

# STAKEHOLDER INVOLVEMENT AND INFLUENCE IN ADDRESSING CONSTRAINTS IN BUILDING ENERGY DATA MANAGEMENT IN SRI LANKA:

## *A Social Network Analysis*

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**Abstract.** With the use of advanced technologies in buildings, a large amount of building energy data is generated in buildings. However, the use of building energy data for decision-making in building energy management is still limited in developing countries like Sri Lanka due to a lack of proper building energy data management. Therefore, this study aims to identify the constraints in building energy data management in Sri Lanka and to study the level of influence and involvement of stakeholders in addressing those constraints using Social Network Analysis (SNA). First, constraints and stakeholders related to building energy data management were identified through a literature review. Most significant constraints in the Sri Lankan context were identified through expert interviews. Subsequently, a questionnaire survey was conducted to prepare the 2-mode matrix for SNA. Degree centrality, closeness, betweenness and eigenvector were used to analyze the level of influence and involvement of stakeholders in addressing constraints. According to the findings, lack of data availability, quality and reliability is the most considerable constraint in building energy data management in Sri Lanka. However, resistance to accepting challenges is the most influential constraint. Governments, energy suppliers, energy service providers, building construction companies, researchers, regulatory authorities, property management companies and certification bodies are the most influential stakeholders. Findings of this study can be used by policymakers to prepare a governance structure of stakeholders in streamlining building energy management. Further, the findings enable obtaining better collaboration and coordination among stakeholders in data-driven decision-making in building energy management.

**Keywords.** *Five keywords – Constraints in Building Energy Data Management, Stakeholders in Building Energy Data Management, Social Network Analysis, Building Energy Data Management, Stakeholder analysis in Building Energy Data Management*

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## 1. Introduction

Building energy consumption contributes a significant portion of the global energy supply and demand. With population growth, building energy consumption has dramatically increased over the past few decades (Ali et al., 2020b). Buildings contribute to one-third of global energy consumption and 36% of global energy-related emissions (International Energy Agency, 2025). Building-related CO<sub>2</sub> emissions have increased by 1% since 2010 (Ali et al., 2020a). Among the total energy consumption, around 60% energy consumption accounts for heating and ventilation purposes (Hannan et al., 2018). Therefore, energy consumption and its impact on climate change are critical challenges in the building sector.

Improperly maintained and controlled building systems might be the reason for the higher energy consumption in buildings (Ali et al., 2020a). Heating, ventilation, and Air conditioning systems and lighting systems consume a significant amount of building energy due to improper system control, poor maintenance and system faults (C. Zhang et al., 2020). According to Li et al. (2024), 15% -30% energy is wasted in buildings due to poor maintenance and inefficient operational practices. By monitoring energy consumption of buildings, detailed information related to individual equipment can be identified (Hannan et al., 2018). Further, Jin et al. (2023) emphasized that city-level energy analysis is a vital part of city-level building energy planning.

Predicting and forecasting building energy consumption is essential for energy planning, energy optimization and management (Runge & Zmeureanu, 2021). In addition, building energy forecasting is used to measure and confirm the effectiveness of energy saving practices, to assume energy needs using trend analysis, and to identify event-specific variations in energy consumption (Mariano-Hernández et al., 2020). Due to the massive amount of building energy data, data-driven approaches are used to understand the building performance (Li et al., 2024). Therefore, several data-driven approaches are used at the building level, city level, country level, regional level and global level for building energy management.

However, accurate building energy data is a vital requirement for accurate and reliable energy forecasts and analysis. Currently, building operational data has been more accessible due to the utilisation of advanced technologies such as smart meters and sensors (H. Zhang et al., 2022). Specifically, building energy datasets enables data driven decision making in building energy management (Johari et al., 2020). In addition, city-level datasets are utilised for multiple purposes such as urban building energy modelling, building performance monitoring, city-level energy planning and renewable energy analysis (Chen et al., 2019). Furthermore, Jin et al. (2023) reviewed open datasets of city-level energy use and their application.

However, collecting detailed information related to different building systems is difficult (Hannan et al., 2018). Several challenges are associated with collecting and managing building energy data. Especially, the absence of publicly available databases restricts the ability to obtain required data for macro-level building energy consumption (Kazmi et al., 2023; Venkatraj & Dixit, 2022). Further, unreliable and unrealistic data lead to discrepancies between energy predictions and reality (Mariano-Hernández et al., 2020). Data acquisition is also challenging due to manual data collection techniques and a lack of modern data collection infrastructures such as smart meters (Krishnan et al., 2022). Manual data collection is prone to human errors, making the collected data irrelevant, incomplete, inconsistent and redundant (Ali et al., 2020b). Due to privacy concerns, many building owners hesitate to disclose their data. High dependence on large historical data demands large data backups which can handle a large amount of heterogeneous data and information (Ali et al., 2021). Moreover, the absence of granularity of data restricts the real-time capabilities (Y. Zhang et al., 2022).

Stakeholder collaboration is a key component in addressing challenges in building energy management. Proper collaboration and coordination among stakeholders in design, construction and operation stages of the building lifecycle to enhance energy efficiency in

buildings (Zou & Alam, 2020). Especially, coordinated support from relevant stakeholders enables the effective utilization of available heterogeneous building energy data for effective building energy management (Marinakis, 2020). According to Y. Li et al. (2017), building energy data management is a collaborative process which involves numerous potential stakeholders and enormous volumes of building energy data. Zedan & Miller (2017) studied stakeholders' influence on energy efficiency in residential buildings. Different stakeholders possess different levels of influence and involvement in addressing different constraints. Therefore, it is important to study how different stakeholders can be involved and influence in addressing different constraints in building energy data management.

Despite the increasing awareness of building energy data management, its application still remains limited and fragmented in developing countries like Sri Lanka (Jin et al., 2023). Existing studies largely focus on technological solutions to promote data-driven building energy management with limited attention to organizational, institutional and stakeholder related issues present in developing countries like Sri Lanka (S. Wang et al., 2025). In particular, there is a lack of empirical understanding of how different stakeholders contribute to or influence the resolution of these constraints within the Sri Lankan context. This creates a critical knowledge gap, as stakeholder coordination is essential for the effective implementation of energy data systems. Therefore, this research focuses on analysing influence and involvement in addressing issues in building energy data management using Social Network Analysis (SNA).

## **2. Literature Review**

### **2.1 BUILDING ENERGY DATA MANAGEMENT**

Effective energy data management is a vital part of building energy management in handling a large amount of building energy data Koseleva & Ropaite (2017). Data-driven insights in energy management serve to reduce energy waste and translate their output into more empirical energy-saving insights Markus et al. (2022). Several emerging technologies, such as Artificial Intelligence (AI), Big Data, Digital Twin (DT), and Internet of Things (IoT), have strengthened the data-driven approaches in building energy management (Adewale et al., 2024). According to Marinakis & Doukas (2018), a large amount of data is being generated in buildings through different sources such as smart meters, IoT devices, and sensors. The building sector is rapidly moving towards a smart future due to emerging advanced technologies. Several data-driven approaches can be identified in buildings, such as forecasting energy demand, load profiling, large-scale energy-consumption mapping, energy performance benchmarking, and global and national-level energy policy formulation (Wei et al., 2018).

### **2.2 CHALLENGES IN BUILDING ENERGY DATA MANAGEMENT**

However, building energy data disclosure and management has become challenging over the years due to several challenges associated with data collection, reporting, and analysis. Table 1 summarizes the literature findings of challenges associated with building energy data management.

*Table 1: Challenges in building energy data management*

<b>Challenge</b>	<b>Notation</b>	<b>Citation</b>
Issues related to data quality, availability and reliability	C1	1,2,3,4,7,8,9
Challenges in handling a large amount of heterogeneous data	C2	5,7,10
Data security and privacy concerns	C3	4,8,9
Challenges in balancing multiple objectives	C4	5, 9,10,
Changes in building operation	C5	2,8
Resistant to take challenges	C6	6,18
Lack of human adaptation	C7	4,8
Incorrect feature identification	C8	1,2,8,10
Lack of interpretability of data	C9	1,2,3,8,9,10
Lack of expertise	C10	1,3,4,5,6
Lack of research and development	C11	8
Lack of interoperability with building systems	C12	3,4,8
Complex technologies	C13	1,5,7,8,9,10
Lack of policy support	C14	1,4
Lack of standard methods	C15	2,3,4,7,10
Higher implementation costs	C16	4,5
Lack of funding and incentives	C17	11,12,13

1-(Clauß et al., 2024); 2-(Alrobaie & Krarti, 2022); 3-(Manfren et al., 2022) ; 4-(Adewale et al., 2024); 5-(Kiavarz et al., 2024); 6-(Markus et al., 2022); 7-(Choi & Yoon, 2024); 8-(Krishnan et al., 2022); 9-(H. Zhang et al., 2022), 10-(Ke et al., 2020), 11-(Onile et al., 2021); 12-(Kazmi et al., 2021); 13-(Guo et al., 2024)

### 2.3 STAKEHOLDERS IN BUILDING ENERGY DATA MANAGEMENT

Stakeholders can be defined as any individual or a group of individuals who have a direct or indirect impact on a project or an interest or influence regarding the project (Li et al., 2017). Heterogeneous stakeholders, which span a large scale from policy makers to building occupants, can be identified in energy management. Effective stakeholder collaboration is a combination of collective decision making, powers, trust, participation, dependency, shared responsibility, perceived benefits, information awareness, and long-term relationships (Wondirad et al., 2020). Transparent information sharing allows stakeholders to access information in influencing decision-making. Further, it enhances the accountability of the stakeholders in supporting energy efficiency and sustainability goals (Chen, 2022). Sharing meaningful information based on their requirement is critical in obtaining their commitment (Ke et al., 2020). Table 2 illustrates the identified stakeholders in building energy data management through the literature review.

*Table 2: Stakeholders in Building Energy Data Management*

<b>Stakeholder</b>	<b>Notation</b>	<b>Citation</b>
Building owners	S1	A,B,D,I
Governments	S2	A,B,C,D,E,F,H
Building operators	S3	A,B,C,D,E,F
Energy suppliers	S4	A,B,C,G,H

Energy service companies	S5	A,B,C
Construction & renovation companies	S6	A,B,E,F
Investment companies	S7	A
Researchers	S8	A,C,E
Occupants	S9	B,C,D
Regulatory authorities	S10	E
Property Management companies	S11	A,B,D,E
Certification bodies	S12	E,j,k

A- (Marinakis, 2020), B-(Y. Li et al., 2017),C-(Balest et al., 2022), D-(Ke et al., 2020), E-(Ali et al., 2021), F-(Natkiewicz et al., 2021), G-(Kazmi et al., 2023), H-(Elomari et al., 2024), I-(Leprince et al., 2021), J-(Chi et al., 2021), K-(Lee et al., 2021)

### 3. Methodology

This study adopts a quantitative research design to examine stakeholder involvement and influence in addressing constraints in building energy data management in Sri Lanka. After a comprehensive literature review to identify constraints and stakeholders in building energy data management, the most significant constraints in the Sri Lankan context were identified through expert interviews with high profiles in the energy policy making in Sri Lanka. Followed by a questionnaire, a survey was conducted using a structured questionnaire to collect primary data for SNA.

#### 3.1 LITERATURE REVIEW

This study involves several stages. First, a comprehensive literature review was conducted to identify constraints and stakeholders related to building energy data management. Peer-reviewed journal papers from the Web of Science database were used for the literature review.

#### 3.2 EXPERT INTERVIEWS

Expert interviews were conducted to filter out the most significant constraints for the Sri Lankan constraints. Interviewees were selected using a purposive sampling method. Experts were selected based on their years of experience and their roles in building energy data management. Profiles of experts are shown in Table 3.

Table 3: Profiles of Experts

Expert Name	Description	Years of experience
E1	Board member of the Sri Lanka Sustainable Energy Authority	18 years
E2	President of the Sri Lanka Energy Managers Association, board member of the Sri Lanka Sustainable Energy Authority	30+ years
E3	Director General of the Sri Lanka Sustainable Energy Authority	25 years
E4	Former president of the Sri Lanka Energy Managers Association, Former Director General of National Engineering Research and Development Centre (RERDC)	35 years

E5	Diputy director (Energy Efficiency Improvement) in the Sri Lanka Sustainable Energy Authority	10 years
E6	Director (Energy Efficiency Improvement) in the Sri Lanka Sustainable Energy Authority	25 years
E7	Director (Demand Side Management) in the Sri Lanka Sustainable Energy Authority	25+ years
E8	PhD holder in building energy management and a member of the Sri Lankan energy benchmarking portal development committee	8 years

Collected data from interviews were manually reviewed using manual content analysis to identify the most applicable constraints applicable for the Sri Lankan context.

### 3.3 QUESTIONNAIRE SURVEY

Subsequently, a questionnaire survey was conducted to prepare the 2-mode network required for the Social Network Analysis. A structured questionnaire was used to capture stakeholder involvement and influence in addressing identified constraints. Structured questionnaires are appropriate for quantitative studies as they enable standardized data collection and facilitate statistical and network-based analysis (Saunders et al., 2019). Respondents were asked to rank the level of influence and impact of each stakeholder in addressing each constraint using a 0-2 Likert scale (0-No/1-Low/2-High). Purposive sampling method was used as the sampling method to collect more relevant and reliable responses. Purposive sampling enhances the rigour of the research and trustworthiness of the data and results by aligning with the aim of the study (Campbell et al., 2020). Professionals who have experience in building energy management for over 4 years were selected as potential respondents for the questionnaire survey. The questionnaire was shared with 30 professionals, and 27 responses were used for the analysis. De Nooy et al. (2018) stated that 20-50 responses would be enough for exploratory mapping because the main focus is to identify factors rather than statistical analysis.

### 3.4 SOCIAL NETWORK ANALYSIS (SNA) IN STAKEHOLDER ANALYSIS

Social Network Analysis (SNA) is a technique which is used to identify patterns of interaction among social actors in social networks. SNA aims to examine the patterns of relationships and contents in social networks to understand the relationships among actors and the implications of relationships (Tabassum et al., 2018). SNA is made up of nodes and edges that connect them to form a social structure. A social network is an application of graph theory that represents social networks using graphs, which consist of nodes connected with edges. Nodes represent the individuals or factors, while edges represent relationships among them (Camacho et al., 2020). In contrast to the 1-mode network, which considers only one mode, 2-mode networks analyze relationships between different mode types. In 2-mode networks, edges exist between different node types and are used to identify relationships between individuals and associated factors (Cui et al., 2022). SNA is one of the highly used methods in stakeholder analysis. According to Singh et al. (2020), SNA can be effectively used for influence maximization that focuses on identifying the individuals who have maximal influence spread in the network. Wang et al. (2024) employed 2-mode SNA to explore the powers and attitudes of stakeholders towards factors affecting big data application in the construction industry. Further,

Li et al. (2022) utilized 2-mode SNA to study stakeholders and their collaboration barriers in urban renewal.

For this study, two-mode matrix for the SNA was developed using the mode value of responses. SNA was conducted using UCINET software, which is one of the most popular software programs for SNA. UCINET facilitates both 1-mode and 2-mode network analysis (Singh et al., 2024). Structural centrality of the stakeholders in addressing constraints was analyzed using 2-mode centrality analysis. Four basic centrality measures are used for the SNA.

- Degree Centrality- A number of links connected to a node
- Closeness- The average of the shortest distances to all other nodes in the network.
- Betweenness- The extent to which a particular node lies on the shortest path between other nodes
- Eigenvector- A measure of the extent to which a node is connected to influential other nodes.

#### 4. Findings

According to the findings of the expert interviews, 9 constraints in building energy data management, which are highly applicable for the Sri Lankan context, were identified. Among them, lack of data availability, quality, and reliability and lack of policy support were identified by all experts as constraints in Sri Lanka. Lack of expertise and knowledge, and lack of standardize methods for data collection and analysis are the second-highest mentioned constraints. Lack of funding and incentives is the third-highest mentioned constraint. 5 experts mentioned that higher implementation costs restrict the implementation of building energy data management practices in Sri Lanka. Confidentiality requirements and industry adaptation issues were mentioned by 4 experts. Fear of accepting challenges was identified by 2 experts as a constraint in building energy data management. According to the experts, other constraints are not applicable to the Sri Lankan context because Sri Lanka is still in a preliminary stage in building energy data management. A summary of the findings of the expert interviews is shown in Table 4.

Table 4: Summary of Expert Interviews

Notation	E1	E2	E3	E4	E5	E6	E7	E8
C1	✓	✓	✓	✓	✓	✓	✓	✓
C3			✓	✓	✓	✓		
C6			✓		✓			
C7	✓		✓		✓	✓		
C10	✓	✓	✓	✓		✓	✓	✓
C14	✓	✓	✓	✓	✓	✓	✓	✓
C15	✓	✓	✓	✓	✓	✓		✓
C16	✓	✓	✓	✓				✓
C17	✓	✓	✓	✓		✓		✓

According to the findings of the SNA, the network diagram between constraints and stakeholders is shown in Figure 1. Blue colour nodes represent Stakeholders while

red colour nodes represent constraints. Edges represent the ability of stakeholders in addressing constraints. Node size represents how important the particular node is in the network.

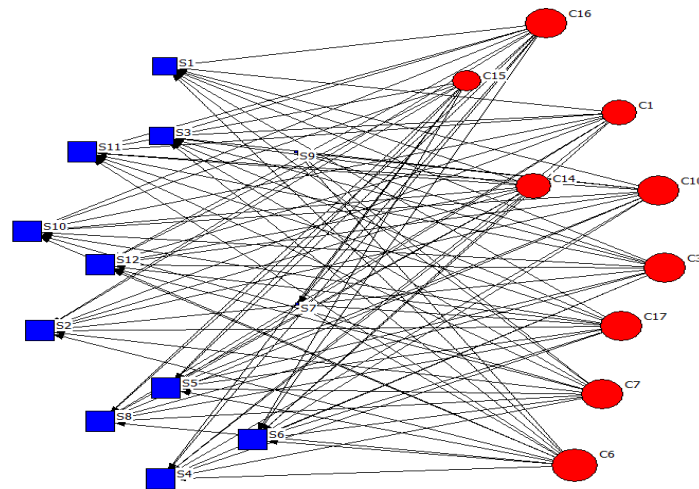


Figure 1: Network Diagram

Four centrality measures were calculated using UCINET, such as degree centrality, closeness, betweenness, and eigenvector. Those measures represent the following network relationships.

- Degree Centrality- Degree centrality counts how many direct connections a stakeholder has and vice versa.
- Closeness- How quickly a stakeholder can resolve constraints and vice versa.
- Betweenness- How often a stakeholder collaborates with others to address constraints and vice versa.
- Eigenvector- how important the connections between stakeholders and constraints.

When considering constraints' degree centrality, resistance to taking challenges has the highest degree centrality. Privacy concerns, lack of expertise, lack of human adaptation, higher implementation cost, and lack of funding and incentives have the second-highest degree of centrality, scoring 0.917. Lack of data quality, availability and reliability and policy support have the third highest degree centrality, scoring 0.833. Lack of standard methods has the lowest degree centrality. Governments, energy suppliers, energy service providers, building construction companies, researchers, regulatory authorities, property management companies and certification bodies possess the highest degree of centrality of stakeholders. Building owners and operational teams have the second-highest degree centrality, while building occupants and investment companies have the least degree centrality. The same pattern continues with the closeness, betweenness, and eigenvector as well. Table 5 presents the summary of centrality measures between constraints and stakeholders.

Table 5: Centrality Measures

Node	Degree	Closeness	Betweenness	Eigenvector
Constraints' Centrality Measures				
C1	0.833	0.875	0.03	-0.326
C3	0.917	0.933	0.051	-0.341
C6	1	1	0.079	-0.356
C7	0.917	0.933	0.051	-0.341
C10	0.917	0.933	0.051	-0.341
C14	0.833	0.875	0.03	-0.326
C15	0.75	0.824	0.034	-0.28
C16	0.917	0.933	0.052	-0.341
C17	0.917	0.933	0.052	-0.341
Stakeholders' Centrality Measures				
S1	0.889	0.939	0.02	-0.286
S2	1	1	0.028	-0.315
S3	0.889	0.939	0.02	-0.286
S4	1	1	0.028	-0.315
S5	1	1	0.028	-0.315
S6	1	1	0.028	-0.315
S7	0.444	0.756	0.004	-0.139
S8	1	1	0.028	-0.315
S9	0.444	0.756	0.004	-0.145
S10	1	1	0.028	-0.315
S11	1	1	0.028	-0.315
S12	1	1	0.028	-0.315

## 5. Discussion

Degree centrality of constraints represents the number of stakeholders that can influence or be involved in addressing particular constraints. Being resistant to taking challenges can be influenced by the highest number of stakeholders. Privacy concerns, lack of expertise, lack of human adaptation, higher implementation cost, and lack of funding and incentives can be influenced by the second-highest number of stakeholders. Lack of data quality, availability and reliability and policy support can be influenced by the third highest number of stakeholders. Lack of standard methods has the influence of the lowest number of stakeholders. Degree centrality of stakeholders represents the number of constraints that influence or involve by each stakeholder. Governments, energy suppliers, energy service providers, building construction companies, researchers, regulatory authorities, property management companies and certification bodies can influence the highest number of constraints. Building owners and operational teams can influence the second-highest number of constraints, while building occupants and investment companies can influence the lowest number of constraints.

Closeness represents the ability of stakeholders to address issues and the ability of constraints to be resolved with the influence and involvement of different stakeholders. The same pattern as the degree centrality continues with the closeness of the network as well. Closeness indicates how fast constraints can be resolved with the involvement of stakeholders and how fast different stakeholders can resolve constraints. Further,

betweenness represents how often a stakeholder lies on the shortest paths between other stakeholders via shared constraints and vice versa. Stakeholders with high betweenness bridge different constraint clusters. They help to obtain the interaction of stakeholders who do not directly interact to address constraints, acting as coordination gatekeepers. Constraints with high betweenness bridges isolated stakeholders. Those constraints can affect the resolution of other constraints which cannot be resolved easily. An eigenvector measures the extent to which a node is connected to influential other nodes. Stakeholders with a high eigenvector indicate that they are involved with constraints that many important stakeholders are involved in. Constraints with high eigenvectors indicate that the constraint is connected to powerful stakeholders.

Since closeness, betweenness, and eigenvector continue the same pattern of the degree centrality, resisting taking challenges is the most influential constraint. Governments, energy suppliers, energy service providers, building construction companies, researchers, regulatory authorities, property management companies and certification bodies are the most influential stakeholders. Privacy concerns, lack of expertise, lack of human adaptation, higher implementation cost, and lack of funding and incentives are the second-highest-influenced constraints. Building owners and operational teams are the second-highest influential stakeholders. Lack of data quality, availability and reliability and policy support are the third highest influenced constraints. Lack of standard methods is the least influential constraint, while building occupants and investment companies are the least influential stakeholders.

First, the identification of stakeholders with a high degree centrality highlights those who are actively involved in addressing multiple constraints and can be leveraged as key implementation partners. Second, stakeholders with high betweenness centrality play a critical role in bridging fragmented actors and should be prioritized in coordination and data-sharing initiatives. Additionally, stakeholders with high eigenvector centrality represent strategically influential actors who can drive systemic change through their connections with other key stakeholders.

Mainly, this study reveals the potential impact and influence of governments and policymakers in addressing multiple constraints in building energy data management. Similarly, urban planners, regulatory authorities, and policy makers can highly influence in resolving data related issues in building energy management (Ali et al., 2021). Jin et al. (2023) emphasized the role of government and policymakers in enforcing laws and regulations to mandate energy data disclosure for data-driven decision making for policy formulation. Further, the findings of this study help to identify the most actively involved stakeholders, understand responsibility distribution, highlight priority stakeholders for intervention, identify different stakeholder roles, and reveal hidden influence patterns for better decision making in policy formulation in building energy management. By offering one of the first empirical evaluations of stakeholder involvement and influence in building energy data management, this work enhances knowledge within the Sri Lankan context. Stakeholder dynamics and their significance in addressing implementation challenges have received little attention in Sri Lanka's prior research, which has mostly concentrated on the technical and policy elements of energy management. Through the use of social network analysis, this study reveals the structural connections between stakeholders and pinpoints important players in charge of resolving particular limitations. This offers fresh

perspectives on Sri Lanka's dispersed energy data management system and emphasises how crucial stakeholder collaboration is to resolving systemic issues. The results close a significant gap in the literature by providing a context-specific perspective that cannot be directly deduced from research done in developed nations.

## **6. Conclusion**

This study focused on identifying constraints in building energy data management in Sri Lanka and analyze the level of influence and involvement of stakeholders in addressing those identified challenges. The study involved a mixed approach consisting of several types of methods in addressing the research gap. Constraints and stakeholders in building energy data management were identified through a literature review, and then, the most applicable constraints in the Sri Lankan context were identified using expert interviews. Lack of data availability, quality and reliability is a highly concerned constrained by all the interviewees. Lack of expertise, knowledge and standardize method of building energy data management were identified as the next significant constraints. The level of influence and involvement of stakeholders in addressing constraints in building energy data management was studied using SNA. Four main centrality measures, such as degree centrality, closeness, betweenness, and eigenvector was used to analyze the level of influence of stakeholders. According to the findings of the SNA, resistance to challenges is the most influential constraint for multiple stakeholders. Governments, energy suppliers, energy service providers, building construction companies, researchers, regulatory authorities, property management companies and certification bodies are the most influential stakeholders. Lack of standard methods is the least influential constraint, with minimum influence from stakeholders, while building occupants and investment companies are the least influential stakeholders that have the lowest involvement in addressing constraints in building energy data management. Findings of this study are limited to the Sri Lankan context due to the Sri Lankan context-based data collection. In addition, this study solely focused on the building sector, limiting its ability to generalize the findings to other sectors. Findings of this research can be used by policymakers and regulatory authorities in Sri Lanka for the formulation of a governance structure of stakeholders to obtain collaborative support for energy data disclosure and management, enabling informed decision making in building energy management. As theoretical implications, this study contributes a measurable analysis of stakeholders beyond the conceptual study of stakeholders through the use of SNA. Further, findings demonstrate multi-dimensional influence beyond just power and influence. Specifically, this study integrates a social network perspective into energy data management to address long last challenges through effective stakeholder collaboration. Finally, this study contributes to strengthening developing-country evidence within building energy data management, which is often missing in the literature. In addition, the findings provide several practical implications for improving building energy data management in Sri Lanka, identifying the patterns of stakeholder collaboration and coordination to address constraints in building energy data management. Policy interventions should adopt a differentiated engagement strategy, recognizing that stakeholders contribute in distinct ways. The results also emphasize the need for institutional mechanisms that enhance collaboration, improve data sharing, and reduce fragmentation within the domain of building energy data.

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