seek up-to-date, innovative, and technology-driven solutions for optimal resource management, this study aims to propose a model for asset lifecycle management through the Internet of Things (IoT). The research, in terms of its aim, is applied-developmental in nature, and methodologically, it is a non-experimental (descriptive) study conducted using a cross-sectional survey approach. Regarding the research method, it should be noted that a qualitative content analysis was first conducted to design an IoT-based asset lifecycle management model by reviewing 60 reputable Persian and English scientific articles published between 2011 and 2023. Additionally, using the grounded theory method, in-depth interviews were conducted with 10 experts and managers in the fields of IoT and asset management. After open coding of the interview transcripts and generating frequency charts for each interview's codes, axial coding was performed to identify major categories. As a result, 7 core themes and 38 sub-themes were extracted and organized into the proposed model for implementing IoT-based asset lifecycle management. The findings revealed that by analyzing and categorizing the descriptive codes extracted from the interview transcripts, a total of 38 sub-themes were identified. These were grouped into 7 main themes based on their semantic proximity and relevance: asset lifecycle management, asset lifecycle planning, asset acquisition, strategic alignment, IoT-enabled reporting, process automation through IoT, and IoT implementation within the organization. The outcomes of the proposed model demonstrate the influential role of the Internet of Things as an emerging technology in asset management. Its practical application can lead to a major transformation in safeguarding and optimizing the management of institutional assets and properties.

Keywords: Asset lifecycle management, Internet of Things, model proposal, emerging technology.

1. Introduction

In today’s rapidly evolving world, the Internet of Things (IoT) is emerging as one of the primary trends shaping technological advancement, particularly within the realm of information and communication technology. This shift from a user-centered internet to an internet designed for communication among physical objects to deliver specific services necessitates a rethinking of some traditional approaches to network management, computing, and service delivery [1].

The emergence of new technologies, particularly the IoT and its associated innovations, often brings societal uncertainty regarding their adoption. Amid the growth of private companies and organizations in this field, governments and regulatory bodies play a crucial role in establishing standards and frameworks that enhance public trust and facilitate acceptance. More importantly, the successful design and implementation of national strategies and standards for IoT significantly increase the potential for leveraging this technology to gain social and economic benefits in any country [2]. IoT can offer a robust framework for detection and reliability in identification processes.

Understanding the sociotechnical interactions among the factors and components of asset management data infrastructures—enabled by IoT—is essential. The Theory of the Duality of Technology conceptualizes technology as both a structural feature and a product of human agency. Actors physically construct technology within a social context, assigning it varied meanings [1, 3]. Technology evolves from the ongoing interaction between human choices and the organizational context, which offers structured conditions for development [4].

Asset and property management is regarded as one of the most sensitive managerial domains within organizations. This function plays a pivotal role in cost reduction through the control and optimal use of assets, particularly in large organizations, making the need for up-to-date and comprehensive information systems indispensable. The integration of IoT with cloud computing infrastructures holds the potential to revolutionize asset management by enabling the collection of precise and extensive data, facilitating more effective cost control, and enhancing service quality. IoT-based systems can introduce improvements and innovations in asset management that are unattainable through conventional systems [5].

Current asset management systems in many organizations face various challenges that undermine their efficiency and effectiveness. One of the most critical issues is the lack of data integration. In numerous organizations, asset-related information is stored across separate and unconnected systems [6]. This fragmentation makes data access difficult and results in decision-making based on incomplete or inaccurate information. Furthermore, this lack of integration increases the time and cost associated with data collection and processing. Another challenge is the inadequate updating and maintenance of asset management systems [7, 8]. Many organizations rely on outdated systems that have not been modernized, leading to erroneous or obsolete data. Such deficiencies negatively impact strategic planning and decision-making, as managers act on inaccurate information. Additionally, these systems often lack advanced analytical capabilities, impairing their ability to assess asset performance or forecast future needs. Non-compliance with legal requirements and industry standards is another serious challenge. Some organizations struggle to adhere to the regulatory frameworks governing asset management, which may lead to legal and financial consequences and damage organizational credibility [6, 9, 10]. Finally, insufficient security protocols may heighten exposure to security threats. Unauthorized access to sensitive information can result in data theft or financial loss. Collectively, these issues diminish system efficiency, raise operational costs, and reduce customer satisfaction—thus necessitating a comprehensive review and enhancement of asset management systems. The key innovation of this study lies in leveraging advanced IoT technologies to optimize asset lifecycle management processes. Real-time and accurate data on asset conditions are gathered, aiding improved decision-making and boosting organizational efficiency. This research seeks to present an integrated model for asset management using IoT, one that enables secure infrastructures through which power and resources in organizations and nations can be strategically managed. Such a model offers a means to enhance global competitiveness and ensure organizational sustainability.

2. Methodology

gThe present study aims to establish a semantic system using an inductive-deductive approach without any prior hypothesis formulation. In terms of its objective, this is an applied-developmental research study, as it seeks to design an asset lifecycle management model through the Internet of Things (IoT). Based on the data collection method, it is a non-experimental (descriptive) research conducted via a cross-sectional survey. Finally, in terms of data analysis techniques, it is a mixed-methods study (qualitative-quantitative). In the qualitative phase, meta-synthesis was employed to collect data. Initially, the primary indicators relevant to the proposed model were extracted by reviewing 60 credible domestic and international articles related to the subject. In the second step, qualitative thematic analysis (editing, summarizing, and interpreting interview content) was used to identify the main and sub-categories of the study through in-depth interviews with 10 experts and managers in the fields of IoT and asset management.

In the quantitative phase of the study, the proposed model was validated by surveying 384 individuals working in the IoT and asset management sectors. MAXQDA software was used for qualitative data analysis, and the quantitative analysis was conducted using the Partial Least Squares (PLS) technique through SMART PLS software.

Sampling in the qualitative section was performed using non-probability and purposive methods. The sampling process continued until theoretical saturation was reached, with a final total of 10 experts participating. The statistical population in the quantitative section consisted of managers and professionals active in the field of asset management. The sample size was estimated using Cohen’s power analysis and G*POWER software, indicating that 110 participants were required to complete the questionnaire. Thematic analysis was conducted using MAXQDA, structural-interpretive modeling was conducted using MICMAC software, and PLS modeling was performed with Smart PLS.

Table 1. Demographic Characteristics of the Qualitative and Quantitative Sections of the Study

Demographic Characteristics	Qualitative		Quantitative	
	Frequency	Percent	Frequency	Percent
Gender				
Male	6	60%	63	57%
Female	4	40%	47	43%
Age				
Under 40 years	1	10%	43	39%
40–50 years	4	40%	39	35%
50 years and older	5	50%	28	25%
Education				
Bachelor's Degree	-	-	34	31%
Master's Degree	3	30%	44	40%
PhD	7	70%	32	29%
Work Experience				
Less than 10 years	-	-	29	26%
10–15 years	4	40%	25	23%
15–20 years	3	30%	32	29%
Over 20 years	3	30%	24	22%
Expert Role				
University Professor	5	50%	-	-
Industry Expert	5	50%	-	-
Total	10	100%	110	100%

Based on the demographic data in Table 1, the qualitative sample consisted of 6 men (60%) and 4 women (40%). In terms of age, 1 person (10%) was under 40, 4 persons (40%) were between 40 and 50, and 5 persons (50%) were 50 years and older. Regarding education, 3 persons (30%) held master's degrees, and 7 persons (70%) held PhDs. In terms of work experience, 4 persons (40%) had 10–15 years of experience, 3 persons (30%) had 15–20 years, and 3 persons (30%) had over 20 years.

According to the quantitative demographic data in Table 1, there were 63 men (57%) and 47 women (43%). In terms of age, 43 participants (39%) were under 40 years old, 39 participants (35%) were aged 40–50, and 28 participants (25%) were 50 years and older. Regarding education, 34 participants (31%) held bachelor's degrees, 44 participants (40%) held master's degrees, and 32 participants (29%) held PhDs. In terms of work experience, 29 participants (26%) had less than 10 years, 25 participants (23%) had 10–15 years, 32 participants (29%) had 15–20 years, and 24 participants (22%) had over 20 years.

In the first phase, based on literature review and expert interviews, indicators for the asset lifecycle management model through IoT were identified, with each expert participating in an average 45-minute interview. After the qualitative analysis, a questionnaire was distributed based on 7 main components and 38 sub-components extracted from the qualitative phase, followed by quantitative data collection from experts. The study then entered its quantitative phase. In the qualitative phase, the foundational elements of the model were identified, while in the quantitative phase, the model was validated using the Lawshe Content Validity Ratio and Cronbach's Alpha Coefficient.

The reviewed articles were required to have been published between 2012 and 2024 and to have been peer-reviewed by specialists in the relevant field. Furthermore, the articles had to provide sufficient data and information relevant to the research objectives. The main data collection tools used in this study were semi-structured interviews and a researcher-developed questionnaire.

In the final phase, the thematic categories defined for analysis were reviewed, redefined, and subsequently used to analyze the collected data.

3. Findings and Results

Through the process of defining and refining, the nature of what each category represents was clarified, and it was determined which aspect of the data each category encompasses. At this stage (Stage Five: Defining and Naming Themes), the primary and sub-themes of the research were named, and each group of codes extracted from the interview transcripts was assigned a specific theme.

Table 2. Primary and Sub-Themes of IoT-Based Asset Lifecycle Management

Primary Theme	Sub-Themes
Asset Lifecycle Management	1. Demand analysis 2. Cost-benefit analysis 3. Risk management 4. Asset monitoring, optimization, and maintenance 5. Decommissioning or replacement of obsolete assets 6. Proper budgeting 7. Performance evaluation
Asset Lifecycle Planning	8. Evaluation of operational adequacy of assets 9. Ensuring resource availability when needed 10. Identification of surplus or underperforming assets 11. Estimation of asset procurement and financing options 12. Ensuring asset retention and commitment

Asset Acquisition	13. Establishing a structured framework for asset oversight 14. Acquiring new assets for the organization 15. Aligning asset allocation with organizational goals 16. Focusing on sustainability and asset growth
Strategic Alignment	17. Value creation from organizational assets 18. Establishment of coordinated and regular activities 19. Responsiveness to organizational needs 20. Organizational orientation toward excellence
IoT-Based Reporting	21. Increased production capacity 22. Availability metrics 23. Equipment reliability 24. Improved equipment efficiency in material or energy use 25. Assessment of internal and external organizational conditions 26. Reduction of fixed organizational costs 27. Improved product and service quality
Process Smartification through IoT	28. Intelligent decision-making 29. Optimal resource allocation 30. Reduced disruptions in organizational processes 31. Use of smart maintenance and repair techniques 32. Ability to identify equipment malfunctions and solutions 33. Coordination among different organizational functions
IoT Implementation in the Organization	34. Cost reduction and savings 35. Productivity improvement 36. Increased return on investment 37. Organizational innovation 38. Optimal utilization of assets

Based on the findings presented in Table 2, the descriptive codes extracted from the interview transcripts were reviewed and categorized. Taking into account their semantic similarities and connections, the findings were organized into seven primary themes: Asset Lifecycle Management, Asset Lifecycle Planning, Asset Acquisition, Strategic Alignment, IoT-Based Reporting, Process Smartification through IoT, and IoT Implementation in the Organization, along with 38 sub-themes.

The Structural Self-Interaction Matrix (SSIM), as presented in Table 3, was constructed based on the constructs of the study and the comparison of their conceptual relationships using four types of conceptual linkages. The resulting data were summarized using the Interpretive Structural Modeling (ISM) method, leading to the creation of the SSIM matrix.

Table 3. Structural Self-Interaction Matrix of Asset Lifecycle Management Constructs via IoT

SSIM	C01	C02	C03	C04	C05	C06	C07
Asset Lifecycle Management (C01)		A	A	O	A	A	A
Asset Lifecycle Planning (C02)			X	A	A	O	A
Asset Acquisition (C03)				A	A	A	A
Strategic Alignment (C04)					A	A	A
IoT-Based Reporting (C05)						X	A
Process Smartification through IoT (C06)							A
IoT Implementation (C07)							

To determine the relationships and hierarchy of the constructs, both the reachability set (row elements representing outputs or influences) and the antecedent set (column elements representing inputs or influences received) must be extracted from the matrix presented in Table 3.

- **Reachability Set**: These are the constructs that can be reached through a specific construct (row elements or outputs/effects).

- **Antecedent Set**: These are the constructs from which a specific construct can be reached (column elements or inputs/being influenced).

Table 3. Input and Output Sets for Level Determination

Constructs	Output: Influence	Input: Influenced By	Intersection
Asset Lifecycle Management (C01)	C01	C01, C02, C03, C05, C06, C07	C01
Asset Lifecycle Planning (C02)	C01, C02, C03	C02, C03, C04, C05, C07	C02, C03
Asset Acquisition (C03)	C01, C02, C03	C02, C03, C04, C05, C06, C07	C02, C03
Strategic Alignment (C04)	C01, C02, C03, C04	C04, C05, C06, C07	C04
IoT-Based Reporting (C05)	C01, C02, C03, C04, C05, C06	C05, C06, C07	C05, C06
IoT-Driven Process Smartification (C06)	C01, C02, C03, C04, C05, C06	C05, C06, C07	C05, C06
IoT Implementation (C07)	C01, C02, C03, C04, C05, C06, C07	C07	C07

The output set includes the construct itself and the constructs it influences. The input set includes the construct itself and the constructs that influence it. The intersection of these sets defines bidirectional relationships between constructs. For a given construct C_i, the reachability set (outputs) includes all constructs that can be accessed through C_i, and the antecedent set (inputs) includes all constructs from which C_i can be accessed. After determining the reachability and antecedent sets, their intersection is calculated. The first construct for which the intersection equals the reachability set is placed at the first level. Therefore, constructs at the first level are the most influenced within the model. After determining the level, the identified construct is removed from all sets, and the process is repeated to determine the next level.

Based on the research findings, the IoT-Based Asset Lifecycle Management Model is illustrated in figure below.

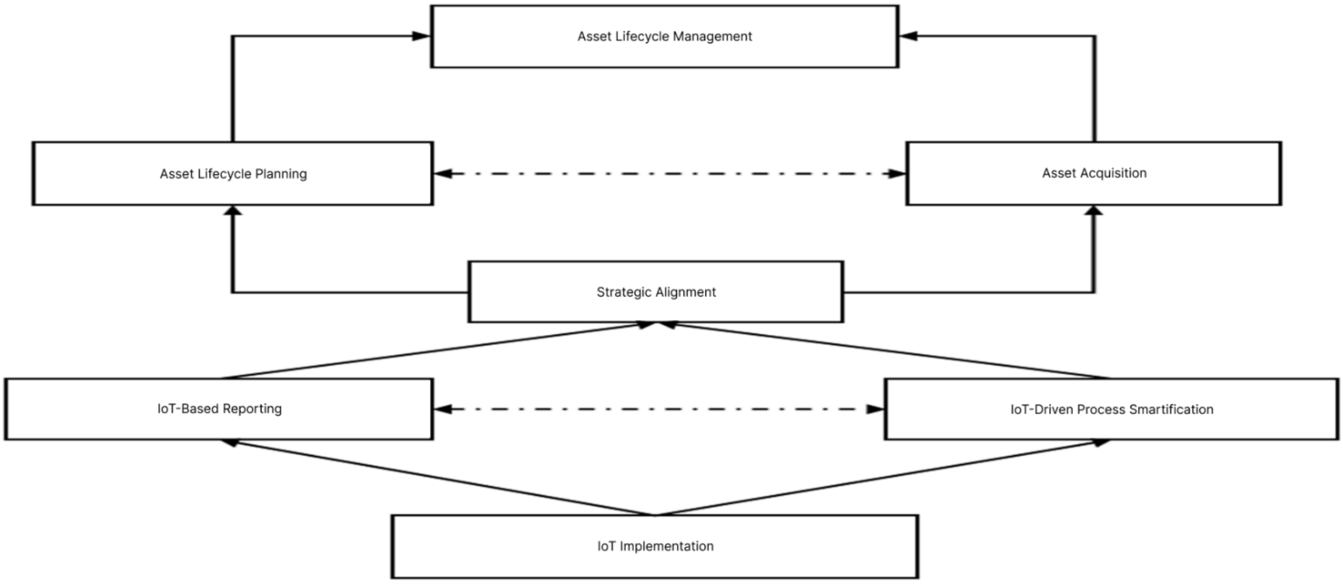

Figure 1. IoT-Based Asset Lifecycle Management Model

Based on the computed results, the sequence of constructs in this study is as follows:

- Asset Lifecycle Management (C01) is at Level 1.
- Asset Lifecycle Planning (C02) and Asset Acquisition (C03) are at Level 2.
- Strategic Alignment (C04) is at Level 3.
- IoT-Based Reporting (C05) and IoT-Driven Process Smartification (C06) are at Level 4.
- IoT Implementation (C07) is at Level 5.

To examine the significance of relationships between model variables, the bootstrapping method was used to calculate t-statistics. At a 5% significance level, if the bootstrap t-value exceeds 1.96, the observed correlations are considered significant.

The strength of the relationship between indicators and their respective constructs was assessed using factor loadings, while significance was evaluated through t-statistics. The results of the outer model (measurement model) are shown in Table 4.

Table 4. Outer Model (Measurement Model) Results

Indicator → Construct	Factor Loading	t-Statistic
Q01 → Asset Lifecycle Management	0.766	33.888
Q02 → Asset Lifecycle Management	0.728	25.945
Q03 → Asset Lifecycle Management	0.709	23.318
Q04 → Asset Lifecycle Management	0.742	28.822
Q05 → Asset Lifecycle Management	0.717	26.464
Q06 → Asset Lifecycle Management	0.703	22.225
Q07 → Asset Lifecycle Management	0.742	29.374
Q08 → Asset Lifecycle Planning	0.729	25.042
Q09 → Asset Lifecycle Planning	0.760	29.613
Q10 → Asset Lifecycle Planning	0.753	29.136
Q11 → Asset Lifecycle Planning	0.755	29.434
Q12 → Asset Lifecycle Planning	0.744	26.255
Q13 → Asset Acquisition	0.767	31.255
Q14 → Asset Acquisition	0.796	36.043
Q15 → Asset Acquisition	0.749	26.466
Q16 → Asset Acquisition	0.735	24.665
Q17 → Strategic Alignment	0.744	27.010
Q18 → Strategic Alignment	0.748	28.730
Q19 → Strategic Alignment	0.764	27.873
Q20 → Strategic Alignment	0.765	29.958
Q21 → IoT-Based Reporting	0.741	28.419
Q22 → IoT-Based Reporting	0.760	35.065
Q23 → IoT-Based Reporting	0.711	24.338
Q24 → IoT-Based Reporting	0.709	24.039
Q25 → IoT-Based Reporting	0.705	23.743
Q26 → IoT-Based Reporting	0.710	24.237
Q27 → IoT-Based Reporting	0.729	27.318
Q28 → IoT-Driven Process Smartification	0.749	28.931
Q29 → IoT-Driven Process Smartification	0.750	31.049
Q30 → IoT-Driven Process Smartification	0.774	37.266
Q31 → IoT-Driven Process Smartification	0.753	29.653
Q32 → IoT-Driven Process Smartification	0.688	23.570
Q33 → IoT-Driven Process Smartification	0.742	27.061
Q34 → IoT Implementation	0.746	28.218
Q35 → IoT Implementation	0.734	24.359
Q36 → IoT Implementation	0.746	27.160
Q37 → IoT Implementation	0.761	33.327
Q38 → IoT Implementation	0.762	29.503

Figure 2. Model with t-values

One of the most significant barriers is sanctions and limited international relations, which directly impact access to technologies and equipment required for IoT implementation. As a result, organizations may be unable to benefit from the latest innovations, reducing their capacity to manage asset lifecycles effectively.

Public awareness and acceptance also pose considerable challenges. Without sufficient knowledge of IoT's benefits and applications, users and stakeholders may resist change and hinder technology adoption, thus lowering implementation effectiveness.

Government support can play a critical role in facilitating the adoption of emerging technologies. The absence of such support can imply a lack of necessary policies, financial incentives, and infrastructure for IoT development—posing a major obstacle in its advancement.

Lack of technical expertise among planners and the absence of human resource skills also constitute major barriers. Without a skilled and trained workforce, implementing and managing IoT-based systems becomes highly challenging. Insufficient infrastructure and inadequate equipment further complicate the process.

High investment and training costs are also key obstacles. Due to budget constraints, organizations may avoid investing in new technologies. Moreover, training-related expenses for employee upskilling can impose additional financial burdens.

Cybersecurity concerns and limited bandwidth are critical challenges as well. Since IoT technologies rely on the exchange of sensitive data, cybersecurity must be prioritized. Additionally, weak infrastructure can reduce the efficiency and reliability of IoT systems.

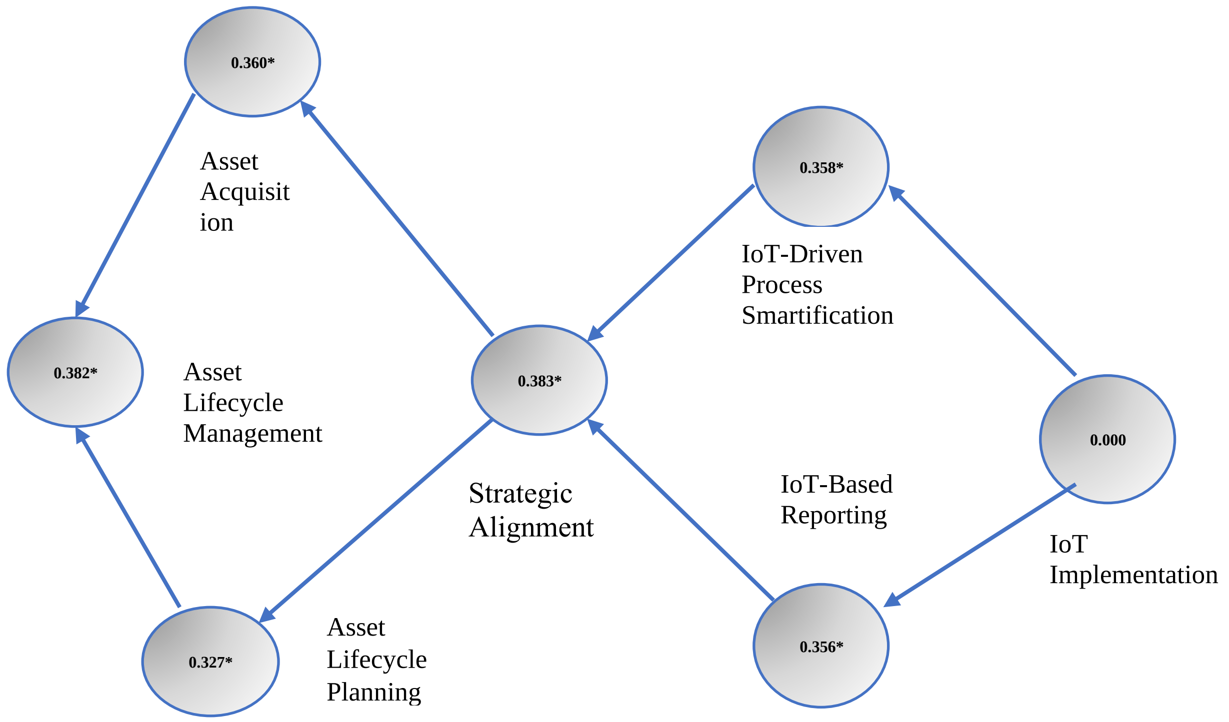

Figure 3. Final IoT-Based Asset Lifecycle Management Model

The Q^2 (predictive relevance) index, as shown in the figure above, was found to be positive across all components, indicating that the final model demonstrates a suitable level of predictive capability.

4. Discussion and Conclusion

The objective of this research is to propose a model for asset lifecycle management through the Internet of Things (IoT), utilizing a mixed-methods approach (qualitative-quantitative) for data analysis. In the qualitative phase, meta-synthesis was used to collect data, with initial indicators relevant to the proposed model extracted through a review of 60 reputable domestic and international articles related to the subject. In the second step, thematic qualitative analysis (involving interview editing, summarization, and interpretation of concepts and terms) was conducted by performing in-depth interviews with 10 experts and managers in the fields of IoT and asset management. In the quantitative phase, the proposed model was validated through a survey of 384 professionals working in the domains of IoT and asset management. For qualitative data analysis, MAXQDA software was employed, and the quantitative phase used the Partial Least Squares (PLS) technique via SMART PLS software to validate the model.

This article emphasizes the integration of IoT within cloud computing infrastructure, highlighting their mutual interdependence and the flexibility they offer in addressing user needs and managerial concerns about investment and data storage/editing costs for IoT applications. The application domains of IoT are extensive, and this study focused specifically on using cloud-based IoT technology in asset management. By deploying this technology, challenges such as asset monitoring, timely fault detection and resolution, theft prevention, and the use of specialized personnel for audits can be effectively addressed. Moreover, with the flexibility and capacity of cloud-integrated IoT systems, organizations can overcome managerial challenges in asset management. Utilizing IoT helps reduce costs, enhance employee commitment to asset stewardship, and enables organizations to focus more on their strategic goals. It also transforms stakeholder, customer, and competitor perceptions, while assisting managers in selecting optimal asset management strategies, improving performance and productivity, and reducing asset-related risks.

Strategic alignment with asset lifecycle planning means ensuring that organizational strategies are compatible with lifecycle planning processes and contribute to achieving organizational objectives. This alignment enhances overall organizational performance and efficiency. Given the significant role of IoT in the evolution and transformation of asset management—which in turn influences core aspects of the accounting profession such as asset identification, measurement, and internal controls—it is expected that the application of IoT in this domain will expand rapidly in the near future.

Ultimately, the outcomes of the proposed model highlight the pivotal role of emerging IoT technologies in asset management. The practical implementation of such a model can drive substantial transformation in safeguarding and optimizing the management of institutional assets. The findings of this study align with the prior results [5, 6, 11, 12], all of which emphasize the importance of adopting modern technologies to enhance efficiency and ensure timely financial reporting through the use of IoT in asset management.

Based on the research findings, the following recommendations are proposed:

It is recommended that public sector asset systems be practically implemented based on the Internet of Things. It is also suggested that IoT-based systems be established to improve asset maintenance processes and to support decisions regarding asset retention or disposal. In this regard, training financial and auditing experts on the utilization of this asset management system is essential. Future researchers are advised to investigate how IoT can be used for asset management based on lifecycle stages in both public and private organizations across the country.

Regarding the limitations of this study, it should be noted that due to time constraints, the evaluation was limited to expert opinions only. Additionally, the inherent limitations of interviews, which may not fully reflect participants' perspectives, and the uncontrolled cultural and personality differences among members of the statistical population—which may have influenced the accuracy of interview responses—should also be acknowledged.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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