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Development of a Visual Decision Support System for Sustainable Redevelopment of Social Housing

A case study for Linstone Housing Association, Scotland

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Title

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Degree: Master in Urban Climate & Sustainability

Abstract

Social housing in Scotland has been reported to have high levels of disrepairs, with over 52% of homes having inadequate quality of essential components in 2019. Furthermore, over 19% of all homes were in a much worse state described as “urgent disrepair”. However, these issues are difficult to address because decision-makers face immense complexities in making decisions with regards to improving social housing in Scotland due to inundation of unorganized data, new policies, and modified guidelines.

However, an effective multi-criteria decision support system (MCDSS) can cater to this issue by encouraging smooth decision-making through use of decision support systems (DSS) to support the implementation of multi-criteria decision-making (MCDM). This MCDSS was developed for Linstone Housing Association and encapsulated the needs and requirements of tenants, housing providers and governing bodies. The method adopted consisted of a case study approach that brought together findings from previous research, stakeholder engagement through questionnaires and interviews and statistical analysis. A series of qualitative and quantitative methods were adopted to identify sustainability attributes in the redevelopment/retrofit of social housing within Scotland, create a hierarchal system using the combined approach of Simple Additive Weighting and Saaty’s 1-9 scale, and prioritize housing units in need of urgent attention.

The results were represented on ArcGIS Dashboard, thereby creating a DSS. This was important as this type of aid can provide an effective visual display for critical information required to achieve ones’ goals and objectives, especially in urban areas. They are also interactive tools which can be adopted to multiple types of developments. In this case, the DSS helped capture data and highlighted critical indicators and hotspots for properties in a simple and interactive way. It also helped simplify complex data for decision-makers and stakeholders. This process also helped identify the data gaps in housing associations, thereby, providing a body of work to collect meaningful data to aid their decision-making processes in the future.

Keywords

Social Housing, Muti-Criteria Decision Support System, SAW, Saaty’s 1-9 Scale

Originality statement. I hereby declare that this Master’s dissertation is my own original work, does not contain other people’s work without this being stated, cited and referenced, has not been submitted elsewhere in fulfilment of the requirements of this or any other award.	**Signature**

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LIST OF ACRONYMS

AHP	Analytical Hierarchy Process
CI	Consistency Index
CR	Consistency Ratio
DM	Decision Makers
DSS	Decision Support System
EESSH	Energy Efficiency in Social Housing Scotland
HA	Housing Associations
LHA	Linstone Housing Association
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MCDSS	Multi-Criteria Decision Support System
RI	Average Random Consistency
RTB	Right to Buy
SAW	Simple Additive Weighting
WSM	Weighted Sum Matrix

Chapter 1: **INTRODUCTION**

1.1. Rationale

It is well recognized that climate change induced by anthropogenic activities presents a significant threat towards unprecedented weather conditions and irreversible natural, economic, and social losses (Dalby, 2020). Statistics from 2019 show that buildings significantly contribute to this as they account for over 38% of energy-related carbon dioxide (CO_2) emissions (United Nations Environment Programme (UNEP), 2020). The percentage is at an all-time high compared to previous years – where it was only 19% in 2010 (Lucon et al., 2014). This is due to the prolonged use of fossil fuels for heating and cooking as well as use of carbon-intensive electricity (UNEP, 2020). Although the new building stock is becoming more energy efficient now due to updated policies, it is believed that 80% of the buildings in the UK alone have already been built until 2050 (UK Green Building Council, 2021), therefore making it pertinent to prioritize the improvement and subsequent decarbonisation of the existing buildings. A particular focus needs to be placed on derelict and aging infrastructure to cater to the increasing population without putting further strain on natural resources (Johnson-Ferdinand, 2014).

This is especially the case for social housing in Scotland where there has been a subsequent decrease in funding for new-build stock (Royal Institute of Chartered Surveyors, 2020) and approvals for new-build plummeted to 54% among Scottish Housing Associations (Wilmore, 2022). The housing in this region has also been reported to have high levels of disrepairs, with over 52% of homes having inadequate quality of essential components in 2019 (Berry, 2021). These essential elements include drainage, insulation and fixtures that are critical to the structural stability of houses. Furthermore, over 19% of all homes were in a much worse state described as "urgent disrepair" (Berry, 2021). About 8,046 properties fail to meet the minimum standard for social housing, with 25,564 further properties exempted from the requirement (Campbell, 2021). These statistics are especially alarming, since in Scotland almost 1.14 million people lived in socially rented houses in 2017 (Scottish Government, 2019). Moreover, with aged population rising drastically due to increased lifespan and decrease in birth rates (National Records of Scotland, 2022) – those over the age of 75 are expected to rise by 55% in 2035 (Government Office for Science, 2016) – the pressure to fix existing housing stock is at an all-time high.

Most social housing stock is also struggling to meet standards set within existing policies and frameworks. This includes the Energy Efficiency in Social Housing Scotland (EESSH 2), post 2020, that aims to eradicate fuel poverty and achieve the Scottish Governments' greenhouse gas and carbon emission related goals (Scottish Government, 2020).

In addition to this, there is a huge amount of unclassified data for these households that inundate decision makers such as architects and housing association personnel. Furthermore, some data to evaluate existing projects is not readily available. It is also important to highlight that the analysed data that is available is mostly not understandable by project managers and relevant professionals. This is especially necessary where funding needs to be arranged for the redevelopment of these buildings. Therefore, multi-criteria decision support systems (MCDSS) become necessary to help automate the decision-making processes that require the analysis of huge amounts of data in a short period of time, while keeping existing policies and standards in mind. This also provides stakeholders like architects and designers with useful information to perform informed decision making (Yang & Ogunkah, 2013).

This project attempts to address this gap by creating a visual DSS which will be used to enable problem solving in an interactive and recursive way. Furthermore, visualization of the data will help decision makers in reaching conclusions in an efficient and conclusive manner. The chosen area for this project is Linstone Housing Association, which is one of the many organizations responsible for ensuring safe and sustainable housing for tenants in need. The HA has over 1,500 properties across Linwood and Johnstone making it one of the largest housing associations in Renefrewshire.

1.2. Aims and Objectives

The overall aim of the project is to develop a framework for a visual MCDSS to enable project managers, architects, and governing bodies to observe identified patterns, and foster collaboration and informed decision-making, thereby, effectively improving efficiency for sustainable (re)development of social housing within Scotland

This aim was achieved by fulfilling the following objectives:

- Baseline assessment to evaluate existing available data, policies, and frameworks in the context of the social housing sector.
- Highlight and define sustainability attributes by significance through development of a comprehensive rating system.

- Visual representation of analysed attributes using ArcGIS dashboard.
- Provide recommendations for applicability and replicability for other housing associations within Scotland.

1.3. Case Study Area – Linstone Housing Association

The Linstone Housing Association is one of the many organizations responsible for ensuring safe and sustainable housing for tenants in need. Since its inception in 1998, the organization has set up over 1500 properties across Linwood and Johnstone and is considered one of the largest housing associations in Renefrewshire (Linstone Housing, 2022). LHA is also responsible for acting as estate managers to over 2,000 owner occupiers and provides factoring services to 480 owners. Being registered with the Social Housing Regulator, LHA is responsible for maintaining and improving the conditions of their existing housing stock.

Figure 1: Distribution of LHA owned properties across Scotland

Figure 1 represents the distribution of properties of LHA across various locations, along with the number of properties in each given area.

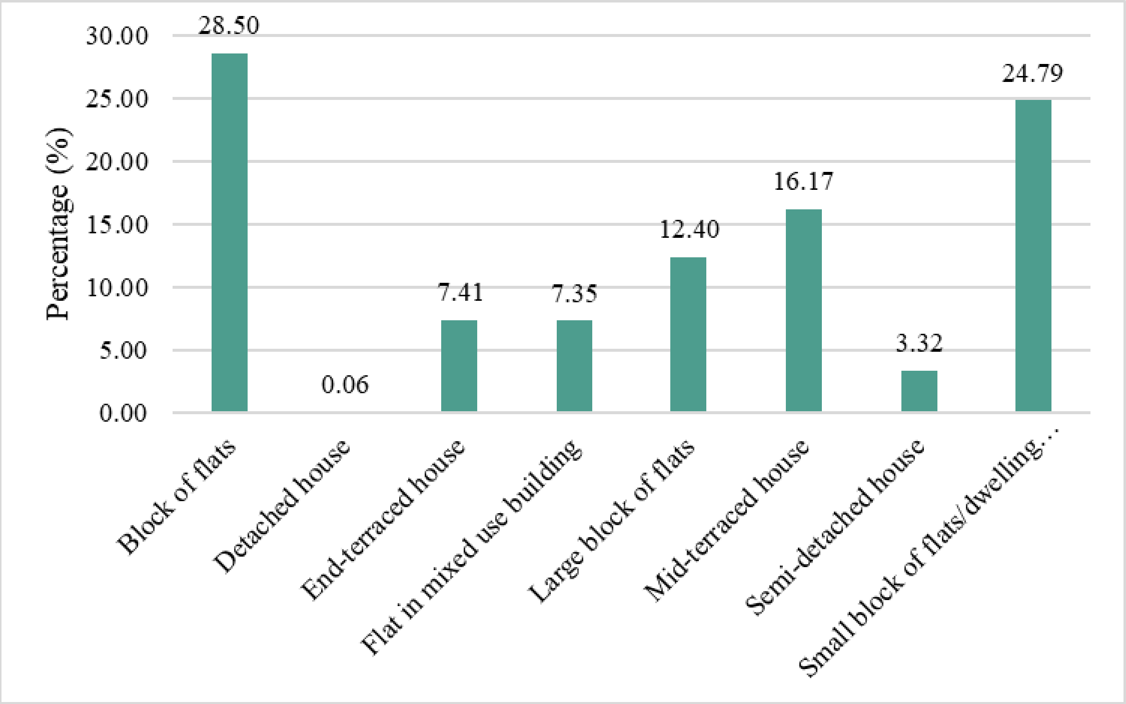

Figure 2: Type of properties owned by LHA

Most of the type of property owned by LHA is comprised of either block of flats (28.5%) or small blocks of flats/dwellings converted into flats (24.79%) (Figure 2). Whereas there is a very small percentage of housing that is either semi-detached or detached. Information acquired from LHA also showed that almost 44% of the housing owned by the HA is in mixed tenure buildings.

Table 1: Age of LHA owned properties

Property Age	Number of Properties
1919-1949	98
1950-1983	1334
1984-1991	35
1992-2002	6
Post-2002	38
Pre-1919	54

Table 1 depicts property age against the number of properties. Since maximum number of properties were developed during 1950 and 1983; this could also lead to properties being more prone to disrepairs and decay in the building envelope as well as indoors.

1.4. Outline

The project adopted a mixed methods case study approach where both qualitative and quantitative data was analysed to gather the most effective results. Qualitative methods approach consisted of conducting a narrative/traditional literature review and carrying out reviews of existing case studies. Quantitative analysis entailed data collection through questionnaires and semi-structured interviews and the responses were used to develop a ranking system using the combined methods of Simple Additive Weighting (SAW) and Saaty's 1-9 scale, which is part of the Multi-Criteria Decision Making (MCDM) process. The analysed data was then used to create a GIS-based dashboard using ArcGIS online to display a decision support system for existing sites of Linstone Housing Association. Finally, the results of the study were utilised highlighted the advantages and disadvantages of replication in other housing associations, the limitations of the current study and the potential threats and opportunities it represented.

1.5. Report Structure

This report is divided into 7 chapters:

Chapter 1 provides the context of the issue and identifies the aims and objectives of the project.

Chapter 2 presents the literature review, demonstrating knowledge and understanding of Scotland's social housing issues, existing policies, defining decision support systems and multi-criteria decision making.

Chapter 3 gives insight into the methodological framework for executing the project. It explains the tools and methods adopted to collect and analyse the data and present the results.

Chapter 4 presents the results along with analysis and reflections on it with regards to the objectives of the research.

Chapter 5 highlights a summary of limitations.

Chapter 6 delves into the recommendations for similar future studies and practical implementation of the DSS into the housing associations.

Chapter 7 provides conclusory remarks.

Chapter 2: **Literature Review**

The literature review in this paper builds the context on the social housing situation in Scotland and highlights standards, policies and acts relevant to the housing associations in terms of housing (re)development. It also places emphasis on the complexities faced by decision makers in making key decisions and prioritizing sites when developing strategies. Finally, the literature review highlights the different methods that exist for collating and organizing data and presenting it in a way that could be useful for stakeholders and decision makers.

2.1. Social housing in Scotland – A brief overview

Social housing is typically understood to be inexpensive housing for vulnerable communities (Muczyński, Dawidowicz, & Źróbek, 2019). The social housing sector in Scotland specifically focuses on delivering homes that are not only affordable but are also compliant to the latest standards, specifically in relation to quality and energy efficiency (Scottish Government, 2021). Previously however, with the ruling of 'Right to Buy' (RTB) in place, the upkeep of housing was becoming increasingly challenging and existing stock was in danger of reducing significantly (McKee, 2010).

To prevent this, The Housing (Scotland) Act 2001 gave local authorities the ability to suspend RTB for new tenants for over 5 years (Serin, Kintrea & Gibb, 2018), which resulted in not only preventing a loss of affordable homes, but also led to a significant decrease in rented homes from local authorities and a rise in renting from housing associations (HA) (Figure 3).

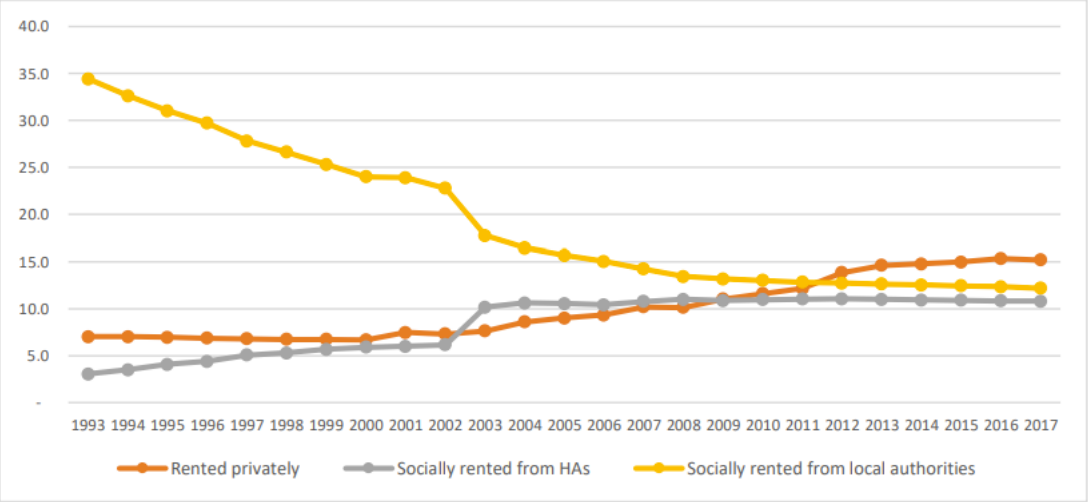

Figure 3: Changes in demand of private and socially rented houses over time (Serin, Kintrea & Gibb, 2018)

The Housing (Scotland) Act was revised again in 2014, eventually abolishing RTB for all social housing tenants within the country, effectively handing responsibility of managing all social housing stock to only two distinct bodies: housing associations and local authorities. This served as one of the ways to ensure proper enhancement and maintenance of the housing.

Due to the increase of ownership of housing stock for HAs over time (Figure 4) and eventually being accountable for over 11% (Scottish Government, 2021) of the total housing stock of Scotland, HAs face immense pressure to ensure that existing standards are met, and simultaneously keep rents low. Furthermore, since HAs are non-profit organisations, they typically receive funding through fixed limited grants provided by the government (Robertson & Serpa, 2014).

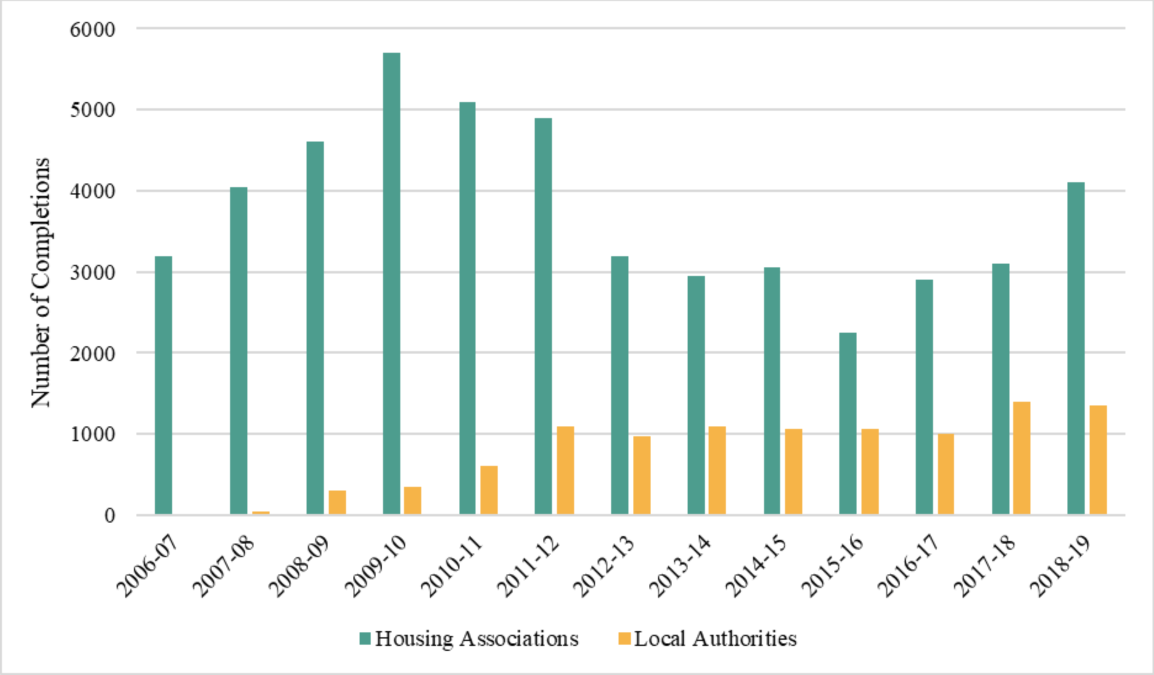

Figure 4: Supply of new-build social sector housing from 2006-07 to 2018-19 (Scottish Government, 2019a)

The Scottish house condition survey of 2019 (Scottish Government, 2019a) highlighted salient features about the current conditions of the social housing owned by housing associations. According to the report, rates of fuel poverty were at 39%. In comparison, only 12% with mortgaged houses reported to be in fuel poverty. In addition, 32% of households in housing associations have an energy efficiency rating of band D and below. However, emission values were lowest for housing associations (66 kg/m^2) and were reported highest for privately rented houses (85 kg/m^2) (Figure 5). In 2019, Housing Association Dwellings reported to have disrepair to critical elements in 48% of buildings and the highest failure rates for compliance with the Social Housing Quality standards (32% failure).

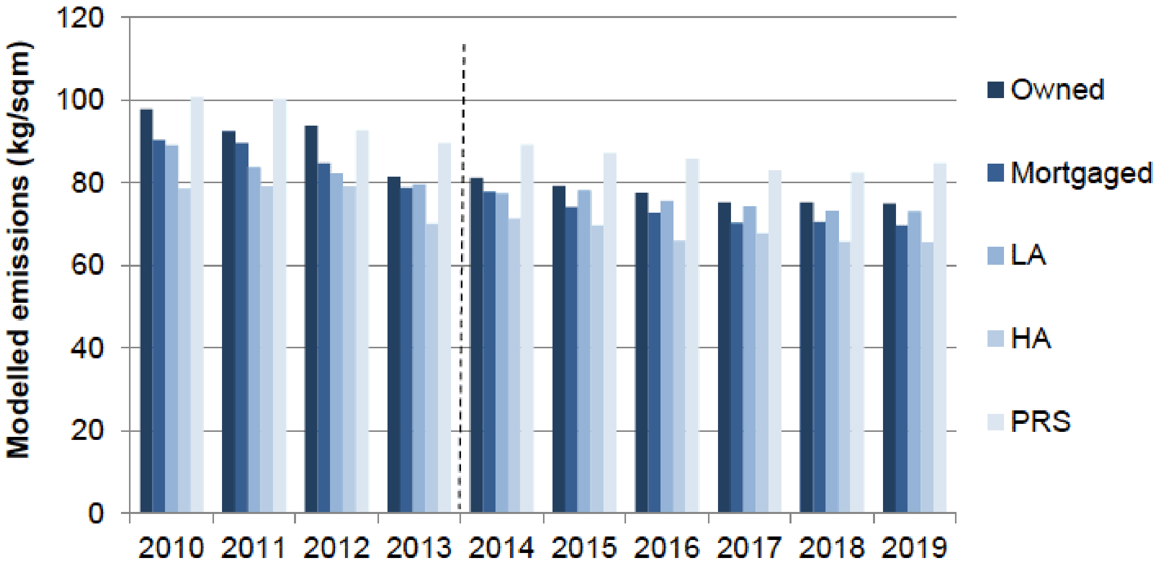

Figure 5:Modelled emissions for housing sector (Scottish Government, 2019a)

2.2. Relevant standards and policies

2.2.1. Energy Efficiency in Social Housing Scotland (EESSH 2) – Post 2020

With over 24.9% of Scottish households living in fuel poverty in 2017 (Dunning et al., 2020), the EESSH 2 is possibly one of the most important standards set by the Scottish Government as the document aims to reduce fuel poverty – which is believed to be driven by lack of energy efficiency – of tenants living in social housing. Through EESSH 2, the Scottish Government plans to improve energy efficiency in the social housing sector by bringing energy efficiency ratings of units up to EPC Band B[1] by 2032 (Scottish Government, 2020). This will also help them achieve the country's climate change emission reduction targets of achieving net-zero emissions by 2045. However, it must be noted that implementing energy efficiency measures require extra investment, which the document suggests should be done through the landlord's own resources. Doing so may take the tenant out of fuel poverty but might lead them into rent poverty.

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[1] EPC or Energy Performance Certificate has various band ratings that suggest how good the energy efficiency is in a housing unit or building. The bands range from A to G, with A being the most energy efficient with 92-100 SAP points and G being the least energy efficient with 1-20 SAP points. Band B implies an EPC rating of 81-91 SAP points.

2.2.2. Housing to 2040 – 2021

The 'Housing to 2040' is a roadmap that outlines a collective vision for what housing will look like in 2040 and provides guidelines to achieve those goals. It also highlights measures that can be taken to overcome possible challenges that may occur while implementing policies and standards (such as EESSH2 and climate change goals). It also plans to tackle derelict properties, improve housing in poor conditions and overcome fuel poverty by attracting private investments, increased self-funding, improve stakeholder engagement, and make relevant changes to improve housing quality (Scottish Government, 2021a).

2.2.3. Social Housing Quality Standards (SHQS) – 2004

The SHQS were implemented to ensure that social landlords keep up to date with the maintenance and upkeep of the social housing units. The standard also focused on the provision of timely repair and ensured that a good quality of services was maintained without incremental changes in the rent. The progress of keeping up with the SHQS is monitored by multiple public bodies that include: The Scottish Social Housing Charter and The Social Housing Regulator. (Scottish Government, 2004).

2.2.4. Tolerable Standards – 2006

The Tolerable Standards are part of a guidance document that aids Local Authorities and Housing Associations for the effective implementation of Housing (Scotland) Act, 2006. Despite multiple revisions to the Act, the document is still frequently referred to by various landlords due to its relevance even today. The tolerable standards essentially provide practical advice for assessors to determine whether a house will be fit to live in by providing an exhaustive list of indicators to gauge.

2.3. The complexities of Decision Making for HAs

Decision makers (DMs) are typically compelled to perform highly complex tasks in environments where data is constantly changing and information is highly cluttered (Baizyldayeva et al., 2013). This is particularly in the case of social housing, where meeting set standards and policies require extensive management, retrofit and (re)development plans but can only be done through accumulating and organizing social, financial, and physical data (Muczyński, Dawidowicz, & Źróbek, 2019).

The Scottish Federation of Housing Associations (SFHA) even pointed out that tenants in social homes are deprived by lack of access to gas, proper heating and are disadvantaged by higher energy distribution costs (Heath, 2022). This, coupled with an overwhelming requirement of fulfilling national and international obligations for greener homes adds to the complexity of decision-making for social homes as some of the problems can be difficult to grapple with. Jankowski and Richard (1994) highlighted that problems are becoming increasingly complex due to higher awareness, hence resulting in a surplus of new rules and regulations. This leads to a significant increase in the number of criteria required to do a complete analysis. In addition to this, a lot of problems that need to be addressed are either ill-structured or include qualitative figures (Vessey, 1991).

While problems are becoming increasingly complicated, finding a solution is even more complex in Scotland's social housing sector because for a lot of housing associations, it is difficult to work with data. This is primarily due to lack of management, organisation and classification of data as it moves within the development chain, hence creating issues for decision makers (Howell, 2022). This also makes it difficult to ascertain which houses are at risk as it makes the data unreliable.

Data organization is fundamental for decision makers (DMs) to assess the ongoing issues and implement the right strategies to meet the requirements of stakeholders. Generally, even the technology used for decision making lags in the social housing sector (Howell, 2022). This is especially alarming since housing associations need to increase their approvals and grants for revitalization of existing homes as well as for new-build properties. Adopting the right kind of decision support system (DSS) can significantly alleviate the issues of collating problems that need to be addressed and presenting the data in a way that makes it easy for DMs to highlight hotspots and problem areas that need urgent attention. It can also help them connect various themes and issues to develop more holistic solutions.

2.4. The role of Multi-Criteria Decision Support Systems

An effective multi-criteria decision support system (MCDSS) can cater to the aforementioned issues faced by decision makers by encouraging smooth decision-making and using decision support systems (DSS) to support the implementation of multi-criteria decision-making (MCDM). Mustajoki and Hämäläinen (2007) highlighted various ways in which digitalisation can elevate the use of MCDM methods. With advancements in technology, it is now possible to create an interactive interface to enable the best kind of decision making; and with the integration of MCDM to a model base of DSS, DMs now have even greater capacity to analyse, explore and compare different alternatives (Razmak & Aouni, 2015).

MCDSS can eventually help DMs visualise data in their preferred way of highlighting risks and priorities. It can also assist in presenting data in a way that make it easy for stakeholders and DMs to consume.

2.4.1. Decision Support Systems (DSS)

According to Malczewski (1999), Decision Support Systems (DSS) were conceptualized and developed in the 1950s and 1960s by Simon and Associates. These systems were initially presented for the purposes of strategic planning and management in the business and commercial industry.

While a unanimous definition of DSS is practically non-existent (Chen et al., 2002), the term commonly refers to a computerised system that assists a decision-maker to solve problems by combining various sources of information (Mackenzie et al. 2006). The DSS also needs to be reproducible, consistent, and justifiable (Barton, Parolin & Weiley, 2004). Malczewski (1999) highlighted that such DSS can be made by keeping certain objectives in mind, which include: ensuring that the DSS adds to the *effectiveness* of the decision-making process rather than *efficiency;* integrating computer-based programmes with professional opinions and judgement of decision makers; creating an interactive system that is clearly visualized and proves to be understandable by various stakeholders. In simpler terms, a DSS can enable DMs to obtain pertinent data across the company and make choices amongst different alternatives by easing the visualization of options (Baizyldayeva *et al.*, 2013).

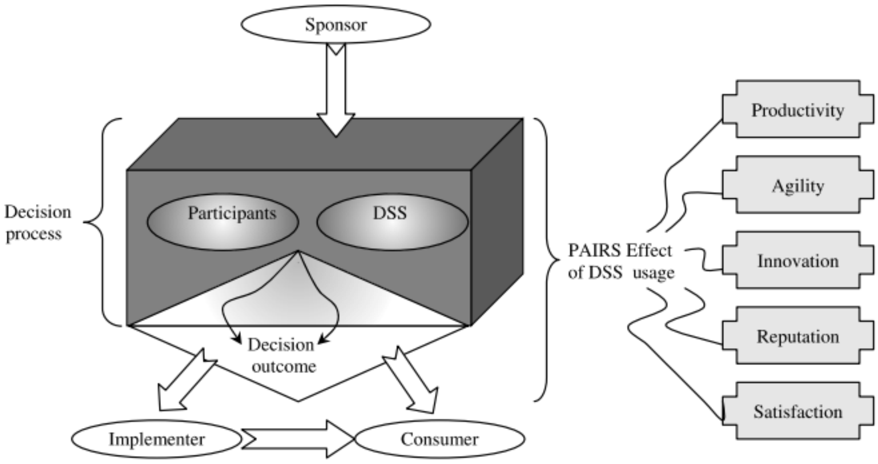


Figure 6: Role of a DSS in decision making (Holsapple, 2008)

DSS are classified into several types, some of which gravitate more towards data management and information processing in the form of text or hypertext. Certain DSS are also oriented towards database management, especially for data warehouses. Another type of DSS is spreadsheet oriented for representing and processing information, while some DSS consider helping to solve multi-criteria decision analysis problems in the form of dashboards (Holsapple, 2008).

2.4.2. Multi-Criteria Decision Making (MCDM)

Part of the DSS requires the consideration of multiple attributes to make strategies which are best carried out by Multi-Criteria Decision Making (Bell, Keeney & Raiffa, 1977). The MCDM process entails making decisions that involve multiple attributes and objectives to consider (MacCrimmon, 1982). It provides a ranking result based on relevant criteria, their matching values and assigned weights (Ozsahin, Ozsahin & Uzun, 2021). These models are also successful in providing the nature of trade-offs required to help reach a decision (Natividade-Jesus, Coutinho-Rodrigues, & Antunes, 2007).

According to Malczewski and Jackson (2000), dealing with multiple attributes and objectives requires stakeholder participation throughout the process to create a weighted ranking. It should also ensure that the DSS framework responds to the changing needs and responses of the individuals. This kind of weighted input is very apt with handling unstructured problems as it brings in the human element into the decision-making process. Having a weighted score also allows multiple criteria to be consolidated and represented by a single number, regardless of the social, environmental, and economic nature of the attribute (Zhu, Liu & Yeow, 2005).

Table 2 provides a brief overview of the types of MDCM methods commonly found in literature (Vassoney et al. 2021). Among these are compensatory techniques (like AHP and SAW) that allow low performance in some criteria to be made up by high performance in another criteria, and non-compensatory methods (such as ELECTRE III) (Banihabib et al. 2017). While all the methods are highly popular and widely used, the selection of the ideal one depends on the type of problem faced, goals to be achieved, variability in the criteria and volume of alternatives that exist (Khan, Amyotte & Amin, 2020).

Research also suggested combining two types of MCDM methods to obtain more accurate and relevant results. Most of these included a combination of AHP with other MCDM methods such as: AHP-TOPSIS, AHP-WP and AHP-SAW (Hadikurniawati et al., 2018).

Table 2: Brief on the types of MCDM methods

Author	MCDM method	Explanation
Fishburn (1967)	Simple Additive Weighting (SAW)/Weighted Sum Model (WSM)	Ranks large groups of alternatives on the basis of their weighted sum performance.
Bridgman (1922)	Weighted Product Method (WPM)	Uses the product of ratios, raised to the power of the corresponding weight of each criterion, to compare alternatives.
Saaty, (1990)	Analytical Hierarchy Process (AHP)	Constitutes of a pairwise comparison of alternate options within each criterion and uses and summation to produce overall performances.
Lai, Liu and Hwang (1981)	Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	Alternatives are ranked on the basis of their Euclidean distance from the most preferred solution and maximum distance from the least ideal solution.
Opricović (1998)	VIKOR	Used to solve decision problems with criteria having varied or conflicting units and seeks to find a compromise which is closest to the ideal.
Roy (1978)	ELECTRE III	Based on an outranking relation between alternatives and on the basis of a pseudo criteria.

2.4.3. Examples of MCDSS in Social Housing

MCDSS is very widely applied in many fields and there are a variety of MCDSS techniques that currently exist. Admittedly, however, there are few MCDSS that exist particularly in the context of management in social housing.

The most relevant one for this project was the one developed by Natividade-Jesus, Countinho-Rodrigues and Antunes (2007) for household evaluation in Portugal, which is a fully automated DSS that employed the use of multiple MCDM tools including AHP, SAW, Electre I and TOPSIS (leaving it at the discretion of the user to choose one). It also allows users to create, change and eliminate attributes according to the project’s needs and eventually generates maps with colours representing the types of classification.

A Spatial Decision Support System (SDSS) for sustainable urban redevelopment (Johnson-Ferdinand, 2014) was also developed for a specific brownfield redevelopment that used Key Performance Indicators to prioritize decision making and eventually used executive ESRI to develop a dashboard to help visualize the high priority development sites.

Another popular one is that by Conte (1999), which was done for the Bari Municipality in Italy. The project depicted concerns for the absence of sustainable management of social housing and lack of strategies to do so. This resulted in the decline of public housing tenants, caused constant maintenance problems, and led to building decays. The structure of Conte's DSS included the integration of scattered data of existing knowledge (housing information, European Union housing policies, legislations) and elementx of stakeholder engagement with policy experts to develop a strategic plan of action, which was critical to the project's success.

These, among other examples of MCDSS assisted in the development of a comprehensive framework for MCDSS in this particular project. Best practices were taken from all case studies and applied to suggest the best possible version.

2.5. Sustainability Attributes

Carrying out an effective MCDSS means identifying important attributes concerning the project needs. Hence, various attributes were identified by conducting extensive review of literature, with a special focus on academic papers and government reports. The studies revealed that environment and sustainability, economic feasibility and social acceptance criteria were the main features considered for assessment. Most of the previous studies also did not assess attributes by assigning weights (Amir, 2016), however, the few studies that did adopt such an approach used a "multiple criteria decision making" method.

Initially, about 150 relevant attributes were identified by taking data from various literature sources, quality assessment methods such as Housing Quality Indicator system (UK) (UK Government, 2011) and BREEAM and The Scottish Government's "Key Attributes of the Scottish Housing Stock" (Scottish Government, 2019). Out of those, about 35 attributes were shortlisted (Table 3) according to perceived relevance to the project.

Table 3: List of identified attributes through literature

Criteria	Attributes	Sub-Attributes
Resource Efficency and environmental sustainability	Embodied energy	-
	Carbon Emissions	
	Critical resource use	-
	Energy Efficiency	
	Current Recycled Contents	-
	Future Reusability	-
	Water use during construction and manufacturing	-
Operational Performance	Durability	Interior of the building
		Building Envelope
	Ease and frequency of maintenance	-
	Thermal performance and thermal mass	-
	Impact on cooling/heating loads	-
	Efficiency of installations	Water supply
		Draining of sewers and pluvial waters
		Gas supply
		Electric energy supplying
		Communications and media
		Mechanical equipment
	Security against intrusion	-
	Safety against fire	-
	Noise transmission	-
User Acceptability	Familiarity with building material/system	-
	Modification Ability	-

	Impacts on the health of the user	-
	Ambient Comfort	Acoustic
		Illumination
		Ventilation
		Thermal
Economic Impact	Construction Cost	-
	Skills Required	-
	Supply Chain	-
	Duration of Construction	-
	Job Creation	-
	Fuel Poverty	-

2.6. Knowledge gaps

While wider-level policies and guidelines exist for social housing, there is limited research available on the extent at which new and existing social homes currently contribute or adhere to set guidelines, especially in policy areas of climate change mitigation, design quality and sustainable development, retrofit and refurbishment. In addition, there is little to no data on housing associations in Scotland that highlights their current housing quality, design, energy efficiency and overall stability. This, along with the changing policies and unorganized existing data creates a lot of issues for decision makers in making informed decisions.

Furthermore, published research on decision support systems to date has focused very little on public/social housing. While research applications of DSS for housing and regional planning are numerous, they are specific and cannot be replicated for social housing because of the social and economic criteria. It is also difficult to implement existing tools due to their lack of dynamic approach and lack of ability to communicate results in a visual and interactive manner.

Decision makers also face a lot of complexity in decision making to unorganized data, multiple data sets and inundation of new policies

This study will help by establishing a baseline on current social housing conditions using data from a housing association using MCDM tools and then further using that data to represent hotspot/priority areas in need of urgent repairs or retrofit through DSS. This will be done to ease the decision-making process for housing associations, help visualize the current scenario and even display it for the purposes of attracting investors and donors.

Chapter 3: **METHODOLOGY**

The methodology adopted for this project followed a case study approach that brought together findings from previous research, stakeholder engagement through questionnaires and interviews and statistical analysis. A series of qualitative and quantitative methods were adopted to identify sustainability attributes in the redevelopment/retrofit of social housing within Scotland, create a hierarchal system using a ranking method and prioritise housing units in need of urgent attention which was done using Microsoft Excel. ArcGIS Dashboards was then used to visualise the key hotspots.

3.1. Research Philosophy

'The term research philosophy refers to a system of beliefs and assumptions about the development of knowledge' (Saunders, Lewis and Thornhill, 2009). This helps establish a foundation and reasoning for choosing essential elements of research methodology. The research onion (Figure 7) can provide insight into the stages of the research process and help in forming a research philosophy.

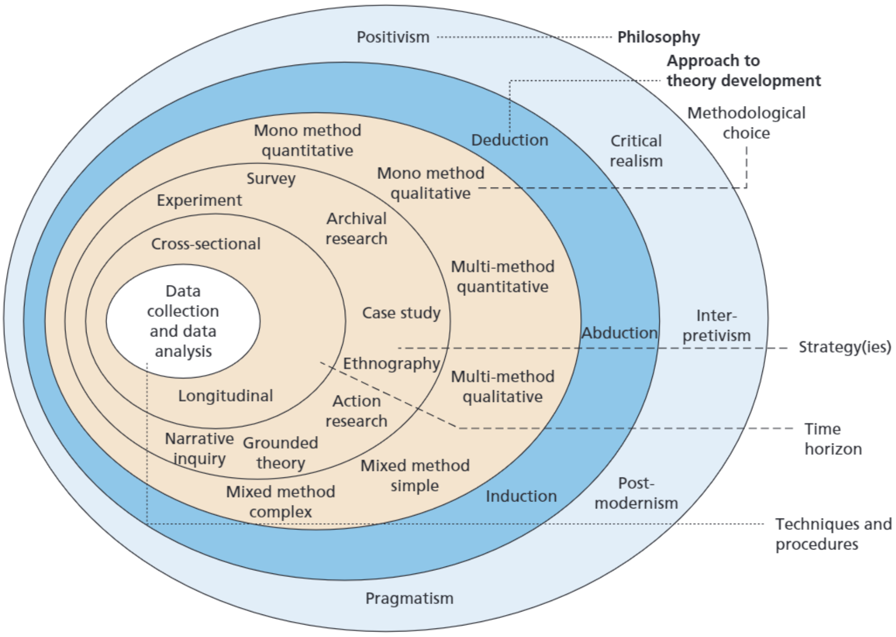


Figure 7: The research onion developed by Saunders (2009)

Going from outside to the inside of the research onion, this project followed a pragmatic approach as it strived to develop solutions that are realistic and well-informed. This kind of approach was best suited for the project as it considered the human element of decision-making tools, therefore it was important to acknowledge that a qualitative aspect would also be a part of the study along with quantitative data analysis. This kind of approach helps to improve knowledge growth in social sciences and other multidisciplinary projects (Onwuegbuzie and Leech, 2005). Owing to this fact, a mixed qualitative and quantitative method was adopted that helped establish a case study for assisting decision making for LHA.

3.2. Literature Review

The literature review (see Chapter 2) followed a systematic approach that consisted of identifying, collecting, and analysing information from acquired research (Snyder, 2019). It essentially helped highlight all evidence available online on social housing and various methods for decision making and provided a broader understanding of the topic area by highlighting the work that had already been done and the methods currently being used.

To do this, an extensive review of policy documents, journal articles and reports was carried out to assess and outline the existing challenges, trends, and opportunities available for sustainable social housing in Scotland. Through this process, various national and international case studies were also identified that were used to derive learning on existing decision support systems used in the housing sector that could potentially facilitate decision-making in the Scottish housing context. Moreover, an initial list of attributes was also collated from available literature.

3.3. Stakeholder surveys and interviews

In order to build upon knowledge extracted from literature and identifying the limitations of research with regards to decision support systems for sustainable social housing, stakeholder engagement was necessary (Yang and Ogunkah, 2013). Moreover, due to the nature of the project, it was necessary to consider the views of professionals who would possibly use the framework of the decision support system at a later stage. The process of stakeholder participation was divided into two stages: shortlisting identified attributes through consultation and ranking shortlisted attributes through questionnaire surveys and interviews. This provided a framework for rank that each attribute should have during the multi-criteria decision analysis.

Respondents for surveys and interviews were selected based on their level of experience in the social housing sector and all respondents belonged to LHA as they were best suited for providing insights on the priority areas that needed attention within their properties. All surveys and interviews were conducted through an online video conferencing platform to avoid potential cost incurred due to travel.

3.3.1. Finalization of attributes through consultation and mock interviews

Given the number and complexity of identified attributes in multi-criteria evaluations, it was imperative that a convenient structure was established for the attributes to ease communication and decision making for the user and to further use that information to create the DSS.

Hence, a list of 30 short-listed attributes were further reduced and altered through consultation with an experienced professional within LHA (Chapter 2). These attributes were selected based on the relevance to the LHA, their significance and applicability in the association's decision-making processes. Eventually, a list of 20 relevant attributes was finalised, with minor adjustments in the remaining attributes (Figure 9). A mock survey and interview were also conducted with the consultant to assess the ease of ranking of identified attributes, as well as to provide structure to the interview format.

During this process, the existing ranking method was also changed to a simple rank order to decrease complexity for respondents. This pragmatic approach later helped gain a more practical response from the study participants.

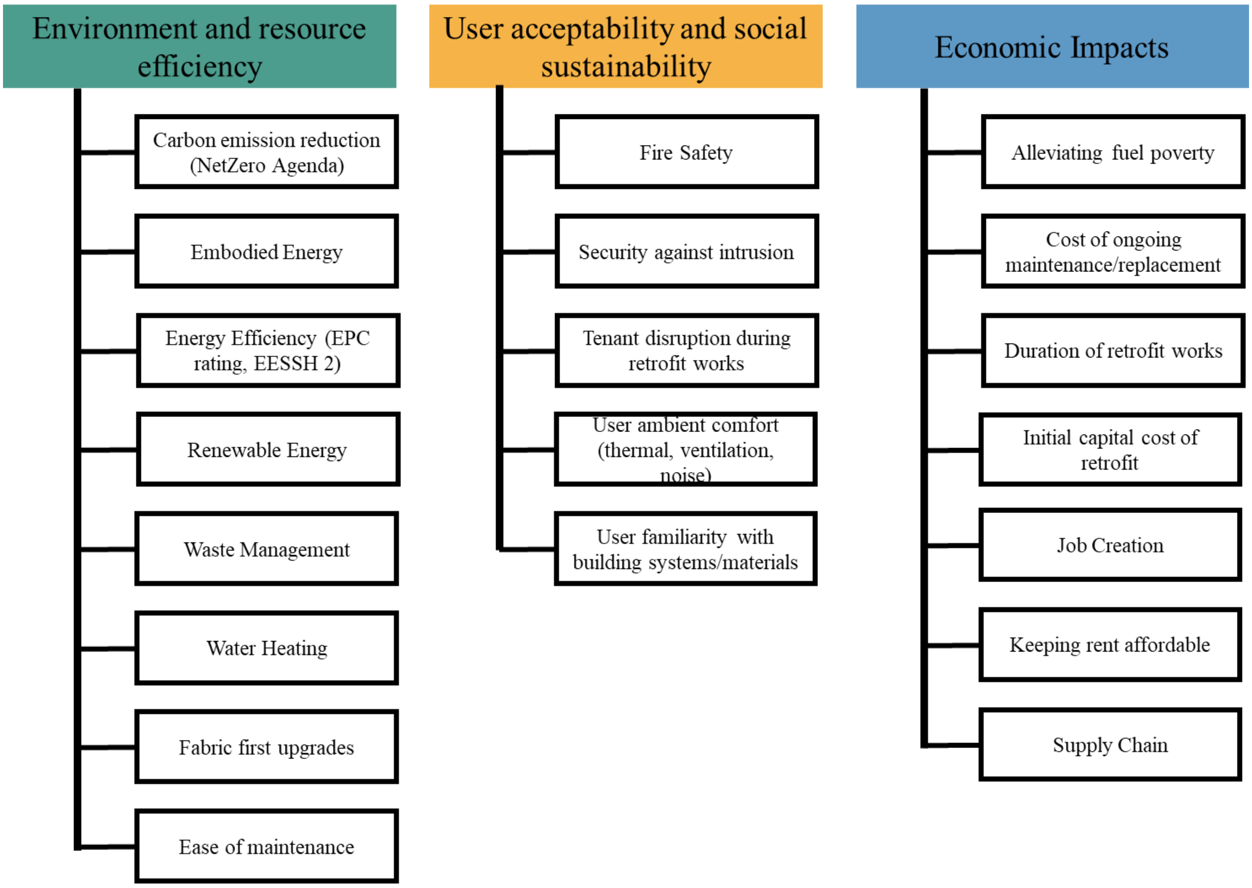


Figure 8: List of attributes finalized for survey and analysis

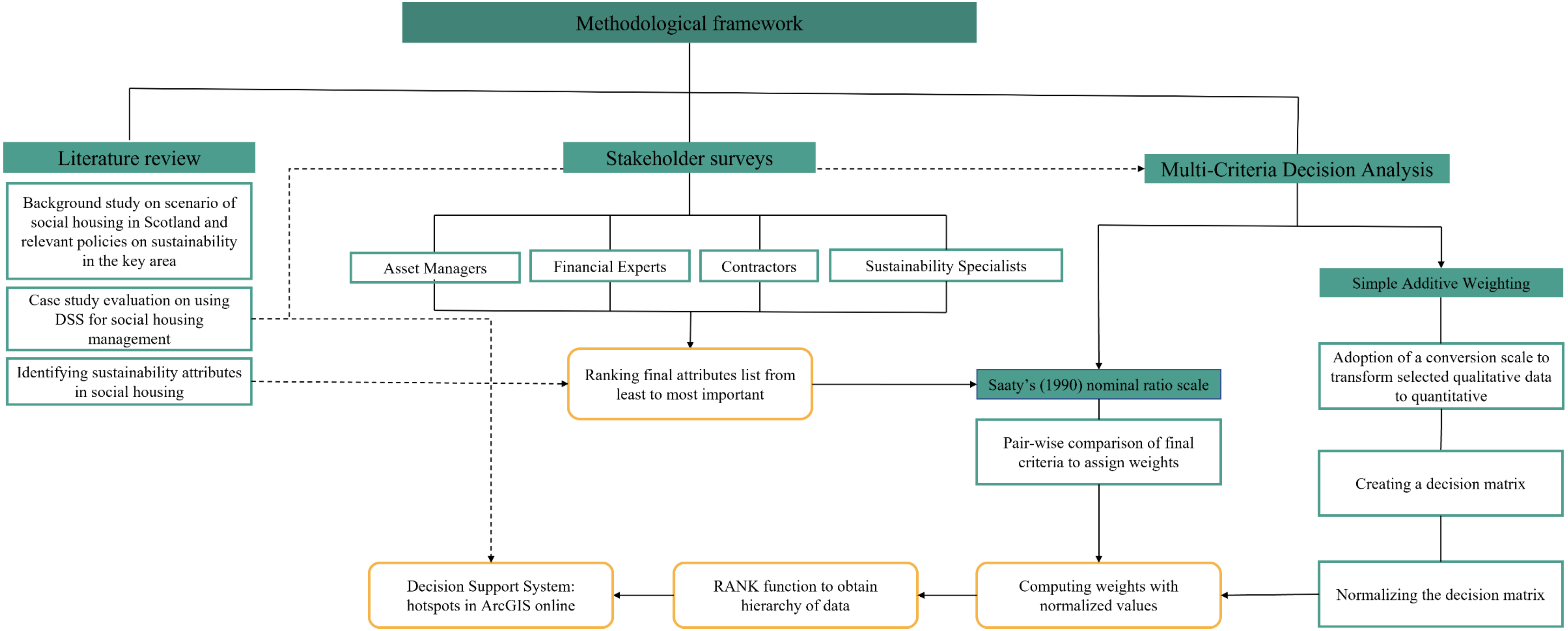


Figure 9: A methodological framework for the project

3.3.2. Surveys and semi-structured interviews

Questionnaires and semi-structured interviews are typically ideal for mixed-method studies (Lai & Waltman, 2008), where questionnaires can provide objective evidence of patterns and qualitative interviews help gather in-depth information on participant judgments, behaviours, and actions (Kendall, 2008). According to Harris and Brown (2010), it is imperative that interview prompts and questionnaires are structured and similar in nature to ensure that data aligns. It is also important that data collection for questionnaires and interviews is done within the same period, so respondents remain clear on the objectives (Randolph et al., 2009).

For this purpose, surveys and interviews with 10 participants from LHA were conducted simultaneously. These participants consisted of contractors, financial experts, asset managers, project managers and sustainability experts from LHA. First, a quantitative questionnaire was conducted where respondents were asked to rank order the list of attributes based on their judgement and experience. Within the same meeting, a semi-structured interview was also conducted to gain insight for the basis of their rankings. The respondents were also asked to highlight the desired features they wanted to see in DSS for retrofitting social housing within LHA. These surveys also acted as a validation and approval method for the identified criteria to make the study more applicable to the specified housing association.

3.3.3. Survey Analysis

Respondents were asked to rate the 20 identified attributes from 1-20 using the simple rank order, with 1 being the most important attribute in management and retrofit of social housing, and 20 being the least important. After each individual had performed the ranking, the average for the assigned ranks against each attribute was calculated using the arithmetic mean formula (1).

$$A = \frac{1}{n}\sum_{i=1}^{n} a_i \qquad (1)$$

$A = arithmetic\ mean$
$n = number\ of\ values$
$a_i = data\ set\ values$

Next the RANK function was applied to the averaged list to obtain a list of whole numbers against each attribute to assign its rank. The function syntax consisted of the arguments highlighted in Table 4.

Table 4: Features of Excel's RANK function

RANK(number, ref, [order])	
Number	The number whose rank needs to be calculated (Required)
Ref	An array or reference to a list of numbers (Required)
Order	Input values 0 or 1 to specify how to rank number i.e. in an ascending or descending order

3.3.4. Semi-structured Interview Analysis

Semi-structured interviews were mainly conducted to improve validity and provide justification for the objective responses in the questionnaire. This process allowed the respondents to change their responses in the questionnaire later if they felt that they gained more insight during the discussion. Detailed notes acquired during the interview process were structured and organized according to the nature of topic and a thematic analysis was conducted. This was done to identify patterns in responses and to condense the acquired data.

3.4. Multi-Criteria Decision Analysis (MCDA)

The MCDA consisted of using a combined decision-making method that consisted of SAW and AHP's Saaty 1-9 scale. Each method was applied at different stages of the MCDA. Saaty's 1-9 scale was used to obtain weights of the ranked attributes from interviews and SAW was used to normalize the data available against the attributes and then compute it against the weights assigned. This process helped refine and organise LHA's property data and identify hotspot locations within.

Due to minor constraints, some relevant data which had to be set against relevant attributes, was absent. This included each property's relevant information against the attributes of rent, fire safety, cost of ongoing maintenance and 12 other relevant attributes that were ranked. Despite the unavailability of data, these attributes were still ranked during surveys because of their highlighted importance by experts and literature in the retrofit of social housing. Furthermore, once relevant data is obtained in the future, these can easily be incorporated into the DSS through a quick analysis using the methods defined below.

The MCDA was therefore performed on the attributes for which data was present. These included: alleviating fuel poverty, keeping rent affordable, fabric first updates, carbon emissions and renewable energy.

3.4.1. Saaty's 1-9 Scale for pair-wise comparison

While the relative ranking of the five attributes was available through the surveys conducted, it was important to ascertain the percentage weightage of each attribute in comparison to the other. For this purpose, a pair-wise comparison matrix (n x n) for the criteria was drawn up using Saaty's 1-9 scale of pairwise comparison (Table 5) and each attribute was compared to the other one-by-one (Saaty, 1990).

Table 5: Saaty's 1-9 scale of pairwise comparison (Saaty, 1990)

Intensity of importance	**Definition**	**Explanation**
1	Equal importance	Two factors contribute equally to the objective
3	Weak importance of one over the other	Experience and judgment slightly favor one over theother.
5	Essential or strong importance	Experience and judgment strongly favor one over the other.
7	Demonstrated importance	Experience and judgment very strongly favor one over the other. Its importance is demonstrated in practice.
9	Absolutely more important	The evidence favoring one over the other is of the highest possible validity.
2,4,6,8	Intermediate value between two adjacent judgments	If compromise is needed
Reciprocals of above values	If activity "i" has one of the above values assigned to it when compared with activity "j", then "j" has a reciprocal value when compared with activity "i"	$a_{ji} = \frac{1}{a_{ij}}, a_{ij} > 0, i, j = 1, 2, \dots, n$

Since it was already clear which criteria was most important, a score was assigned to determine how much more important one criteria is to the other, hence providing an objective weightage to the criteria. This was displayed in the form of a comparison matrix (denoted by matrix A), where a_{ij} denoted the relative importance of criteria *i* with *j* (Liang *et al.*, 2017).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \dots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} \quad (2)$$

Each element within the comparison matrix was then computed with the column total and then the priority vector was obtained by finding the row averages. This provided the weights of the attributes (Afshari, Mojahed & Yusuff, 2010).

Finally, the consistency ratio was determined to ascertain whether the judgment was consistent throughout the pair-wise comparison. This was carried out by:

- Determining weighted sum matrix *(u)* by taking the product of the pairwise comparison matrix with the priority vector (*w)*.

$$\begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \dots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} \begin{vmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{vmatrix} = \begin{vmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{vmatrix} \quad (3)$$

- Dividing the weighted sum matrix by the priority vector element

$$\begin{vmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{vmatrix} / \begin{vmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{vmatrix} \quad (4)$$

- Computing the average of the values to obtain λ_{max}
- Finding the Consistency Index (CI) using the equation as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

$$n = size\ of\ the\ matrix$$

- Finally computing the consistency ratio, CR, as follows:

$$CR = \frac{CI}{RI} \quad (6)$$

Where RI is the average random consistency against the size of the matrix (Table 6). The matrix has predetermined values against the matrix size. In this case, the size of the matrix was 5 (due to 5 attributes being evaluated). The RI is computed into (6) and is used to find the CR. The CR is acceptable only if the value does not exceed 0.1 (Cahyapratama and Sarno, 2018).

Table 6: Average random consistency (RI)

Size of Matrix	Random Consistency
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

----► Size of matrix for this study

3.4.2. Simple Additive Weighting (SAW)

Simple Additive Weighting (SAW) is a multi-attribute decision making system that is used to find the weighted sum of performance for each alternative within each attribute. This method is one of the most used (Nurmalini & Rahim, 2017) among other MCDM methods and is typically applied when there is a high number of alternatives as it provides accurate results at a quick pace (Ibrahim & Surya, 2019). This method also helped establish hotspot areas within the data provided.

A decision matrix of (m x n) was constructed that contained 'm' housing units and 'n' criteria. A normalised decision matrix was then constructed for beneficial and non-beneficial criteria using the linear: max normalisation technique that placed values on a uniform 0-1 scale. Normalisation was a process adopted to organise a large dataset. It also ensured uniformity in how the data looked, read, and could be utilised. This was particularly important since the properties' attributes consisted of different units of measurement (i.e., there was a different unit for energy efficiency and a separate one for fuel poverty) and it was pertinent to bring all the data on one scale so it could be analysed and eventually ranked effectively.

Therefore, the process of normalisation for a positive criteria used the following formula:

$$n_{ij} = \frac{r_{ij}}{r_j^*} \quad i = 1 \ldots..m, \quad j = 1 \ldots\ldots.n \tag{7}$$

$$r_{ij} = performance\ value\ of\ individual\ housing\ unit\ within\ each\ cell\ against\ a\ specific\ attribute\ column\ (j)$$

$$r_j^* = maximum\ number\ of\ r\ in\ the\ column\ j$$

For negative criteria:

$$n_{ij} = \frac{r_j^{min}}{r_{ij}} \quad i = 1 \ldots..m, \quad j = 1 \ldots\ldots.n \tag{8}$$

$$r_j^{min} = minimum\ number\ of\ r\ in\ the\ column\ j\ (attributes)$$

While three other normalisation techniques are present, the maximum linear normalisation technique proves to provide the best results for the SAW method. This was determined by Vafaei, Ribeiro and Camarinha-Matos (2021), who used plurality voting to determine the number of times each different technique places first rank when various judgment metrics are applied, and their results determined the max linear normalisation technique to be the most suitable out of all others.

3.4.3. Computing weights with normalised values (combining SAW + Saaty's scale)

After normalisation, each alternative A_i was evaluated by finding the product of the score of each alternative with the weighted criteria that was established when Saaty's 1-9 scale was implemented.

$$A_i = \sum w_j . x_{ij} \tag{9}$$

$$x_{ij} = score\ of\ the\ i_{th}\ alternative\ with\ respect\ to\ the\ j_{th}\ criteria$$
$$w_j = the\ weighted\ criteria$$

This finally provided the rank of each alternative housing unit, highlighting the ones in need of the most retrofit and maintenance.

3.5. Decision Support System – Development of a user-friendly interface

It was important to communicate acquired results in a way that is relevant to the stakeholders. Information visualisation is a critical process that represents data in multiple meaningful ways, such as bar charts, maps, and scatterplots. Ideally, information visualisation converts raw data into useful information and allows users to interpret the provided information with much more ease (García & Montané-Jiménez, 2020).

Dashboards specifically can provide an effective visual display for critical information required to achieve ones’ goals and objectives, especially in urban areas. They are also interactive tools which can be adopted to multiple types of developments. Decision-makers use these dashboards to monitor the operation of a city by using multiple performance indicators. For this purpose, an online interface of ArcGIS Dashboards was used to present results in an interactive manner.

For this project, the ArcGIS dashboard was used to represent property data in order of established ranking system. The goal of creating a dashboard was to show prioritisation of various sites to ease the decision-making process. This will also serve as a framework for creation of a fully automated DSS where rankings are established according to the user’s needs and relevant results are generated instantaneously on the dashboard.

Chapter 4: **Results and Discussion**

This chapter presents the results which includes the outcomes of the survey and interview, the application of the combined MCDM methods and the development of a dashboard. It consists of five main sections: expert survey results, weighing attributes using Saaty's 1-9 scale, normalization of data using SAW, obtaining final ranks and ArcGIS dashboard. The chapter discusses comparisons with the literature and briefly touches upon various limitations identified while executing the project.

4.1. Expert Survey Results

The survey aimed to establish weightings of the 20 identified sustainability attributes and gather insight on various challenges and opportunities to make social housing more sustainable. A total of 10 responses were acquired from leaders in the LHA thorough discussions and questioning. To avoid any skewed results, it was ensured that the group selected for surveys had multiple years of experience in the field. All the respondents for this study had an average of 15 years of work experience working with social housing. Furthermore, to gather information from various perspectives, the respondent list consisted of a wide range of stakeholders, which included asset managers, financial experts, contractors, and sustainability experts.

The analysis of the survey results showed rankings for the 20 attributes (Table 7). For seven out of 10 respondents, alleviating fuel poverty and keeping rent affordable were at the top of the list because of their importance in the social housing sector. Apart from that, it was apparent during discussions that respondents leaned more towards some attributes than others due to their own bias based on their experiences and job descriptions. As predicted, the financial expert leaned more towards prioritizing "initial capital cost of retrofit" and "cost of ongoing maintenance", whereas maintenance managers preferred "fabric first upgrades". Odu (2019) also highlighted the probability of decision-makers preferring one criterion to another due to their own personal preferences, thereby adding further complexity in the decision-making process. However, personal interactive interviews – conducted after the survey – helped detect and mitigate such biases by implementing an effective discussion and feedback mechanism.

Table 7 – *Final rank of attributes from surveys*

Final rankings from surveys	1	Alleviating fuel poverty
	2	Keeping rent affordable
	3	Cost of ongoing maintenance/replacement of new technology
	4	Energy efficiency (EPC rating, EESSH2)
	5	Fire Safety
	6	Initial capital cost of retrofit
	7	Ease of maintenance
	8	Fabric first upgrades
	9	User ambient comfort (thermal, acoustic, ventilation)
	10	Carbon emissions (net zero agenda)
	11	Tenant disruption
	12	Duration of retrofit works
	13	Renewable energy
	14	Supply chain
	15	User familiarity with building materials/systems
	16	Waste management
	17	Water heating
	18	Security against intrusion
	19	Embodied Energy
	20	Job creation

Job creation was ranked the lowest as it was not considered to be a main goal for LHA while carrying out projects. It was, however, pointed out by one respondent that there is a shortage of skills in the social housing sector which could possibly contribute to issues with retrofit projects. ‘Security against intrusion’ was another attribute that was ranked quite low because it was believed that the areas were actually quite secure and did not face challenges in terms of theft or burglary.

Some challenges for retrofit were also highlighted by respondents, where a few of them stated that due to the mixed tenure nature of some buildings, it was nearly impossible to carry out energy efficiency works. They also mentioned that installing new technologies might also be an issue as it is difficult to inculcate behavioural change in some tenants. Furthermore, shifting to renewable energy would also be quite difficult due to high capital costs. Some respondents stated that fire safety is a big issue in most units due to old age of buildings and their constructions.

However, the LHA had certain projects in their pipeline to not only overcome these challenges, but also adopt a collaborative approach towards achieving their objectives. It was apparent that the housing association was taking steps to ensure that social housing is made as sustainable as possible. This included installation of solar powered heat pumps, staying up to date with stock conditions through surveys, conducting fire risk assessment and adopting a fabric first approach.

The combination of surveys and interviews for the study provided a holistic view of experts' opinions. Moreover, this process also helped address any problems or misunderstandings the participants may have had while filling the survey. This was also supported by Marttunen, Lienert and Belton (2017) who stated that an interactive interview process can help resolve any misunderstandings regarding the questions and can be used as a means to verify the weights assigned by the interviewee.

The research also highlighted that while expert opinions gave quick results, they do not necessarily highlight stakeholder preferences, which leads to stakeholders not being involved and only informed of the changes. While this does not affect the accuracy of the results, it may lead to stakeholders being less willing to accept change, especially in the case of this study where, due to time constraints, tenants were not consulted during the development of the decision-making framework.

4.2. Weighing Attributes using Saaty's 1-9 Scale

While the surveys provided a rank of each attribute, their weights still had to be assigned. This was done using Saaty's comparison matrix where each attribute was compared to the other and assigned a value between one to nine. The initial ranking extracted from the survey was kept the same and their percentage weightage was assigned based on the information extracted from interview discussions.

During surveys, all attributes were considered and ranked because of their critical importance in the decision-making process for public housing. However, due to unavailability of data for most attributes, they were not considered in the weighing criteria to keep the results as accurate as possible. Therefore, only five attributes were taken into consideration, which include: Alleviating fuel poverty, keeping rent affordable, fabric first upgrades, carbon emissions and renewable energy. The pair-wise comparison values for these attributes are presented in Table 8, which indicate the relative importance of attributes in the rows compared to the attributes in the columns. Speaking to experts revealed that ensuring energy efficiency and alleviating fuel poverty were almost of equal importance as they were interconnected, hence a value of 1 was assigned. Installation of renewable energy technologies was rated quite low especially in comparison to energy efficiency and alleviating fuel poverty because the technology is still quite expensive and would not be prioritised until other criteria were met first. Whereas the criterion of fabric first upgrades was given more importance due to the aging infrastructure of properties and potential that improving insulation showed towards ultimately reducing heating costs.

Table 8: Pair-wise comparison of values

	Alleviating fuel poverty	**Energy Efficiency**	**Fabric first upgrades**	**Carbon Emissions**	**Renewable Energy**
Alleviating fuel poverty	1	1	4	6	8
Energy Efficiency	1	1	2	7	8
Fabric first upgrades	1/4	1/2	1	4	3
Carbon Emissions	1/6	1/7	1/4	1	2
Renewable Energy	1/8	1/8	1/3	1/2	1

$$Sum\ of\ column\ 1 = 2.542$$
$$Sum\ of\ column\ 2 = 2.768$$
$$Sum\ of\ column\ 3 = 7.583$$
$$Sum\ of\ column\ 4 = 18.5$$
$$Sum\ of\ column\ 5 = 22$$

After dividing each value in a column with its corresponding sum, its weight was calculated (Table 9). The final weight for each of the five criteria is depicted in Figure 10. As stated in the initial ranking system, the order of the criteria remained the same, however, now they have assigned weightage, with the criterion of alleviating fuel poverty having the highest weight of

40% and renewable energy having the lowest weight of 4%. Energy efficiency, fabric first upgrades and carbon emissions were in the middle with percentage weights of 35%, 15% and 6% respectively. Ultimately, the weights provided an indication of the decision-maker's influence and the importance of a specific criterion within the MCDM process.

Table 9: Results for weights obtained

	Alleviating fuel poverty	**Energy Efficiency**	**Fabric first upgrades**	**Carbon Emissions**	**Renewable Energy**	**Weights obtained (Average of each row)**
Alleviating fuel poverty	0.393	0.361	0.527	0.324	0.364	**0.394**
Energy Efficiency	0.393	0.361	0.264	0.378	0.364	**0.352**
Fabric first upgrades	0.098	0.181	0.132	0.216	0.136	**0.153**
Carbon Emissions	0.066	0.052	0.033	0.054	0.091	**0.059**
Renewable Energy	0.049	0.045	0.044	0.027	0.045	**0.042**

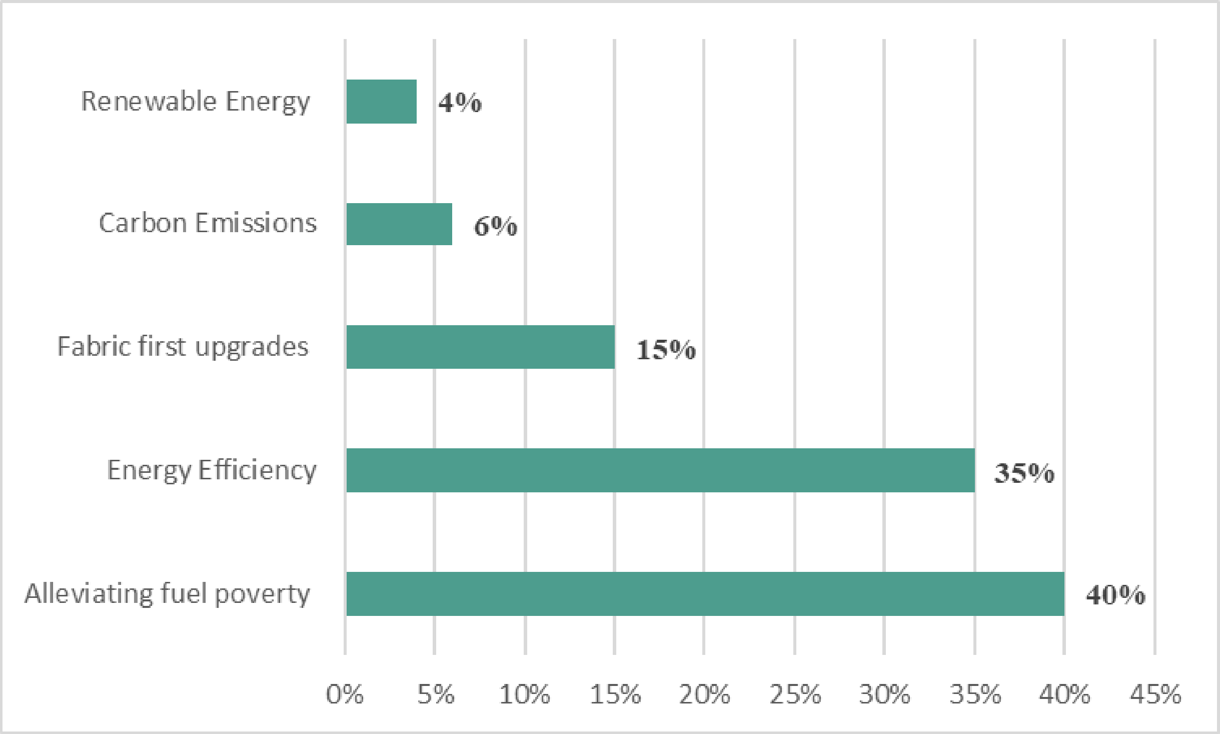


Figure 10: Final weights of 5 selected attributes

The results were then tested for consistency using the consistency rating method. For this, WSM was calculated:

$$\begin{bmatrix} 1 & 1 & 4 & 6 & 8 \\ 1 & 1 & 2 & 7 & 8 \\ 0.25 & 0.5 & 1 & 4 & 3 \\ 0.17 & 0.14 & 0.25 & 1 & 2 \\ 0.12 & 0.12 & 0.66 & 0.5 & 1 \end{bmatrix} x \begin{vmatrix} 0.394 \\ 0.352 \\ 0.153 \\ 0.059 \\ 0.042 \end{vmatrix} = \begin{vmatrix} 2.048 \\ 1.802 \\ 0.789 \\ 0.297 \\ 0.216 \end{vmatrix}$$

Next the consistency vector (CV) was calculated where each cell of the WSM was divided with the corresponding cell of the assigned weights:

$$\begin{vmatrix} 2.048 \\ 1.802 \\ 0.789 \\ 0.297 \\ 0.216 \end{vmatrix} / \begin{vmatrix} 0.394 \\ 0.352 \\ 0.153 \\ 0.059 \\ 0.042 \end{vmatrix} = \begin{vmatrix} 5.198 \\ 5.118 \\ 5.172 \\ 5.040 \\ 5.120 \end{vmatrix}$$

$$\lambda_{max} = \frac{5.198 + 5.118 + 5.172 + 5.040 + 5.120}{5} = 5.1297$$

Obtaining the CI:

$$CI = \frac{5.1297 - 5}{5 - 1} = 0.032$$

The CR was calculated by taking the amount from the RC based on the size of the matrix (which, in this case was 5):

$$CR = \frac{0.032}{1.12} = 0.029$$

A value of 0.029 was obtained for CR, which is less than the threshold value of 0.1, indicating sufficient consistency.

The application of Saaty’s 1-9 scale derived from the AHP method proved to be quite advantageous as it helped create a hierarchal structure to an otherwise unstructured problem and processed qualitative data using quantitative measures. It also considered the limit for inconsistencies during comparison of different criteria and alternatives. Pertiwi, Daniawan and Gunawan (2019) also highlighted these benefits while combining the AHP and SAW methods to design a DSS for selecting majors in school. They also highlighted certain disadvantages such as the complexity of the method and that in order to make improvements, one has to start from the initial stage. However, in this project, having less attributes to analyse decreased the complexity of the comparison matrix and allowed for more consistent results. Overall, Saaty’s 1-9 scale is proven to be very efficient in term of obtaining weights of the criteria in relation to the importance of the weights in a consistent manner.

4.3. Normalization of data using SAW

Available data values for the properties that could be used against each attribute was then identified (Table 10). Some available data was not used, like exposure to wind-drive rain zone, because the values/conditions were similar throughout the properties. Similarly, data for other types of renewable energy types was also present but was not considered because their installation was unsuitable for all properties (such as wind turbines, biomass boilers and ground source heat pumps).

Other available data could also not be considered because additional information was required to derive relevant values. For example, the total energy consumption per property was provided, but the data for number of people living in each property was missing. Due to this, a standard value for consumption per capita could not be calculated to provide a true picture of which property has a higher energy consumption value.

Furthermore, some of the available data consisted of predictions such as in the case of loft and wall insulation instead of the actual scenario, leading to limitations in the authenticity of the data available. However, the confidence intervals were also provided with the prediction values. High confidence intervals decreased the degree of uncertainty in the given quantitative or qualitative values.

Table 10: Data types and description of attributes

Attributes	Corresponding data of properties	Data Type	Description of data
Alleviating fuel poverty	Probability of fuel poverty (fuel bill >10% of income after housing)	Discrete – Quantitative (Percentage)	This value is a percentage of the estimated amount of fuel poverty of a property if it needs to spend more than 10% of the total household income on energy to maintain satisfactory heating.
Energy Efficiency	Current energy efficiency (SAP) rating band	Ordinal – Qualitative	Assessing for energy efficiency includes identifying areas of heat or energy loss, checking for the efficiency of the heating and water system, assessing the insulation of the property, whether lighting is energy efficient, among many other factors. Meeting energy efficiency ratings then ensures an EESSH compliance in the property
	EESSH Compliant	Nominal – Qualitative	
Fabric First Upgrades	Wall insulation prediction	Nominal – Qualitative	Fabric first upgrades refer to the prioritization of repairs, insulation, draught-proofing and ensuring proper ventilation. It also ensures the required thermal mass of the building before implementing any secondary measures like renewable energy technologies.
	Loft insulation prediction	Continuous – Quantitative	

	Glazing type	Nominal – Qualitative	
Carbon Emissions	RdSAP CO2 emissions estimate (tCO2/year)	Discrete – Quantitative	
	Environmental impact rating band	Ordinal – Qualitative	
Renewable Energy	Solar PV suitability	Nominal – Qualitative	Renewable energy data refers to the potential of installing renewable energy technologies in a given property.

4.3.1. Application of conversion scales

To apply SAW effectively, the existing data (or alternatives) had to be pre-processed to make it easy to manipulate and evaluate. For this purpose, a conversion scale was adopted where string variables were converted to numerical ones. This was done for all alternatives within the attributes.

4.3.1.1. Conversion scale for variables in energy efficiency

Table 11: Energy efficiency ratings of LHA properties

Energy Efficiency Rating Band	Conversion Scale
A-B	5
C	4
D	3
E	2
F-G	1

Table 12: EESSH Compliance data of LHA properties

EESSH Compliance	Conversion Scale
Compliant	3
Risk of non-compliance	2
Likely not compliant	1

4.3.1.2. Conversion scale for variables in carbon emissions

Table 13: Environmental Impact Rating Band range of LHA housing units

Environmental Impact Rating Band	Conversion Scale
A-B	5
C	4
D	3
E	2
F-G	1

4.3.1.3. Conversion scales for fabric first upgrades

Table 14: Fabric first upgrade options in LHA housing units

Fabric First Upgrades	
Wall insulation	**Conversion Scales**
Insulated	2
Uninsulated	1
Loft insulation	
250mm+	4
100-249mm	3
0-99mm	2
No Loft	1
Glazing	
Double/Triple	2
Single/Partial	1

4.3.1.4. Conversion scale for renewable energy

Table 15: Suitability of installing solar PV within LHA housing units

Solar PV suitability	Conversion Scale
Not suitable	2
Suitable	1

4.3.1.5. Conversion scale for fuel poverty prediction

Despite fuel poverty being a numerical value (percentage), normalisation technique was not applicable to discrete data sets. Therefore, a conversion scale had to be applied for this specific attribute in order to later normalize the data on a 0-1 scale.

Table 16: Probability of fuel poverty

Probability of Fuel Poverty	Conversion Scale
$0 \leq x \leq 20$	5
$20 < x \leq 40$	4
$40 < x \leq 60$	3
$60 < x \leq 80$	2
$80 < x \leq 100$	1

Overall, a higher score was assigned to data that was in a desirable condition while lower values were assigned to conditions of attributes that required change. For example, EESSH compliant properties (Table 11) were assigned a value of 3, while properties that were likely not compliant were assigned a lower value of 1. Similarly, for properties having a higher environmental impact band rating (i.e., A-B or C), a higher value was assigned as compared to properties having a lower band rating (Table 12). The condition changed when it came to renewable energy technologies as lower rating was assigned for properties where solar PV installation was suitable (conversion scale value 1) as compared to properties where it was unsuitable (conversion scale value 2). This is because only properties that were suitable for solar PV could be changed, while for unsuitable sites, change could not be implemented.

Nurmalini and Rahim (2017) also highlighted that establishing conversion scales (or a weight criteria) can ease the process of creating a normalisation matrix as qualitative data can then be examined quantitatively and provide a more logical output.

4.3.2. Normalisation of data

According to Nurmalini and Rahim (2017), the SAW method typically divides its attributes into cost and benefit to prioritize beneficial criteria over criteria that could potentially have a negative impact on the alternative. However, this depends on the type of data and the kind of analysis to be made. For some studies, all criteria can also be beneficial or positive, such as in the study for personnel selection where all 7 criteria for selection of an employee were considered beneficial (Ashrafi, Mojahed & Yusuff, 2010). Similarly, for this study, all the attributes were considered beneficial as each attribute contributed significantly towards creating sustainable social housing. Furthermore, the conversion values were assigned such that each hotspot had a lower overall value than the property in one of the best conditions.

Since all attributes were considered beneficial, the data for 1,565 properties was then normalised by dividing the data value by the maximum value in the column; this created a uniform maximum value of 1 for data against each attribute. An overview of the normalised values is provided in Table 17.

Table 17: Normalized property data against attributes

Property		**Fuel Poverty (40%)**	**Energy Efficiency (35%)**		**Fabric First (15%)**			**Carbon Emissions (6%)**	**Renewable Energy (4%)**
Sr. No.	**UPRN**	**Probability of Fuel Poverty**	**Energy Efficiency Rating**	**EESSH Compliance**	**Wall Insulation**	**Loft Insulation**	**Glazing**	**Environmental Impact Rating Band**	**Solar Energy Potential**
1	**123021651**	1.00	0.80	0.67	1.00	0.75	1.00	0.60	0.50
2	**123021652**	1.00	0.80	1.00	1.00	1.00	1.00	0.80	0.50
3	**123021654**	0.80	0.80	1.00	1.00	1.00	0.50	0.80	0.50
4	**123021657**	1.00	0.80	1.00	1.00	1.00	1.00	0.80	1.00
5	**123021659**	0.80	0.80	0.67	1.00	1.00	0.50	0.60	1.00
6	**123021665**	0.40	0.80	1.00	1.00	1.00	1.00	0.60	1.00
7	**123021672**	1.00	0.80	1.00	1.00	1.00	1.00	0.80	1.00
….	**….**	….	….	….	….	….	….	….	….
….	**….**	….	….	….	….	….	….	….	….
….	**….**	….	….	….	….	….	….	….	….

1558	**123025952**	0.20	0.80	0.67	1.00	1.00	1.00	0.80	1.00
1559	**123025953**	0.20	0.80	1.00	1.00	0.25	1.00	0.80	1.00
1560	**123025950**	0.20	0.80	1.00	0.50	1.00	1.00	0.80	1.00
1561	**123025951**	0.20	0.80	1.00	1.00	1.00	1.00	0.80	1.00
1562	**123025957**	0.20	0.80	1.00	1.00	0.25	1.00	0.80	1.00
1563	**123025958**	0.20	0.80	0.67	1.00	1.00	1.00	0.80	1.00
1564	**123025955**	0.20	0.80	1.00	1.00	1.00	1.00	0.80	1.00
1565	**123025956**	0.20	0.80	0.67	1.00	1.00	1.00	0.80	1.00

4.4. Obtaining final ranks through a combined approach

The normalised data was then multiplied by the corresponding weight of the attribute. Attributes with multiple types of data were assigned an average percent weight. For example, fabric first upgrades had an overall weightage of 15%, thereby, assigning 5% weight to each of its corresponding data (wall, insulation, loft insulation and glazing). Lastly, each row was summed, and the values obtained were assigned a ranking using the RANK function of excel. The highest value indicated a site of high priority in terms of retrofit and redevelopment, while the lowest value indicated the lowest priority (Table 18). The ranks were later organized in an ascending order. As an example, the details and attributes of the highest priority sites are presented in Figures 11, 12 and 13. These properties presented the highest level of fuel poverty as well as the lowest energy efficiency band ratings. They also showed similar values in terms of their carbon emissions. In terms of insulation of building envelope, the properties did not rank very low, but due to the high weightage and value of fuel poverty, these properties were categorised as the highest priority.

An observable drawback of using SAW was that it could also select certain properties with some attributes that are performing well as high-risk areas. This was caused by the weightage assigned to each attribute; for example some properties unsuitable for RE technologies were placed at a higher priority list than properties which were suitable for RE technologies because of the former property having a higher risk of fuel poverty and bad energy efficiency rating. Bester (2004) also noted this and highlighted that during the compilation of criteria, there is a likelihood that poorly performing alternatives can be selected as ideal solutions. As an example, Bester (2004) stated that an alternative which is performing well in two attributes but lacks in one could be considered above an alternative that is doing well in all three attributes. However, in certain decision-making areas, the second alternative might be preferred. The results obtained by SAW are reasonable as it uses relatively simplistic calculations and less execution times than some MCDM methods. This was especially beneficial while working with a large data set. It also provided a way to normalise the decision matrix, which is not a feature of some MCDM methods. Furthermore, since SAW is a proportional linear transformation method, it allowed the relative order of the standardised scores to remain the same.

Overall, the collaborative use of SAW and Saaty’s 1-9 scale proved to be effective in highlighting hotspots for retrofit of properties owned by LHA. This combination was ultimately chosen because Saaty’s 1-9 scale adds a human element to the analysis and essentially operates at a functional level, while SAW can easily analyse alternatives and improve the decision-making process significantly.

By combining the use of Saaty's scale to determine importance of attributes and then using SAW to weigh various alternative properties using the predetermined weights, large amounts of quantitative and qualitative data was analysed and a computerised system for decision making was ultimately created. Previous studies successfully implemented a combination of the two methods and observed that the decisions obtained were accurate and valid. This was especially observed in a study where the AHP-SAW approach was used to select suitable landfill sites in Iraq (Alqradaghi, Ali & Al-Ansari, 2020) as well as for selection of natural fibre reinforced non-asbestos organic brake friction composites (Kumar *et al.* 2019).

 *Figure 11: Highest priority area – PA3 3LY*	Probability of Fuel Poverty: **99.5%** Solar PV suitability: **Not Suitable** EESSH Compliant: **Not Likely** Energy Efficiency Rating: **F-G** CO$_2$ emissions: **7.3 tCO$_2$/year** Glazing Type: **Double/Triple** Loft Insulation: **No Loft** Wall Insulation: **Insulated**
 *Figure 12: Second Highest Priority Area – PA3 3LY*	Probability of Fuel Poverty: **99.5%** Solar PV suitability: **Not Suitable** EESSH Compliant: **Not Likely** Energy Efficiency Rating: **F-G** CO$_2$ emissions: **5.9 tCO$_2$/year** Glazing Type: **Double/Triple** Loft Insulation: **No Loft** Wall Insulation: **Insulated**
 *Figure 13: Third Highest Priority Area – PA3 3LY*	Probability of Fuel Poverty: **99.3%** Solar PV suitability: **Not Suitable** EESSH Compliant: **Not Likely** Energy Efficiency Rating: **F-G** CO$_2$ emissions: **7.3 tCO$_2$/year** Glazing Type: **Double/Triple** Loft Insulation: **0-99 mm** Wall Insulation: **Insulated**

Table 18: Final Rankings obtained through multiplication of weights and summing the rows

Property		**Fuel Poverty (40%)**	**Energy Efficiency (35%)**		**Fabric First (15%)**			**Carbon Emissions (6%)**	**Renewable Energy (4%)**	**Weights (Sum of Rows)**	**RANK**
Sr. No.	**UPRN**	**Probability of Fuel Poverty**	**Energy Efficiency Rating**	**EESSH Compliance**	**Wall Insulation**	**Loft Insulation**	**Glazing**	**Environmental Impact Rating Band**	**Solar Energy Potential**		
1	**123021651**	0.4	0.14	0.117	0.05	0.0375	0.05	0.036	0.02	0.454805662	**390**
2	**123021652**	0.4	0.14	0.175	0.05	0.05	0.05	0.048	0.02	0.539035288	**94**
3	**123021654**	0.32	0.14	0.175	0.05	0.05	0.025	0.048	0.02	0.50942093	**434**
4	**123021657**	0.4	0.14	0.175	0.05	0.05	0.05	0.048	0.04	0.561765437	**22**
5	**123021659**	0.32	0.14	0.117	0.05	0.05	0.025	0.036	0.04	0.45958551	**509**
6	**123021665**	0.16	0.14	0.175	0.05	0.05	0.05	0.036	0.04	0.541631745	**684**
7	**123021672**	0.4	0.14	0.175	0.05	0.05	0.05	0.048	0.04	0.580048217	**22**
….	….	….	….	….	….	….	….	….	….	….	**….**
….	….	….	….	….	….	….	….	….	….	….	**….**
….	….	….	….	….	….	….	….	….	….	….	**….**
1558	**123025952**	0.08	0.14	0.175	0.05	0.0125	0.05	0.048	0.04	0.516011168	**1180**
1559	**123025953**	0.08	0.14	0.175	0.025	0.05	0.05	0.048	0.04	0.528511235	**1015**

1560	**123025950**	0.08	0.14	0.175	0.05	0.05	0.05	0.048	0.04	0.553510906	**956**
1561	**123025951**	0.08	0.14	0.175	0.05	0.0125	0.05	0.048	0.04	0.516011324	**830**
1562	**123025957**	0.08	0.14	0.117	0.05	0.05	0.05	0.048	0.04	0.495177592	**1015**
1563	**123025958**	0.08	0.14	0.175	0.05	0.05	0.05	0.048	0.04	0.553511161	**1180**
1564	**123025955**	0.08	0.14	0.117	0.05	0.05	0.05	0.048	0.04	0.495177592	**830**
1565	**123025956**	0.08	0.14	0.117	0.05	0.05	0.05	0.048	0.04	0.495177592	**1180**

4.5. ArcGIS dashboard

An interactive display was created using ArcGIS dashboard that served as a framework for a decision support tool. The final ranks and corresponding data were uploaded, and the prioritised areas were identified by classifying the data into natural breaks. Through this, properties ranked 1-391 were classified as low priority, those ranked 392-782 were classified as medium priority, 783-1174 were classified as high priority and any rank above that (till 1565) was classified as very high priority.

Figure 14: Map created on ArcGIS online highlighting priority areas

Two variations of the dashboard were also developed to highlight hotspot areas. This was done to show the possible visualisation techniques that can be adopted while developing a comprehensive and customisable DSS (which will be able to show all dashboards in one specific map, hence allowing the user to display the attributes they wish to work on or present). The GIS dashboard is overall highly customisable, which is also a property that should be kept in mind while developing an automated DSS.

The first variation consisted of data related to emissions, fuel, and environmental factors (Figure 15). It showed the percentage of properties having a low EPC band rating, as well as emitters with high carbon emissions. This type of information was useful. The dashboard also helped to display the number of properties with a very high probability of fuel poverty. Through this dashboard, it was possible to develop an interactive list that showed data against the attributes of the top 100 properties with the highest priority. The dashboard was also able to highlight properties on the map and zoom into the layer if a specific property was selected, hence showing its accurate location.

The second variation depicted information about the building envelope such as wall insulation, loft insulation, room in roof prediction and glazing type for windows (Figure 16). This was done to provide information that could help the decision-making process for fabric-first upgrades in properties. Even here, the use of tables and mapping allowed a better visualisation of data against the relevant ranking.

Environmental, Fuel and Emissions Data

This dashboard highlights priority areas for retrofit and redevelopment in LHA properties and statistics of important parameters

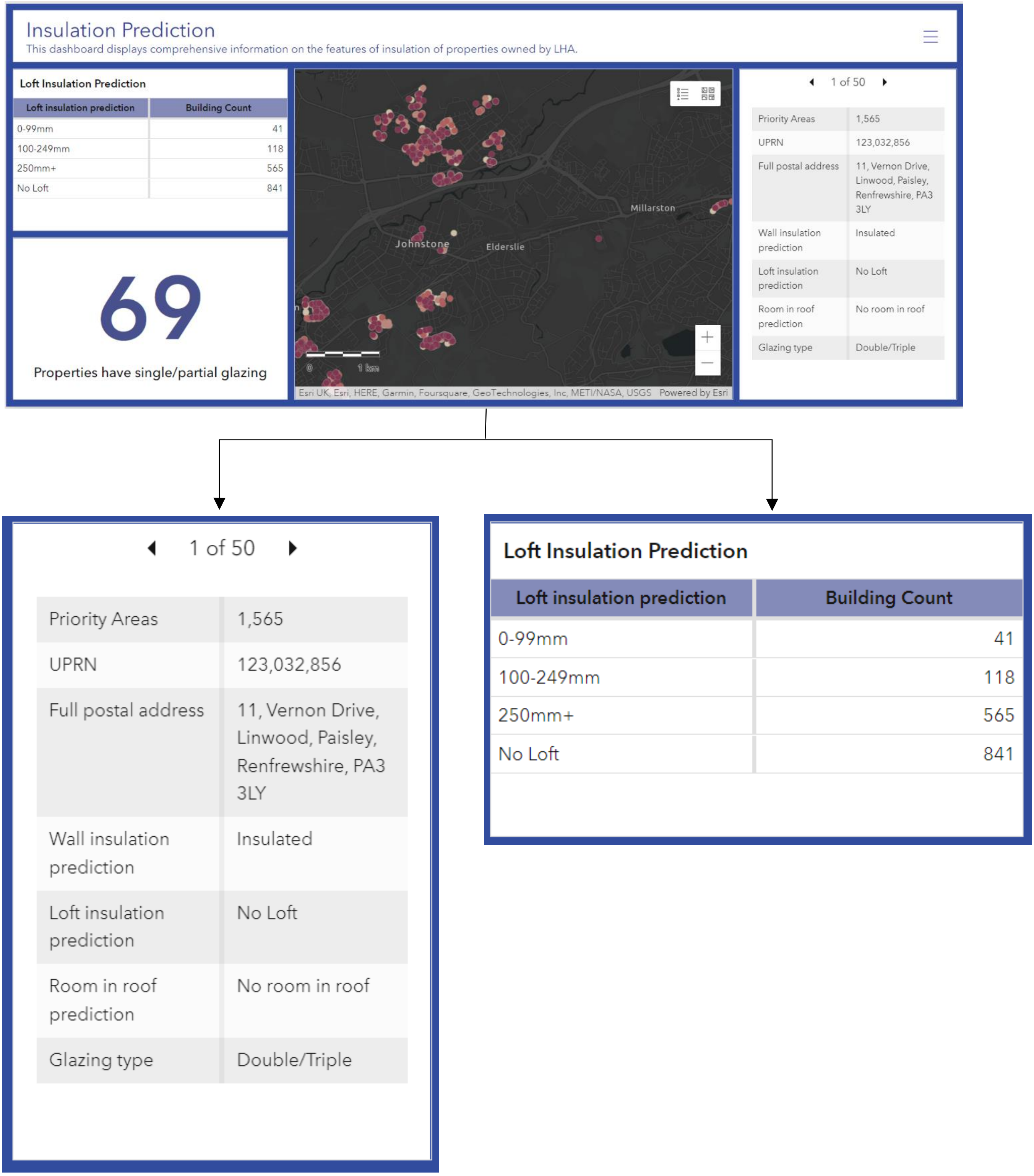
Hotspot Features

Site ID: 123,032,856
CO2 emissions: 7.30
Energy Efficiency Rating: F-G
EESSH Compliant: Likely not compliant
Solar PV Suitability: Not suitable
Probability of Fuel Poverty: 0.99

Site ID: 123,032,869
CO2 emissions: 5.90
Energy Efficiency Rating: F-G
EESSH Compliant: Likely not compliant
Solar PV Suitability: Not suitable
Probability of Fuel Poverty: 0.99

Site ID: 123,022,765
CO2 emissions: 7.30
Energy Efficiency Rating: F-G
EESSH Compliant: Likely not compliant
Solar PV Suitability: Not suitable
Probability of Fuel Poverty: 0.99

Figure 15: Salient features of the Environment, fuel, and emissions dashboard



Insulation Prediction

This dashboard displays comprehensive information on the features of insulation of properties owned by LHA.

Loft Insulation Prediction

Loft insulation prediction	Building Count
0-99mm	41
100-249mm	118
250mm+	565
No Loft	841

69

Properties have single/partial glazing

1 of 50

Priority Areas	1,565
UPRN	123,032,856
Full postal address	11, Vernon Drive, Linwood, Paisley, Renfrewshire, PA3 3LY
Wall insulation prediction	Insulated
Loft insulation prediction	No Loft
Room in roof prediction	No room in roof
Glazing type	Double/Triple

1 of 50

Priority Areas	1,565
UPRN	123,032,856
Full postal address	11, Vernon Drive, Linwood, Paisley, Renfrewshire, PA3 3LY
Wall insulation prediction	Insulated
Loft insulation prediction	No Loft
Room in roof prediction	No room in roof
Glazing type	Double/Triple

Loft Insulation Prediction

Loft insulation prediction	Building Count
0-99mm	41
100-249mm	118
250mm+	565
No Loft	841

Figure 16: Salient features of the insulation dashboard framework

Furthermore, the insulation dashboard highlights different kinds of features of the dashboard which can be adopted to a DSS. This includes representing all relevant data by order of rank on the dashboard, which can help decision makers assess and compare data. Other tables and figures also provide a snapshot of the current conditions of properties owned by the housing associations, which may help in prioritising.

Upon carrying out a user engagement process, it was found that the dashboard presented accurate findings that could help LHA not only address the issues faced by their properties in an organized manner but also help them gather grants and funding to carry out those activities. It was also highlighted that more data will need to be acquired and added into the dashboard to create a holistic and comprehensive dashboard. It was also found that the dashboard was quite user-friendly and can be easily used by managerial staff without requiring extensive programming and IT knowledge. Hence it will also be easily understandable by non-expert observers or users.

There is a drawback, however, to developing a dashboard like this. A user cannot change the information provided in the dashboard to observe new kinds of information in real-time. This will need to be done in the back end to display new results or observations. However, since this project only aimed to provide a framework for a dashboard, future works can focus on creating an automated version of it.

Overall, developing a framework for a DSS helped capture current data and highlighted critical indicators and hotspots in the realm of social housing in a simple and interactive way. Adam and Pomerol (2008) pointed out that the key element of the dashboard is not the design of the interface, meaning that a good dashboard does not necessarily require extensive programming, but should be able to express accurate data. This is what the dashboard aimed to represent and highlight.

Eventually the dashboard could ease the decision-making process for DMs and help them understand the patterns and quality of data. It can also help them visualize it in a more meaningful way by taking away the unnecessary issues regarding data management, such as cleaning up multiple data sets and analysing them collectively and showing them a clear picture of the current scenario. It can specifically help LHA highlight and display hotspots to potential donors.

Chapter 5: **Summary of Limitations**

- This project considered the human element of decision-making through surveys and discussions. However, this presented some challenges regarding the acquisition of ranking attributes, where AHP could not be applied for the survey due to the complexity that respondents would face while carrying out pair-wise comparison of 20 attributes. Therefore, a more pragmatic solution had to be adopted and a simple ranking system was established that was easy for the respondents to follow. The pairwise comparison was later carried out for select attributes whose data was available and was then verified by a representative of LHA.
- There are very few discussions in literature over using a combined approach of SAW and Saaty's 1-9 scale (which is part of the AHP). Though the method is proven to be successful in other projects, the effectiveness of the method needs to be established in a social housing context.
- 15 out of 20 identified attributes did not have corresponding data available; this was especially the case for social attributes where thermal comfort and user familiarity of residents was unknown. Furthermore, some data needed supporting information to be further analysed with the attributes. For example, although the information of fuel bills per property were provided, but it was unknown how many rooms or appliances were present in each property or even the number of residents that shared those bills.
- A lot of the data acquired consisted of predictions, instead of actual values or information. This can be slightly problematic while identifying hotspots and creating an action plan for the retrofit of selected properties as there could be a possibility that the stated issue is untrue.
- The MCDM method was chosen based on the secondary information acquired through literature. If not for time constraints, the methods should have been tested out before final application to derive results. This would have resulted in finding the most accurate method that worked in the context of this project.
- During compilation of criteria, there is a chance that SAW can select data that is performing well in two criteria and poorly in one, instead of well in all three because of the assigned weights. This can cause issues for a decision-maker who might want to select data where all criteria perform well.

- A dashboard’s strength of presenting data visually can also be quite limiting as it only provides an overview of data against predefined metrics. This usually prevents users from asking and answering new questions and exploring new interactions with different types of data. Users can also not go into the data to observe the causes of the top results.

Chapter 6: **Recommendations**

The following recommendations were drafted to fulfil the fourth objective of assessing the applicability and replicability of the current results and dashboard on other housing associations in Scotland. These were derived based on the results and the limitations of the project.

- Develop a data collection strategy to fill missing information on environmental, social, and economic attributes for each property and create a centralised open-source database for constant updating. The type of data includes demographic data, information on current rent, fire safety information of each property, average capital costs of retrofit works, user ambient comfort and user familiarity with building systems and materials. Once data for the 15 attributes is collected, the ranking system can automatically assign weights to the data and the new hotspots can then be presented on the ArcGIS dashboard.
- The current results can also be combined with geographical and socio-economic data to provide a holistic view on the current situation of social housing in Scotland from a broader perspective.
- Engage residents in the retrofit works through awareness programmes to sensitise residents on the value of sustainability and study their needs to apply design changes to enhance their comfort. This also consists of including the residents and other experts in the dashboard application process.
- The decision-maker can control the risk of recommending alternatives that are performing poorly in certain areas by using the Ordered Weighting Averaging (OWA) approach.
- For certain criteria having a qualitative structure or uncertain structure, fuzzy numbers can be used to obtain an evaluation matrix and the proposed model can be enlarged using fuzzy numbers.
- The current dashboard framework can be further refined by using more sophisticated visualisation methods that allow the user to add and subtract data easily, and essentially visualise based on their preferences and needs. This will also include creating a software that encapsulates the MCDM method to generate results automatically through automated data retrieval, analysis and presentation on a GIS-based system. Therefore, there is a need for integrated tools, which produce automatic graphic output (plots and graphs).
- The possibility of expanding the dashboard to allow the decision maker to explore different scenarios by modifying the input and maximising returns. This can be especially useful

when making complex decisions that not only affect residents but also need to address policies and guidelines laid out by the government.

- The dashboard can also be made visually customisable to make it appropriate for the type of audience that is visualising or using it i.e. display of data and phrases can be changed according to whether it’s a layman or an expert.
- A collaborative approach will need to be adopted to scale the project and make it applicable to other housing associations within Scotland. This would include dialogue and consultations with all housing associations as well as the Scottish Government to create a comprehensive ranking system where all stakeholder priorities are considered.

Chapter 7: **Conclusion**

Decision makers face immense difficulties and complexities in making decisions with regards to improving social housing in Scotland due to inundation of unorganized data, new policies, and modified guidelines. Therefore, it is imperative to develop comprehensive multi-criteria decision support system that encapsulate the needs and requirements of tenants, housing providers and governing bodies. This project developed a case study for Linstone Housing Association and developed a framework for a dashboard that can facilitate their decision-making processes. This was done through extensive literature review, stakeholder discussions, and a combined approach of using SAW and Saaty's 1-9 scale.

Attributes to help identify hotspots were shortlisted through literature review and mock interviews. Next, experts were identified and interviewed to establish rankings of over 20 attributes. Five attributes, which consisted of "alleviation of fuel poverty", "energy efficiency", "carbon emissions", "fabric first upgrades" and "renewable energy technologies", for which corresponding data of properties was available, were compared and weighed against each other using Saaty's 1-9 scale. SAW was then applied for normalisation of the corresponding data and establishing the final ranks, which helped identify the hotspots. Through the simple use of MS Excel, a large dataset of 1,565 properties could be reorganised and arranged based on their features and attributes. When compared with previous research, the combined use of SAW and Saaty's 1-9 scale can improve the accuracy ranking results and can also serve as a basic guideline for decision making. The MCDM approach can further be enhanced by obtaining and adding the missing data against attributes, thereby, making the existing rankings much more elaborate and fruitful.

Presenting the results on ArcGIS dashboards provided a useful visual aid that could potentially help decision-makers prioritise properties during the retrofit and redevelopment process, as well as gain funding for the process. This type of DSS also helped provide an interactive mode of decision making that helps the user make basic changes by using filters and interact with charts. A more automated and visually sophisticated DSS dashboard can also be developed that enhances user experience and make the decision-making process quicker and less work intensive.

The current study can be extended to other housing associations by applying the same methodology and recommendations provided. Further research and collaborative effort will be required to create a combined DSS that could be applicable to all housing associations in Scotland.

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